FALL 2025

DATA SCIENCES + OPERATIONS

# DSO 599

## CAUSAL INFERENCE WITH MACHINE LEARNING FOR BUSINESS ANALYTICS

Section(s): 16349

MW 3:30 – 4:50pm


Instructor: Mladen Kolar

mkolar@marshall.usc.edu


Units: 3

Office: BRI-306B

## WHY TAKE THIS COURSE?

Go beyond prediction and uncover real cause-and-effect in business decision-making! This advanced elective combines causal inference with machine learning to help you design experiments, analyze data, and generate actionable insights using Python. Ideal for MSBA students looking to strengthen their analytics toolkit and stand out in the job market.

SCHEDULE OF CLASSES

## COURSE OBJECTIVES

Master the tools to estimate causal effects, design experiments, and drive data-informed decisions. This course emphasizes hands-on application of causal inference and machine learning to real-world business challenges.

## KEY CONCEPTS

Explore core concepts in causal inference including experimental design, treatment effect estimation, and bias reduction. Learn advanced tools like double machine learning, synthetic control, and causal forests through hands-on coding, real-world data, and interactive case studies.

## Course Description

This course focuses on using causal inference and machine learning to move beyond prediction and understand the true impact of business decisions. Students will learn how to design experiments, analyze observational data, and estimate treatment effects using tools like randomized experiments, instrumental variables, difference-in-differences, and double machine learning. Through Python-based assignments, case studies, and a group project, students will apply these methods to real-world problems in marketing, finance, and operations. Designed for MSBA students, this hands-on, advanced elective equips students to generate actionable insights and drive strategic, data-informed decisions. DSO 530 is a prerequisite for this course, and while students should be familiar with Python, the use of AI copilots to assist with coding is encouraged.

USC Marshall
School of Business

**DSO-599: Causal Inference w/ Machine Learning for Business Analytics**
**Fall 2025**
**3 Units, Mon/Wed 3:30-4:50 pm**

**Instructor:** *Mladen Kolar*
**Office:** *TBD*
**Office Hours:** *TBD*
**Email:** *mkolar@usc.edu*

## COURSE DESCRIPTION

The ability to differentiate causation from correlation is essential for strategic decision-making in modern business. With organizations relying increasingly on data-driven insights, it is not enough to predict outcomes—businesses must understand the impact of interventions such as marketing campaigns, operational changes, or public policies. This course provides students with a comprehensive introduction to causal inference frameworks, blending classical methods with state-of-the-art machine learning techniques to address real-world challenges.

The course begins with foundational methods like randomized experiments, instrumental variables (IV), and difference-in-differences (DiD) and progresses toward more advanced techniques such as Double Machine Learning (DML), causal forests, and synthetic control methods. Students will explore these tools through hands-on coding assignments using Python and apply them in real-world scenarios across fields such as marketing, finance, and operations. Unlike courses focused solely on predictive analytics, this elective emphasizes causal reasoning—understanding what happens when a policy or decision changes, not just what is likely to happen. Through group projects, case studies, and interactive coding sessions, students will develop the ability to design experiments, conduct causal analysis, and generate actionable insights to solve business problems.

This course is designed for MSBA students and expands the analytics curriculum by providing tools to tackle high-dimensional data, observational studies, and complex causal relationships. By the end of the semester, students will have the skills to evaluate the effectiveness of business strategies, forecast policy impacts, and solve challenges that require a deep understanding of both causal inference and machine learning.

## COURSE OBJECTIVES

Upon successful completion of this course, students will be able to:

1. Design and analyze experiments to estimate causal effects using methods such as A/B testing, randomized experiments, and adaptive trials.
2. Apply advanced causal inference techniques, including Double Machine Learning (DML), synthetic control methods, and causal forests, to high-dimensional and observational data.
3. Develop and implement Python-based solutions for causal inference challenges, incorporating libraries such as EconML and scikit-learn to estimate treatment effects.
4. Communicate data-driven insights effectively by interpreting results and delivering actionable recommendations through group presentations and written reports.
5. Evaluate the limitations and assumptions of causal models and assess the robustness of findings through sensitivity analysis and diagnostic testing.

