Syllabus: Introduction to Computational Social Science

Yongjun Zhang, PhD*

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Time and Location: July 15-July 19 9AM-12:30PM Beijing Time
Email: Yongjun.Zhang@stonybrook.edu/yz1981@nyu.edu
Virtual Office Hours: Appointments as needed

Disclosure: The syllabus should be treated as a resource. We are not going to cover all of these materials. The grades will follow NYU Shanghai Policy, but you should not worry about it because this course will serve as a platform to connect you with other colleagues working on some interesting projects.

Course Description

A multidisciplinary introduction to computational social science (CSS), emphasizing how social scientists develop and make use of computational-related social theory and methods to understand and analyze social behavior in the digital era. Topics include the CSS history and its latest development as well as how to use computational methods to collect, process, analyze, and visualize large-scale data from the real world to address social problems. This course also introduces state-of-the-art tools such as Python, R, and its scientific libraries for web-scraping, natural language processing, topic modeling, and machine learning techniques for text, image, and video data.

Note that computational methods related to NLP and computer vision are growing fast, and our course focuses more on how we can use these methods for social science research instead of surveying all state-of-the-art techniques.

Course Learning Objectives

This course provides students a set of computational social science toolkits to acquire the knowledge or skills necessary to achieve the following learning outcomes:

1. Understand the history and development as well as the major concepts in computational social science.
2. Understand the methods of inquiry used by social scientists to explore social and behavioral phenomena.
3. Master the ability to apply computational tools and knowledge to problem-solving.
4. Design and build computational systems to explore and analyze some aspects of the human world.

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Textbooks and Other Useful Materials

Required:

1. Justin Brimmer, Margaret E. Roberts, and Brandon M. Stewart. 2022. Text as Data: A New Framework for Machine Learning and the Social Sciences. Princeton University Press.
2. Ian Goodfellow, Yoshua Bengio and Aaron Courville. Deep Learning. https://www.deeplearningbook.org/.
3. Hadley Wickham and Garrett Grolemund. 2016. R for Data Science. https://r4ds.had.co.nz/
4. Francois Chollet. Deep Learning with Python, Second Edition. OR Deep Learning with R.

Optional:

1. Matthew J. Salganik. 2017. Bit by Bit: Social Research in the Digital Age. Princeton University Press. http://www.bitbybitbook.com
2. Steven Bird, Ewan Klein, and Edward Loper. 2009. Natural Language Processing with Python. O'Reilly Media. https://www.nltk.org/book/
3. Hadley Wickham. Advanced R. https://adv-r.hadley.nz/
4. Kieran Healy. Data Visualization. https://socviz.co/
5. Eli Stevens, Luca Antiga, Thomas Viehmann. Deep Learning with PyTorch.

Course website:

Our course materials, schedule, and announcements will be hosted on intro2css https://yongjunzhang.com/intro2css/.

Course Requirements and Evaluation

The course will be broadly divided into three modules: CSS basics, Text as Data, and Image as Data. Each module will introduce the basic and latest methods as well as relevant social research using associated methods. Students can choose the specific module that is particularly helpful in their research to develop their final research proposal. For each meeting, it is a mix of mini-lecture, guest speech, instructor or student-led discussions, and lab training. In the mini-lecture, the instructor will give an overview of the field and the development of research methods. In the mini-lab, the RAs will use R, Python, and relevant programming languages to walk through each method and prepare students with the necessary computational skills for their research. Students will be evaluated based on the following aspects:

Research Proposal.

Students are required to develop a short research proposal (or use an existing one) integrating at least one of the methods introduced in the course. Particularly students are encouraged to use large-scale administrative and digital trace data hosted by Google BigQuery and other platforms or scraped by themselves.

Coding Challenge.

Students are required to complete four coding challenges. The instructor will release problem sets as the semester progresses. Students need to submit a code report as well as the R or python script.

Class Participation.

Students are required to attend every session and prepare the assigned readings before each session. Students are also required to participate in the class discussion.

