**Artificial Intelligence in the Social Sciences**

**2022 - Bogotá Summer School**

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1. **Summary and Course Objectives**

Artificial intelligence (AI) for social sciences allows the study of social phenomena using data-driven methods to generate insight from large-scale, digital trace data. Data of human traces has become abundant in the digital age, as human and machine agents interact to build increasingly complex, diverse, and interdependent systems. For example, people connect and interact through online social networks, allowing them to participate in various social activities and thereby enables new managerial insights. In this course, we will attend to these prospects and challenges of AI for businesses and organizations, as well as to innovative use cases. Key aspects include the use of novel (often unstructured) datasets, scaling analyses to large-scale datasets with large population sizes, and using AI to generate new insights for social sciences and improve decision-making for the better of society. Among others, we will answer specific questions of immediate impact in our course (e.g., How can AI help reaching the United Nations’ Sustainable Development Goals? How can explainable AI help in management decision-making?).

This course will introduce you to some of the major applications of AI in social sciences (e.g., management, economics, etc.), as well as the downstream implications for social sciences in general. One major objective of this course is to introduce a formal framework to address some of these issues. To do so, we will introduce students to common machine learning algorithms: linear regression, nearest neighborhood, decision trees, random forests and to the statistical foundations that support most of machine learning applications: approximation vs estimation tradeoff (i.e., bias vs. variance), model validation methodologies (cross validation, bootstrapping, bagging, etc.), regularization techniques, etc.

With this basic machine learning toolbox, we will frame formally some of these challenges. We will learn the difference between prediction and causality and how, what actually works, is related to identifying causality relations. We will study tools for explainability in specific models and we will also learn how privacy can be preserved through appropriate technical systems and governance standards. Across the lectures we will illustrate many some of these challenges using real world examples: crime prediction models, credit allocation, public health, etc.

This course will be taught half in English and half in Spanish.

1. **Contents**

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| **Day** | **Topic** | **References** |
| **1** | **Theory:**  Statistical Learning Theory Fundamentals.  **Application:** Prediction vs. Causality  **Practical session:**  Introduction to Python | **Theory:**  [LS]  [JWHT]: Capítulo 1,2.,  [HTF]: Capítulo 1,2.  **Application:**  Athey, Imbens [2019]. |
| **2** | **Theory:**  Basic techniques: Linear regression, nearest neighbor, logistic regression, trees, random forest, regularization cross validation, bagging, ROC curve.  **Application:**  Mangrove Ecosystem Mapping Satellite Images and  Random Forest.  **Practical session:**  The basic ML techniques in Python. | **Theory:**  [JWHT]: Chapters 3,4,5,6  **Application:**  Mangrove Ecosystem Mapping Using Sentinel-1 and Sentinel-2 Satellite Images and Random Forest Algorithm in Google Earth Engine |
| **3** | **Theory**  Explainability: Variable importance, partial dependence plots,SHAP values, etc.  **Application:**  Crime prediction  **Practical sesssion:** Crime Models: Kernel Density Estimation | **Theory:**  **Application:** Benavides, H., Gomez O., Dulce M., Rodriguez, P., Riascos, A., and Moreno, J. *2021.* |
| **4** | **Theory:**  Causality in Machine Learning*.*  **Application:**  Causal impact of police patrolling  **Practical session:** | **Theory:**  [D]: An Introduction to Causal Inference.  Kleinberg, Ludwig, Mullainathan, Obermeyer [2015], Zhao y Hastie (2019) |
| **5** | **Theory:**  Privacy  **Practical session:**  Modelo de Warner | **Theory:**  Catherine F. Higham, Desmond J. Higham. [2018] |
| **6** | **Theory:**  Bringing AI into practice  **Practical session:** (extra time to wrap-up from last week) | **Theory:**  Ng [2019]  Fountaine [2016] |
| **7** | **Theory:**  AI in financial forecasting  **Practical session:**  (predict stocks/macro) | **Theory:**  Kraus [2017] |
| **8** | **Theory:** AI in public policy: Monitoring progress toward Sustainable Development Goals  **Practical session:**  (predict SDGs) | **Theory:**  Vinuesa [2020]  Toetzke [2022] |
| **9** | **Theory:** Session:  Leveraging open data for AI in social sciences  **Practical session:**  (e.g. predict check-ins from POIs or predict crime from POIs) | **Theory:**  Wang [2022] |
| **10** | **Theory:** The human-AI interface: Explainable AI to empower managers  **Practical session:** Feature importance / SHAP (e.g. in crime prediction) | **Theory:**  Senoner [2021] |

1. **Methodology**

The course will be graded in the following way:

* Programming assignment 1 (30% of the final grade)
* Programming assignment 2 (30% of the final grade)
* Capstone project proposal (10% of the final grade)
* Capstone project (30% of the final grade)

1. **Grading System**

Grades will be numeric between zero and five with two decimal places.

1. **University Rules and MAAD Protocol**

This course is subject to the University of los Andes general guidelines and principles as stated in: <https://secretariageneral.uniandes.edu.co/images/documents/reglamento-maestria-web-2020.pdf>

Any member of the community that is subject to, witnesses or has knowledge of a conduct of mistreatment, harassment, threat, discrimination, sexual or gender violence (MAAD) must report the case to the University. This, in order that institutional actions can be taken to handle the case, ensuring the well-being of the affected people.

For additional information please visit: <https://decanaturadeestudiantes.uniandes.edu.co/index.php/es/sobre-la-decanatura/827>

or write to: [lineamaad@uniandes.edu.co](mailto:lineamaad@uniandes.edu.co)

1. **Main References**

* [LS]: Luxburg, U., B. Scholkopf. 2008. Statistical Learning Theory: Models, Concepts and Results.  
  [http://arxiv.org/abs/0810.4752](about:blank)
* [JWHT]: Introduction to Statistical Learning with Applications in R.

[http://www-bcf.usc.edu/~gareth/ISL/](about:blank)

* [HTF]: Hastie, T., Tibshirani, R. y J. Hastie. 2009. The Elements of Statistical Learning: Data Minning, Inference and Prediction. Segunda Edición. Springer

[http://web.stanford.edu/~hastie/local.ftp/Springer/OLD/ESLII\_print4.pdf](about:blank)

* [P]. Pearl, J. 2016. Causal Inference in Statistics - A Primer. Wiley.
* [AP]: Joshua Angrist and Jörn-Steffen Pischke. 2009. Mostly Harmless Econometrics. Princeton University press.
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* Fountaine, McCarthy, Saleh. 2016. What Artificial Intelligence Can and Can’t Do Right Now. Harvard Business Review. <https://hbr.org/2016/11/what-artificial-intelligence-can-and-cant-do-right-now>
* Kraus, Feuerriegel. 2017. Decision support from financial disclosures with deep neural networks and transfer learning. Decision Support Systems.
* Vinuesa, et al. 2020. The role of artificial intelligence in achieving the Sustainable Development Goals. Nature Communications.
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* Wang, Gopal, Shankar, Pancras. 2022. Forecasting venue popularity on location-based services using interpretable machine learning. Production & Operations Management.
* Senoner, Netland, Feuerriegel. 2021. Using explainable artificial intelligence to improve process quality: Evidence from semiconductor manufacturing. Management Science.