## COURSE MATERIALS

Course lecture notes will be posted online.

Readings from the following textbooks will be assigned before each class. Note that these textbooks are freely available online. We will not be linearly working our way through any of them.

- Hernan MA, Robins JM, Causal Inference: What If
- Cunningham S, Causal Inference: The Mixtape
- Chernozhukov V, Hansen C, Kallus N, Spindler M, Syrgkanis V, Applied Causal Inference Powered by Machine Learning and AI.

The following two references will be useful for reviewing machine learning topics:

- James, G., Witten, D., Hastie, T., & Tibshirani, R. (2021). An Introduction to Statistical Learning: With Applications in R (2nd ed.).
- Hastie, T., Tibshirani, R., & Friedman, J. (2009). The Elements of Statistical Learning: Data Mining, Inference, and Prediction (2nd ed.).

They are freely available online.

Statistical Software:

- We will be using the Python programming language.

You are responsible for ensuring that you have the necessary computer equipment and reliable internet access. Marshall has site licenses for a variety of software that students can access free of charge. A list of available software is located here. You are invited to explore what lab or loaner options exist. Contact the Marshall HelpDesk (213-740-3000 or HelpDesk@marshall.usc.edu) if you need assistance.

| GRADING |
| --- |

Final grades represent how you perform in the class relative to other students.

| | |
| --- | --- |
| Homework | 35% (7 assignments; each worth 5%) |
| Midterm | 20% (in week 9) |
| Final Project | 35% (60% write-up; 40% in-class presentation) |
| Participation | 10% |

PARTICIPATION

Participation will be evaluated based on classroom discussions, submission of in-class hands-on assignments, and contributions to the course discussion forum. Students are expected to engage actively during lectures, case studies, and group discussions, demonstrating thoughtful insights that connect the course material to real-world applications. Participation also includes the completion of in-class coding exercises using Python, ensuring that students develop practical skills and stay engaged throughout the course. Additionally, students are required to contribute to the online discussion forum by asking questions, responding to peers, and discussing key concepts and challenges.

Participation rubrics are detailed in Appendix II.

HOMEWORK

The course will include seven individual homework assignments designed to assess students' understanding and application of causal inference methods. While students are encouraged to discuss the homework assignments in groups, each student must submit their own work individually. This ensures that every student develops personal mastery of the material and can independently apply the concepts learned. Collaboration is allowed only at the level of conceptual discussion—directly sharing code or solutions will not be permitted, ensuring the integrity of individual work.

To accommodate unforeseen challenges that may arise during the semester, you have five late days for the problem sets. Each late day allows you to turn in an assignment up to 24 hours late. (Any fraction of a late day counts as one late day.) You may use multiple late days on the same problem set. Work submitted beyond the allowed late days will not receive credit.

Please note that we have provided the late day policy to help provide flexibility to you in managing your course load during the semester. If circumstances arise that require further accommodations, we encourage you to contact your academic advisor as well as the Office of Student Accessibility Services (OSAS) (see below) to help make appropriate arrangements. Out of fairness to all students, in the absence of an OSAS Accommodation Letter, we will generally be unable to provide accommodations beyond the late day policy above.

You will submit homework through Gradescope.

Each part of each homework will be graded as follows:
- You will receive zero points if you do not attempt it.
- If you attempt it, but there are either substantial methodological errors or major conceptual misunderstandings of the material, you will receive 2 points.

- If you attempt it and there are no substantial methodological errors or major conceptual misunderstandings of the material, you will receive 3 points.