Course Policies

We all share responsibility for maintaining an appropriate learning environment. For this reason, please mute yourself if attending zoom meetings or when others are speaking so that your peers are not distracted. Finally, all offline or online classroom behavior and discourse should reflect the values of respect and civility.

Composition of Final Grades

Research Proposal x 1	30
Coding Challenge (4 x 15)	60
Class Participation	10
Total	100 points

Grade Scale:

95-100 = A	75-79 = B-	0-59 = F
90-94 = A-	70-74 = C+	
85-89 = B+	65-69 = C	
80-84 = B	60-64 = C-	

Schedule

Note: The instructor reserves the right to modify the schedule as deemed necessary.

Module 1: CSS Basics

Day 1 (07-15-2022)

Unit 1. Welcome and Introduction to CSS

Topics: CSS, Big Data, and Data Science.

Assigned Readings:

1. Lazer et al. 2009. "Computational Social Science." Science. https://www.science.org/doi/full/10.1126/science.1167742
2. David M. J. Lazer et al. 2020. "Computational social science: Obstacles and opportunities." Science, 369, 6507, Pp. 1060-1062. Publisher's Version Copy at https://j.mp/2YIuWdh
3. Edelman et al. 2020. "Computational Social Science and Sociology." Annual Review of Sociology. https://doi.org/10.1146/annurev-soc-121919-054621
4. David Donoho. 2015. 50 Years of Data Science. http://courses.csail.mit.edu/18.337/2015/docs/50YearsDataScience.pdf
5. Buyalskaya, A., Gallo, M. and Camerer, C.F., 2021. The golden age of social science. Proceedings of the National Academy of Sciences, 118(5). https://www.pnas.org/doi/10.1073/pnas.2002923118

Lab:

1. Github and version control; understand basic git commands, like git clone, git fetch, git pull, and git push;
2. install all necessary software like python, R, Rstudio, notebook, colab, github desktop, etc;
3. Understand how to use the command line, like how to run Python using terminal, etc.

Unit 2. Conceptualizing CSS and Programming

Topics: methodological approach; algorithm bias; measurement bias; research ethics; etc.

Assigned Readings:

1. Laura K. Nelson. 2017. Computational Grounded Theory: A Methodological Framework. Sociological Methods and Research. https://journals.sagepub.com/doi/full/10.1177/0049124117729703
2. Justin Brimmer, Margaret E. Roberts, and Brandon M. Stewart. 2022. Text as Data. Chapter 2 Social Science Research and Text Analysis.
3. Obermeyer, Ziad, et al. 2019. "Dissecting racial bias in an algorithm used to manage the health of populations." Science 366.6464: 447-453. https://www.science.org/doi/full/10.1126/science.aax2342
4. Schwemmer, Carsten, et al. 2020. "Diagnosing gender bias in image recognition systems." Socius. https://journals.sagepub.com/doi/full/10.1177/2378023120967171
5. Wagner, Claudia, et al. 2021. "Measuring algorithmically infused societies." Nature 595.7866: 197-204. https://www.nature.com/articles/s41586-021-03666-1
6. Lazer, David, et al. 2021. "Meaningful measures of human society in the twenty-first century." Nature 595.7866: 189-196. https://www.nature.com/articles/s41586-021-03660-7
7. R for data science. Chapter 1-3. (Lab reading, Pls spend some time reading these chapters)

Lab:

1. Basic programming in R or python
2. Understand how to read/save files
3. Basic data wrangling using tidyverse etc.
4. Understand regular expression

Unit 3. Machine Learning

Topics: Basics on supervised machine learning, deep learning

Assigned Readings:

1. Ian Goodfellow, Yoshua Bengio and Aaron Courville. Deep learning. Chapter 5 and chapter 6. https://www.deeplearningbook.org/lecture_slides.html
2. Grimmer, Justin, Margaret E. Roberts, and Brandon M. Stewart. "Machine Learning for Social Science: An Agnostic Approach." Annual Review of Political Science 24 (2021): 395-419. https://www.annualreviews.org/doi/abs/10.1146/annurev-polisci-053119-015921
3. Molina, Mario, and Filiz Garip. "Machine learning for sociology." Annual Review of Sociology 45 (2019): 27-45. https://osf.io/a6r9g/download
4. Athey, Susan, and Guido W. Imbens. "Machine learning methods that economists should know about." Annual Review of Economics 11 (2019): 685-725. https://arxiv.org/abs/1903.10075
5. Mehrabi, N., Morstatter, F., Saxena, N., Lerman, K. and Galstyan, A., 2021. A survey on bias and fairness in machine learning. ACM Computing Surveys (CSUR), 54(6), pp.1-35. https://dl.acm.org/doi/abs/10.1145/3457607
6. Francois Chollet. Deep Learning with Python, Second Edition. Chapter 1-3.
7. Optional: Max Kuhn and Kjell Johnson. Applied Predictive Modeling. https://link.springer.com/content/pdf/10.1007/978-1-4614-6849-3.pdf
8. Optional: R caret Package: https://topepo.github.io/caret/

Lab:

1. Using R caret package to do some basic supervised machine learning
2. Train a model to predict the gender of U.S. baby names using SSA data (code challenge)
3. SSA baby name data

Module 2: Text as Data

Day 2 (07-16-2022)

Unit 4. Making sense of text as data

Topics: Natural Language Processing; Big Data and Parallel Computing

Assigned Readings:

1. Grimmer, Justin, Stewart, Brandon M. 2013. "Text as Data: The Promise and Pitfalls of Automatic Content Analysis Methods for Political Texts." Political Analysis 21:267–97. https://www.jstor.org/stable/pdf/24572662.pdf

2. Barberá, P., Boydstun, A.E., Linn, S., McMahon, R. and Nagler, J., 2021. Automated text classification of news articles: A practical guide. Political Analysis, 29(1), pp.19-42. https://doi.org/10.1017/pan.2020.8

3. Monroe, Burt L., Colaresi, Michael P., Quinn, Kevin M.. 2008. "Fightin' Words: Lexical Feature Selection and Evaluation for Identifying the Content of Political Conflict." Political Analysis 16:372–403. https://doi.org/10.1093/pan/mpn018

4. Nardulli, Peter F., Althaus, Scott L., Hayes, Matthew. 2015. "A Progressive Supervised-learning Approach to Generating Rich Civil Strife Data." Sociological Methodology 45:148–83. https://journals.sagepub.com/doi/full/10.1177/0081175015581378

Lab:

1. Introduction to basic text analysis

2. How to run basic NLP tasks in R or Python

3. Read Chapters 1-3. Natural Language Processing with Python.

Unit 5. Getting Textual Data: Web Scraping, API, and Big Data

Topics: Introducing web scraping and API.

Assigned Readings:

1. Sobel, Benjamin LW. "A New Common Law of Web Scraping." Lewis Clark L. Rev. 25 (2021): 147.

2. Luscombe, A., Dick, K. and Walby, K., 2022. Algorithmic thinking in the public interest: navigating technical, legal, and ethical hurdles to web scraping in the social sciences. Quality Quantity, 56(3), pp.1023-1044.

3. Twitter Academic API: https://developer.twitter.com/en/products/twitter-api/academic-research

4. Lin, H., Nalluri, P., Li, L., Sun, Y. and Zhang, Y., 2022, May. Multiplex Anti-Asian Sentiment before and during the Pandemic: Introducing New Datasets from Twitter Mining. In Proceedings of the 12th Workshop on Computational Approaches to Subjectivity, Sentiment & Social Media Analysis (pp. 16-24). https://aclanthology.org/2022.wassa-1.2/