TEAM/GROUP PROJECT

The course will include a group project designed to apply causal inference and machine learning techniques to a real-world business problem. Students will collaborate to identify a business challenge, apply appropriate causal methods, and analyze data using Python. The project will be evaluated through both a written report (60%) and an in-class presentation (40%). The report must clearly define the business problem, explain the methodology, present analytical results, discuss limitations, and offer actionable recommendations. Each group will present their findings, with every member participating to demonstrate collaborative effort. A peer evaluation component will ensure individual accountability within the group, with final grades reflecting both group performance and individual contributions. This project encourages the integration of course concepts with teamwork, effective communication, and practical business insights.

Students will work in teams of (up to) 6. Students will self-organize into teams.

EXAMS

The midterm exam will assess students' understanding of the core concepts and frameworks introduced in the first half of the course. The midterm exam will focus on the conceptual application of causal inference techniques to practical business problems. In addition to theoretical questions, the exam will include short coding exercises where students will apply relevant methods to a case-based scenario.

THE IMPORTANCE OF COURSE EVALUATIONS

The student course evaluations are valuable. This course is continuously improved, based on feedback from students and instructor observations.

EMERGENCY PREPAREDNESS

In case of a declared emergency if travel to campus is not feasible, the USC Emergency Information web site (https://www.usc.edu/emergency/) will provide safety and other information, including electronic means by which instructors will conduct class using a combination of USC's Brightspace learning management system (TBD), teleconferencing, and other technologies.

USE OF RECORDINGS

Pursuant to the *USC Student Handbook* (https://policy.usc.edu/studenthandbook/, pages 13 and 27), students may not record a university class without the express permission of the instructor and announcement to the class. In addition, students may not distribute or use notes, recordings, exams, or other intellectual property based on USC classes or lectures without the express permission of the instructor for purposes other than personal or class-related group study by students registered for the class. This restriction on unauthorized use applies to all information that is distributed or displayed for use in relationship to the class. Distributing course material without the instructor's permission will be presumed to be an intentional act to facilitate or enable academic dishonesty and is strictly prohibited. Violation of this policy may subject an individual or entity to university discipline and/or legal proceedings.

**USE OF AI GENERATORS**

In this course, you will be using Github Copilot to create code for data analysis in class, for assignments and on exams. However, no other generative AI tools are permitted on exams. The use of non-Copilot AI tools on assignments, while not strictly forbidden, is discouraged since the purpose of assignments is for you to learn the material and using these tools might negatively affect your learning process. To adhere to our university values, you must cite any non-Copilot, AI-generated material (e.g., text, images, etc.) included or referenced in your work and provide the prompts used to generate the content. Using an AI tool to generate content without proper attribution will be treated as plagiarism and reported to the Office of Academic Integrity. Please review the instructions in each assignment for more details on how and when to use AI Generators for your submissions.

## COURSE OUTLINE AND ASSIGNMENTS

*Week 1*

Lecture 1: Overview of Causality in Business Analytics
- Introduction to causal inference and its importance in business decision-making
- Correlation vs. Causation
- Examples from marketing, finance, and operations
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Lecture 2: Causal Inference Frameworks
- The Rubin Causal Model and potential outcomes
- Basics of treatment effects (ATE, ATT, ATC)
- Introduction to treatment assignment mechanisms

*Readings*

"Why Big Data Isn't Enough" by Sen Chai and Willy Shih. MIT Sloan Management Review
- What are the risks of relying solely on big data without causal analysis?
- How can domain knowledge enhance the insights gained from data analytics?
- Can machine learning models capture causality, or do they need to be supplemented with other methods?

What If, Chapter 1

*Week 2*

Lecture 3: Design and Analysis of Randomized Experiments
- Fundamentals of Randomization
- Control Groups and Treatment Groups
- Statistical Power and Sample Size Calculation
- Common Challenges in Randomized Experiments

Lecture 4: A/B Testing in Business Contexts
- What is A/B Testing?
- Designing an A/B Test
- Analyzing A/B Test Results

*Readings*

"Artea: Designing Targeting Strategies" by Eva Ascarza and Ayelet Israeli. HBP
What If, Chapter 2: Randomized Experiments.

### *Week 3*

Lecture 5: Advanced Design of Experiments and Adaptive Experiments
- Advanced Design of Experiments
  - Factorial Design
  - Crossover Design
- Blocking and Stratification
- Adaptive Experiments
  - Multi-armed bandit algorithms
  - Thompson Sampling

Lecture 6: Introduction to Graphical Models and Directed Acyclic Graphs (DAGs)
- Graphical Models: An Overview
- Causal Interpretation of DAGs
- Applications of DAGs in Business

*Readings*

*What If*, Chapter 6: Causal Diagrams

### *Week 4*

Lecture 7: Identifying Causal Effects and Applications of Graphical Models
- Identifying Causal Effects with Graphical Models
  - Backdoor and Frontdoor Criteria
  - Conditional Independence
- Causal Discovery and Model Selection
- Business Applications Using Graphical Models

Lecture 8: Hands on example: graphical models in action
- Introducing tools for construction of DAGs
- Building DAGs
- Identifying Confounders
- Estimating Causal Effects

*Readings*

What If, Chapter 6: Causal Diagrams
Applied Causal Inference Powered by ML and AI, Chapter 7 and 8

### *Week 5*

Lecture 9: Introduction to Propensity Score Estimation

- What is a Propensity Score? How to use Propensity Scores?
- Methods of Estimating Propensity Scores
- Uses of Propensity Scores
    - Matching
    - Weighting
    - Stratification

Lecture 10: Propensity Scores with Machine Learning

- Why Use Machine Learning for Propensity Score Estimation?
- Machine Learning Methods
    - Random Forests
    - Gradient Boosting
    - Neural networks

*Readings*

Causal Inference: Powered by ML and AI, Chapter 4 and 5

### *Week 6*

Lecture 11: Introduction to Doubly Robust (DR) Methods

- What are Doubly Robust Methods?
- Advantages of Doubly Robust Methods
- Implementing DR Methods with Machine Learning
- Hands-On Session: Applying Propensity Scores and DR Methods in Practice

Lecture 12: Introduction to Instrumental Variables (IV)

- When to Use Instrumental Variables
- IV Requirements
- Examples of Instruments in Business Contexts

*Readings*

Causal Inference: Powered by ML and AI, Chapter 12

### *Week 7*

Lecture 13: Hands on Applications of Instrumental Variables (IV) in Business Contexts

- Two-Stage Least Squares (2SLS)
- IV Estimation with Machine Learning

- Testing the Validity of Instruments
- IV Estimation Using Python

Lecture 14: Introduction to Heterogeneous Treatment Effects (HTE)

- Why Study Heterogeneous Treatment Effects?
- Average Treatment Effect (ATE) vs Heterogeneous Treatment Effects (HTE)
- Use Cases in Business
- Modeling HTE with Causal Trees and Causal Forests

*Readings*

Causal Inference: Powered by ML and AI, Chapter 14 and 15

"Generalized Random Forests" by Athey et al. (2019).

### *Week 8*

Lecture 15: Estimation of HTE Using Causal Forests

- Generalized Random Forests (GRF)
- Estimating Individual Treatment Effects (ITE)
- Hands-On Session

Lecture 16: Validation and Inference for HTE

- Cross-Validation for Causal Forests:
- Inference Methods for HTE
- Business Applications of HTE Validation
- A case study

Readings:

Causal Inference: Powered by ML and AI, Chapter 14 and 15

### *Week 9*

Lecture 17: Midterm Review Session

Lecture 18: Midterm

### *Week 10*

Lecture 19: Introduction to Double Machine Learning (DML)

- Why use DML?
- How does DML work?
- Example Application in Business

Lecture 20: Implementing DML in Practice

- hands-on practice using Python
- How to interpret results and assess model robustness
- Handling Model Complexity
- Limitations

*Readings*

"Double/Debiased Machine Learning for Treatment and Structural Parameters" by Chernozhukov et al. (2018).