5. Google Cloud APIs: https://cloud.google.com/apis

6. Google API Key: https://developers.google.com/maps/documentation/maps-static/get-api-key

7. Google BigQuery: https://cloud.google.com/bigquery/docs/quickstarts

8. Lazer, D. and Radford, J., 2017. Data ex machina: introduction to big data. Annual Review of Sociology, 43, pp.19-39. https://www.annualreviews.org/doi/abs/10.1146/annurev-soc-060116-053457

9. Brown, J.R. and Enos, R.D., 2021. The measurement of partisan sorting for 180 million voters. Nature Human Behaviour, 5(8), pp.998-1008. https://www.nature.com/articles/s41562-021-01066-z

10. Hofstra, B., Kulkarni, V.V., Galvez, S.M.N., He, B., Jurafsky, D. and McFarland, D.A., 2020. The diversity–innovation paradox in science. Proceedings of the National Academy of Sciences, 117(17), pp.9284-9291. https://www.pnas.org/doi/epdf/10.1073/pnas.1915378117

11. Congressional Record for the 43rd-114th Congresses: Parsed Speeches and Phrase Counts https://data.stanford.edu/congress_text

Lab:

1. Using R or python to scrape data from websites or social media platforms (e.g., twitter) (code challenge)

2. Understand how to use webdriver in data scraping

3. Understand how to use Google Cloud Service/Google API (e.g., How to use python to get data from bigquery)

Unit 6. Retrieving Information: Topic Modeling

Topics: LDA and Structural Topic Model; Model Applications.

Assigned Readings:

1. Blei, David M. 2012. “Probabilistic Topic Models.” Communications of the ACM 55:77–84. (LDA) https://dl.acm.org/doi/10.1145/2133806.2133826

2. Mohr, John W., Bogdanov, Petko. 2013. “Introduction—Topic Models: What They Are and Why They Matter.” Poetics 41 (6): 545–69. https://www.sciencedirect.com/science/article/pii/S0304422X13000685

3. Roberts, M.E., Stewart, B.M. and Tingley, D. 2014. stm: R package for structural topic models. Journal of Statistical Software, 10(2), pp.1-40.****** (A package intro paper) http://statistik-jstat.uibk.ac.at/article/view/v091i02

4. DiMaggio, Paul, Nag, Manish, Blei, David. 2013. “Exploiting Affinities between Topic Modeling and the Sociological Perspective on Culture: Application to Newspaper Coverage of U.S. Government Arts Funding.” Poetics 41:570–606. https://www.sciencedirect.com/science/article/pii/S0304422X13000661

5. Roberts, M.E., Stewart, B.M., Tingley, D., Lucas, C., Leder-Luis, J., Gadarian, S.K., Albertson, B. and Rand, D.G., 2014. "Structural topic models for open-ended survey responses." American Journal of Political Science, 58(4), pp.1064-1082. (STM) https://onlinelibrary.wiley.com/doi/full/10.1111/ajps.12103

6. Barron, A.T., Huang, J., Spang, R.L. and DeDeo, S., 2018. "Individuals, institutions, and innovation in the debates of the French Revolution." Proceedings of the National Academy of Sciences, 115(18), pp.4607-4612. https://www.pnas.org/doi/abs/10.1073/pnas.1717729115

7. Choudhury, P., Wang, D., Carlson, N.A. and Khanna, T., 2019. Machine learning approaches to facial and text analysis: Discovering CEO oral communication styles. Strategic Management Journal, 40(11), pp.1705-1732. https://onlinelibrary.wiley.com/doi/full/10.1002/smj.3067

8. Barberá, P., Casas, A., Nagler, J., Egan, P.J., Bonneau, R., Jost, J.T. and Tucker, J.A., 2019. Who leads? Who follows? Measuring issue attention and agenda setting by legislators and the mass public using social media data. American Political Science Review, 113(4), pp.883-901. https://doi.org/10.1017/S0003055419000352

9. Grootendorst, M., 2022. BERTopic: Neural topic modeling with a class-based TF-IDF procedure. arXiv preprint arXiv:2203.05794. https://doi.org/10.48550/arXiv.2203.05794

Lab:

1. Steps to implement topic models via R (R library stm and topicmodels).

2. Steps to implement topic models via python gensim

Day 3 (07-16-2022)

Unit 7. Word Embedding and Transformers

Topics: Word embedding and transformers

Assigned Readings:

1. Mikolov, T., Sutskever, I., Chen, K., Corrado, G.S. and Dean, J., 2013. Distributed representations of words and phrases and their compositionality. Advances in neural information processing systems, 26. https://arxiv.org/abs/1310.4546

2. Rong, Xin. "word2vec parameter learning explained." arXiv preprint arXiv:1411.2738 (2014).

3. Pennington, J., Socher, R. and Manning, C.D., 2014, October. Glove: Global vectors for word representation. In Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP) (pp. 1532-1543). https://aclanthology.org/D14-1162.pdf

4. Wu, X., Lin, W., Wang, Z. and Rastorgueva, E., 2020. Author2vec: A framework for generating user embedding. arXiv preprint arXiv:2003.11627. https://arxiv.org/abs/2003.11627

5. Nikhil Garg, Londa Schiebinger, Dan Jurafsky, and James Zou. 2018. Word embeddings quantify 100 years of gender and ethnic stereotypes. PNAS 201720347 (2018). doi: 10.1073/pnas.1720347115

6. Nelson, Laura K. "Leveraging the alignment between machine learning and intersectionality: Using word embeddings to measure intersectional experiences of the nineteenth century US South." Poetics (2021): 101539. https://www.sciencedirect.com/science/article/pii/S0304422X21000115

7. Kozlowski, A.C., Taddy, M., and Evans, J.A., 2019. The Geometry of Culture: Analyzing the Meanings of Class through Word Embeddings. American Sociological Review. https://journals.sagepub.com/doi/abs/10.1177/0003122419877135

8. Rheault, L. and Cochrane, C., 2020. Word embeddings for the analysis of ideological placement in parliamentary corpora. Political Analysis, 28(1), pp.112-133. https://doi.org/10.1017/pan.2019.26

9. Murray, D., Yoon, J., Kojaku, S., Costas, R., Jung, W.S., Milojević, S. and Ahn, Y.Y., 2020. Unsupervised embedding of trajectories captures the latent structure of mobility. arXiv preprint arXiv:2012.02785. https://arxiv.org/abs/2012.02785

10. Devlin, Jacob, et al. "Bert: Pre-training of deep bidirectional transformers for language understanding." arXiv preprint arXiv:1810.04805 (2018). https://arxiv.org/abs/1810.04805

11. Wankmüller, Sandra. "Neural Transfer Learning with Transformers for Social Science Text Analysis." arXiv preprint arXiv:2102.02111 (2021). https://arxiv.org/abs/2102.02111

12. Liu, Q., Kusner, M.J. and Blunsom, P., 2020. A survey on contextual embeddings. arXiv preprint arXiv:2003.07278. https://arxiv.org/abs/2003.07278

13. Vicinanza, P., Goldberg, A. and Srivastava, S., 2021. Quantifying Vision through Language Demonstrates that Visionary Ideas Come from the Periphery. https://osf.io/j24pw/download

Lab:

1. How to use word embedding/transformer in R or Python to achieve NLP tasks

Unit 8. Text as Data (4)-Sentiment Analysis

Assigned Readings:

1. Paxton, Pamela, Kristopher Velasco, and Robert W. Ressler. "Does use of emotion increase donations and volunteers for nonprofits?." American Sociological Review 85.6 (2020): 1051-1083. https://journals.sagepub.com/doi/abs/10.1177/0003122420960104

2. Flores, René D. "Do anti-immigrant laws shape public sentiment? A study of Arizona's SB 1070 using Twitter data." American Journal of Sociology 123.2 (2017): 333-384. https://www.journals.uchicago.edu/doi/abs/10.1086/692983