### *Week 11*

Lecture 21: Causal Inference in Time-Series Data

- Challenges in Time-Series Causal Inference
- Granger Causality
- Interrupted Time-Series Design

Lecture 22: Synthetic Control Methods

- What is Synthetic Control?
- How Does Synthetic Control Work?
- Use Cases in Business and Policy

*Readings*

What If, Chapter 19

Abadie, A., Diamond, A., & Hainmueller, J. (2010). "Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Program."

## *Week 12*

Lecture 23: Introduction to Difference-in-Differences (DiD)

- Difference-in-Differences (DiD) Framework
- Parallel Trends Assumption
- Evaluating the impact of a targeted advertising campaign by comparing changes in sales in the targeted region with a control region

Lecture 24: Longitudinal Data Models for Time-Series Causal Inference

- Panel Data Models
- When to Use Fixed vs. Random Effects
- Analyzing the effect of seasonal promotions on customer spending patterns across multiple stores

*Readings*

Applied Causal Inference Powered by ML and AI, Chapter 16

Wooldridge, J. (2010). "Econometric Analysis of Cross Section and Panel Data."

## *Week 13*

Lecture 25: Introduction to Matrix Completion Methods

- The Matrix Completion Problem
- Low-Rank Matrix Completion
- Applications
    - Collaborative Filtering
    - Imputation
    - Forecasting

Lecture 26: Implementation and Applications of Matrix Completion

- hands-on experience implementing matrix completion algorithms
- the power of matrix completion in business applications
- imputation of missing panel data

*Reading*

Agarwal, A., Dahleh, M., & Shen, D. (2021). "Causal Matrix Completion."

"Matrix Completion Methods for Causal Panel Data Models" by Susan Athey, Mohsen Bayati, Nikolay Doudchenko, Guido Imbens, Khashayar Khosravi

### *Week 14*

*Lecture 27: Introduction to Regression Discontinuity Design (RDD)*

- What is RDD?
- RDD Assumptions
    - Continuity Assumption
    - Local Average Treatment Effect
- Applications in Business and Policy
    - Estimating the effect of a loyalty discount on customer retention, where the discount applies only to high-spending customers.

Lecture 28: Hands-On Implementation of RDD

- Implement RDD in Python
- Assess the validity of the continuity assumption and interpretation of LATE
- Discuss limitations of RDD

*Reading*

Applied Causal Inference Powered by ML and AI, Chapter 16

### *Week 15*

Lecture 29: In-Class Presentations (Day 1)

Lecture 30: In-Class Presentations (Day 2) & Course Wrap-Up

### *Finals week*

Work on the final project report. It is due during the University scheduled final exam day/time.

**Homework Assignments**

The deadline for the homework assignment is on Friday end of day (11.59PM). The following are the list of due dates:

| **Homework** | **Due Date** |
| --- | --- |
| HW 1 | Week 2 |
| HW 2 | Week 4 |
| HW 3 | Week 6 |
| HW 4 | Week 8 |
| HW 5 | Week 11 |
| HW 6 | Week 13 |
| HW 7 | Week 15 |

## OPEN EXPRESSION AND RESPECT FOR ALL

An important goal of the educational experience at USC Marshall is to be exposed to and discuss diverse, thought-provoking, and sometimes controversial ideas that challenge one's beliefs. In this course we will support the values articulated in the USC Marshall "Open Expression Statement" (https://www.marshall.usc.edu/open-expression-statement).

## ACADEMIC INTEGRITY

The University of Southern California is foremost a learning community committed to fostering successful scholars and researchers dedicated to the pursuit of knowledge and the transmission of ideas. Academic misconduct is in contrast to the university's mission to educate students through a broad array of first-rank academic, professional, and extracurricular programs and includes any act of dishonesty in the submission of academic work (either in draft or final form).