3. Hassan, Tarek A., et al. "Firm-level political risk: Measurement and effects." The Quarterly Journal of Economics 134.4 (2019): 2135-2202. https://doi.org/10.1093/qje/qjz021

4. De Amicis, C., Falconieri, S. and Tastan, M., 2021. Sentiment analysis and gender differences in earnings conference calls. Journal of Corporate Finance, 71, p.101809. https://www.sciencedirect.com/science/article/pii/S0929119920302534

5. Cook, Gavin, Junming Huang, and Yu Xie. "How COVID-19 has Impacted American Attitudes Toward China: A Study on Twitter." arXiv preprint arXiv:2108.11040 (2021). Cook,G.,Huang,J.andXie,Y.,2021.HowCOVID-19hasImpactedAmericanAttitudesTowardChina:AStudyonTwitter.arXivpreprintarXiv:2108.11040.

Lab:

1. How to conduct sentiment analysis in R or Python.

2. Use Twitter data to train a sentiment analysis model (code challenge).

Module 3: Image as Data

Day 4 (07-17-2022)

Unit 9. Making sense of image as data

Topics: why image as data? How do we use images for social research?

Assigned Readings:

1. Torres, M. and Cantú, F., 2022. Learning to see: Convolutional neural networks for the analysis of social science data. Political Analysis, 30(1), pp.113-131. https://doi.org/10.1017/pan.2021.9

2. Jean, N., Burke, M., Xie, M., Davis, W.M., Lobell, D.B., and Ermon, S., 2016. Combining satellite imagery and machine learning to predict poverty. Science, 353(6301), pp.790-794. https://www.science.org/doi/abs/10.1126/science.aaf7894

3. Jean, N., Burke, M., Xie, M., Davis, W.M., Lobell, D.B., and Ermon, S., 2016. Combining satellite imagery and machine learning to predict poverty. Science, 353(6301), pp.790-794. Read the supplement: https://science.sciencemag.org/content/sci/suppl/2016/08/19/353.6301.790.DC1/Jean.SM.pdf

4. Joo, J. and Steinert-Threlkeld, Z.C., 2018. Image as data: Automated visual content analysis for political science. arXiv preprint arXiv:1810.01544. https://arxiv.org/abs/1810.01544

5. Han Zhang and Jennifer Pan. 2019. CASM: A Deep-Learning Approach for Identifying Collective Action Events with Text and Image Data from Social Media. Sociological Methodology. https://journals.sagepub.com/doi/abs/10.1177/0081175019860244

6. Deng, J., Dong, W., Socher, R., Li, L.J., Li, K. and Fei-Fei, L., 2009, June. Imagenet: A large-scale hierarchical image database. In Computer Vision and Pattern Recognition, 2009. CVPR 2009. IEEE Conference on (pp. 248–255). Ieee. https://ieeexplore.ieee.org/abstract/document/5206848/

7. Denton, E., Hanna, A., Amironesei, R., Smart, A. and Nicole, H., 2021. On the genealogy of machine learning datasets: A critical history of ImageNet. Big Data & Society, 8(2), p.20539517211035955. https://journals.sagepub.com/doi/abs/10.1177/20539517211035955

8. Reeves, B., Robinson, T. and Ram, N., 2020. Time for the human screenome project. https://www.nature.com/articles/d41586-020-00032-5

Lab:

1. Basic knowledge about using R or Python to obtain and process images

2. Extra Resource: http://neuralnetworksanddeeplearning.com/

Unit 10. A brief survey of computer vision tools for social sciences

Topics: Methods to implement image recognition, extract useful image information, machine learning methods, transfer learning approach, etc.