This course will follow the expectations for academic integrity as stated in the USC Student Handbook. All students are expected to submit assignments that are original work and prepared specifically for the course/section in this academic term. You may not submit work written by others or "recycle" work prepared for other courses without obtaining written permission from the instructor(s). Students suspected of engaging in academic misconduct will be reported to the Office of Academic Integrity.

Other violations of academic misconduct include, but are not limited to, cheating, plagiarism, fabrication (e.g., falsifying data), knowingly assisting others in acts of academic dishonesty, and any act that gains or is intended to gain an unfair academic advantage.

Academic dishonesty has a far-reaching impact and is considered a serious offense against the university. Violations will result in a grade penalty, such as a failing grade on the assignment or in the course, and disciplinary action from the university itself, such as suspension or even expulsion.

For more information about academic integrity see the student handbook or the Office of Academic Integrity's website, and university policies on Research and Scholarship Misconduct.

Please ask your instructor if you are unsure what constitutes unauthorized assistance on an exam or assignment or what information requires citation and/or attribution.

## STATEMENT ON UNIVERSITY ACADEMIC AND SUPPORT SYSTEMS

**Students and Disability Accommodations:**

USC welcomes students with disabilities into all of the University's educational programs. The Office of Student Accessibility Services (OSAS) is responsible for the determination of appropriate accommodations for students who encounter disability-related barriers. Once a student has completed the OSAS process (registration, initial appointment, and submitted documentation) and accommodations are determined to be reasonable and appropriate, a Letter of Accommodation (LOA) will be available to generate for each course. The LOA must be given to each course instructor by the student and followed up with a discussion. This should be done as early in the semester as possible as accommodations are not retroactive. More information can be found at osas.usc.edu. You may contact OSAS at (213) 740-0776 or via email at osasfrontdesk@usc.edu.

**Student Financial Aid and Satisfactory Academic Progress:**
To be eligible for certain kinds of financial aid, students are required to maintain Satisfactory Academic Progress (SAP) toward their degree objectives. Visit the Financial Aid Office webpage for undergraduate- and graduate-level SAP eligibility requirements and the appeals process.

**Support Systems:**

*Counseling and Mental Health - (213) 740-9355 – 24/7 on call*
Free and confidential mental health treatment for students, including short-term psychotherapy, group counseling, stress fitness workshops, and crisis intervention.
*988 Suicide and Crisis Lifeline - 988 for both calls and text messages – 24/7 on call*
The 988 Suicide and Crisis Lifeline (formerly known as the National Suicide Prevention Lifeline) provides free and confidential emotional support to people in suicidal crisis or emotional distress 24 hours a day, 7 days a week, across the United States. The Lifeline consists of a national network of over 200 local crisis centers, combining custom local care and resources with national standards and best practices. The new, shorter phone number makes it easier for people to remember and access mental health crisis services (though the previous 1 (800) 273-8255 number will continue to function indefinitely) and represents a continued commitment to those in crisis.
*Confidential Advocacy, Resources, and Education Center (CARE-SC) - (213) 740-9355(WELL) – 24/7 on call*
Free and confidential therapy services, workshops, and training for situations related to gender- and power-based harm (including sexual assault, intimate partner violence, and stalking). (New name as of 11/24)

*Office for Equity, Equal Opportunity, and Title IX (EEO-TIX) - (213) 740-5086*
Information about how to get help or help someone affected by harassment or discrimination, rights of protected classes, reporting options, and additional resources for students, faculty, staff, visitors, and applicants.

*Reporting Incidents of Bias or Harassment - (213) 740-2500*
Avenue to report incidents of bias, hate crimes, and microaggressions to the Office for Equity, Equal Opportunity, and Title for appropriate investigation, supportive measures, and response.

*The Office of Student Accessibility Services (OSAS) - (213) 740-0776*
OSAS ensures equal access for students with disabilities through providing academic accommodations and auxiliary aids in accordance with federal laws and university policy.

*USC Campus Support and Intervention - (213) 740-0411*
Assists students and families in resolving complex personal, financial, and academic issues adversely affecting their success as a student.