Assigned Readings:

1. LeCun, Y., Bengio, Y. and Hinton, G., 2015. Deep learning. Nature, 521(7553), pp.436-444. https://www.nature.com/articles/nature14539

2. Goodfellow et al. Deep Learning. Chapter 6-10.

3. Watch the video and read notes of Introduction to Convolutional Neural Network: http://cs231n.github.io/convolutional-networks/

4. Krizhevsky, A., Sutskever, I. and Hinton, G.E., 2012. Imagenet classification with deep convolutional neural networks. In Advances in neural information processing systems (pp. 1097–1105).https://dl.acm.org/doi/10.1145/3065386

5. Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., Erhan, D., Vanhoucke, V. and Rabinovich, A., 2015. Going deeper with convolutions. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 1-9). https://www.cv-foundation.org/openaccess/content_cvpr_2015/html/Szegedy_Going_Deeper_With_2015_CVPR_paper.html

6. Bressem, K.K., Adams, L.C., Erxleben, C., Hamm, B., Niehues, S.M. and Vahldiek, J.L., 2020. Comparing different deep learning architectures for classification of chest radiographs. Scientific reports, 10(1), pp.1-16. https://www.nature.com/articles/s41598-020-70479-z

7. Li, Shan, and Weihong Deng. "Deep facial expression recognition: A survey." IEEE transactions on affective computing (2020). https://ieeexplore.ieee.org/abstract/document/9629313/

8. Liu, Zhuang, et al. "A ConvNet for the 2020s." arXiv preprint arXiv:2201.03545 (2022). https://arxiv.org/abs/2201.03545

9. Dosovitskiy, A., Beyer, L., Kolesnikov, A., Weissenborn, D., Zhai, X., Unterthiner, T., Dehghani, M., Minderer, M., Heigold, G., Gelly, S. and Uszkoreit, J., 2020. An image is worth 16x16 words: Transformers for image recognition at scale. arXiv preprint arXiv:2010.11929. https://arxiv.org/abs/2010.11929

10. Liu, Z., Lin, Y., Cao, Y., Hu, H., Wei, Y., Zhang, Z., Lin, S. and Guo, B., 2021. Swin transformer: Hierarchical vision transformer using shifted windows. In Proceedings of the IEEE/CVF International Conference on Computer Vision (pp. 10012-10022). https://arxiv.org/abs/2103.14030

11. Chaudhari, S., Mithal, V., Polatkan, G. and Ramanath, R., 2021. An attentive survey of attention models. ACM Transactions on Intelligent Systems and Technology (TIST), 12(5), pp.1-32. https://dl.acm.org/doi/abs/10.1145/3465055

12. Khan, S., Naseer, M., Hayat, M., Zamir, S.W., Khan, F.S. and Shah, M., 2021. Transformers in vision: A survey. ACM Computing Surveys (CSUR). https://dl.acm.org/doi/abs/10.1145/3505244

Lab: Image data storage, cleaning, and processing in Python.

Day 5 (07-16-2022)

Unit 11. Main frameworks to analyze image data

Topics: how to use Keras (or Pytorch) frameworks to analyze image data and train your neural network.

Assigned Readings:

1. Chollet, Francois. Deep learning with Python. Simon and Schuster, 2021. Chapter 4-9.
2. Deep Learning with Pytorch. Chapter 1-8.
3. TensorFlow Tutorial: https://www.tensorflow.org/tutorials
4. Explore some code examples: https://keras.io/examples/
5. Pytorch Tutorial: https://pytorch.org/tutorials/beginner/deep_learning_60min_blitz.html
6. Check facenet project: https://github.com/davidsandberg/facenet
7. Check openface project: http://cmusatyalab.github.io/openface/

Lab

1. Google Cloud Service; TensorFlow; Keras; R packages (torch or keras).
2. An example using pytorch to replicate the Jean et al's result: https://github.com/joshzyj/predicting-poverty-replication
3. Use google map api to obtain google images/Use Jean's model to predict economic outcomes/visualize and map the outcomes (code challenge)

Optional Module: Audio and Video as Data

Unit 12. Audio and Video data

Topics: Introducing basic methods to process acoustic data and speech recognition; Introducing basic methods to process video data; introducing social research based on video data