*Diversity, Equity and Inclusion - (213) 740-2101*
Information on events, programs and training, the Provost's Diversity and Inclusion Council, Diversity Liaisons for each academic school, chronology, participation, and various resources for students.

*USC Emergency - UPC: (213) 740-4321, HSC: (323) 442-1000 – 24/7 on call*

Emergency assistance and avenue to report a crime. Latest updates regarding safety, including ways in which instruction will be continued if an officially declared emergency makes travel to campus infeasible.

*USC Department of Public Safety - UPC: (213) 740-6000, HSC: (323) 442-1200 – 24/7 on call*
Non-emergency assistance or information.

*Office of the Ombuds - (213) 821-9556 (UPC) / (323-442-0382 (HSC)*
A safe and confidential place to share your USC-related issues with a University Ombuds who will work with you to explore options or paths to manage your concern.

*Occupational Therapy Faculty Practice - (323) 442-2850 or* otfp@med.usc.edu
Confidential Lifestyle Redesign services for USC students to support health promoting habits and routines that enhance quality of life and academic performance.

**Appendix II. SAMPLE CLASS PARTICIPATION STATEMENTS**

Class participation is an extremely important part of the learning experience in this course as the richness of the learning experience will be largely dependent upon the degree of preparation by *all* students prior to each class session.

A course that incorporates the frequent use of case analyses to illustrate the practical application of concepts and practices requires the student to diligently and thoroughly prepare cases and actively offer the results of the analyses and conclusions derived as well as recommendations during each class session. My expectation and that of your classmates are that you are prepared for *all* classes and will actively participate in and meaningfully contribute to class discussions.

In-class participation is also a critical part of this course's learning experience. Cold calling may take place to encourage active participation and to gain multiple perspectives and points of view, thus lending itself to the richness of the learning experience. In-class participation grading will be based on students' demonstrated willingness to participate and the quality of the comments expressed, rather than quantity. While some students are far more comfortable than others with class participation, *all* students should make an effort to contribute meaningfully.

Students will offer their opinions in group settings many times in their careers; thus, class participation serves to prepare students for this business experience.
The evaluating of in-class participation is based on the following:

- *Relevance* – Does the comment or question meaningfully bear on the subject at hand? Irrelevant or inappropriate comments can detract from the learning experience.
- *Responsiveness* – Does the comment or question connect to what someone else has said?
- *Analysis* – Is the reasoning employed consistent and logical? Has data from course materials, personal experience, or general knowledge been employed to support the assertions/findings?
- *Value* – Does the contribution further the understanding of the issues at hand?
- *Clarity* – Is the comment concise and understandable?

During class sessions, I frequently assume the role of a facilitator to encourage a discussion that includes perspectives from a variety of viewpoints and, secondly, to help pull together prevailing analyses and recommendations. The direction and quality of a discussion is the *collective responsibility of the class*.

For each in-class session two (2) points will be awarded to a student for relevant and meaningful participation, one (1) point for modest contributions to the class and zero (0) points for no participation or absence.

Class Participation—Behavioral Anchor Rating Scale:

Excellent Performance

- Initiates information relative to topics discussed
- Accurately exhibits knowledge of assignment content
- Clarifies points that others may not understand
- Shares personal experiences or opinions related to topic
- Offers relevant / succinct input to class
- Actively participates in class exercises
- Demonstrates ability to apply, analyze, evaluate & synthesize course material.
- Demonstrates willingness to attempt to answer unpopular questions
- Builds on other students' contributions

Average Performance

- Participates in group discussions when asked
- Demonstrates knowledge of course material
- Offers clear, concise, "good" information on class assignments
- Offers input, but tends to reiterate the intuitive
- Attends class regularly

Unacceptable Performance

- Fails to participate even when directly asked
- Gives no input to discussions
- Does not demonstrate knowledge of the readings
- Shows up to class: does nothing
- Distracts group / class
- Irrelevant discussion