Assigned Readings:

1. Dietrich, Bryce J., Matthew Hayes, and Diana Z. O'brien. "Pitch perfect: Vocal pitch and the emotional intensity of congressional speech." American Political Science Review 113.4 (2019): 941-962. https://doi.org/10.1017/S0003055419000467

2. Dietrich, Bryce J. "Using motion detection to measure social polarization in the US House of Representatives." Political Analysis 29.2 (2021): 250-259. https://doi.org/10.1017/pan.2020.25

3. Qin and Yang. 2019. What you say and how you say it matters. Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, Florence, Italy. https://aclanthology.org/P19-1038/?ref=https://codemonkey.link

4. Choudhury, Prithwiraj, et al. "Machine learning approaches to facial and text analysis: Discovering CEO oral communication styles." Strategic Management Journal 40.11 (2019): 1705-1732. https://onlinelibrary.wiley.com/doi/abs/10.1002/smj.3067

Lab:

1. Using Keras, Tensorflow, and DeepSpeech to build and train a speech recognition model and object detection model.

2. Explore Essentia: https://essentia.upf.edu/documentation.html and https://mtg.github.io/essentia-labs/news/tensorflow/2020/01/16/tensorflow-models-released/

3. Explore librosa:https://librosa.org/doc/latest/index.html

4. Stanford Cable TV News Analyzer: https://tvnews.stanford.edu/methodology

5. YOLO3: https://pjreddie.com/media/files/papers/YOLOv3.pdf

6. Explore YOLO3 (You Only Look Once–for Object Detection): https://www.youtube.com/watch?v=MPU2HistivI&feature=youtu.be&ab_channel=JosephRedmon

7. Here is the instruction of how to use YOLO3: https://pjreddie.com/darknet/yolo/

Optional Module: Place and Map as Data

Unit 13. Place and Map data

Topics: Introducing basic methods to process geospatial data.

Assigned Readings:

1. Moro, E., Calacci, D., Dong, X. and Pentland, A., 2021. Mobility patterns are associated with experienced income segregation in large US cities. Nature communications, 12(1), pp.1-10. https://www.nature.com/articles/s41467-021-24899-8

2. Chang, S., Pierson, E., Koh, P.W., Gerardin, J., Redbird, B., Grusky, D. and Leskovec, J., 2021. Mobility network models of COVID-19 explain inequities and inform reopening. Nature, 589(7840), pp.82-87. https://www.nature.com/articles/s41586-020-2923-3?te=1&nl=opinion-today&emc=edit_ty_20201216

3. Hou, X., Gao, S., Li, Q., Kang, Y., Chen, N., Chen, K., Rao, J., Ellenberg, J.S. and Patz, J.A., 2021. Intracounty modeling of COVID-19 infection with human mobility: Assessing spatial heterogeneity with business traffic, age, and race. Proceedings of the National Academy of Sciences, 118(24). https://www.pnas.org/content/118/24/e2020524118.short

4. Athey, S., Ferguson, B.A., Gentzkow, M. and Schmidt, T., 2020. Experienced segregation (No. w27572). National Bureau of Economic Research. https://www.nber.org/papers/w27572

5. Wang, Q., Phillips, N.E., Small, M.L. and Sampson, R.J., 2018. Urban mobility and neighborhood isolation in America's 50 largest cities. Proceedings of the National Academy of Sciences, 115(30), pp.7735-7740. https://www.pnas.org/content/115/30/7735.short

6. Small, M.L., Akhavan, A., Torres, M. and Wang, Q., 2021. Banks, alternative institutions and the spatial–temporal ecology of racial inequality in US cities. Nature Human Behaviour, 5(12), pp.1622-1628. https://www.nature.com/articles/s41562-021-01153-1

Lab

1. Learn how to use QGIS, R, and Python to conduct geo-spatial analysis.

Unit 14. Research Paper Presentation

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