Overview

This course provides a foundational understanding of static and dynamic discrete-choice models, with applications drawn from quantitative marketing and economics. The course will take a “hands on” approach to research. Class will be a combination of lectures, discussions of assigned articles, and hands-on empirical analysis. What you get out of this course depends on what you are willing to put into it.

To this end, the course has three broad goals: (1) to provide students with a conceptual understanding of key empirical methods; (2) to expose students to classic papers and recent research in marketing and empirical industrial organization in economics; (3) to give you the hands-on experience of implementing some of these methods in code.

The course material can be divided into three roughly equal parts:

1. Static discrete-choice models with individual-level data (sessions 1-3)
   - Random-utility maximization (RUM), multinomial logit, nested logit
   - Unobservable heterogeneity (latent class model, mixed logit)
   - State dependence, brand loyalty, learning

2. Static discrete-choice models with aggregate-level data (sessions 4-6)
   - Homogeneous aggregate logit model
   - Heterogeneous aggregate logit model
   - The supply-side model and equilibrium restrictions

3. Dynamic discrete-choice models with individual- or aggregate-level data (sessions 7-9)
   - Theory: Introduction to dynamic programming, recursive formulation with Bellman’s equation, contraction mapping theorem
   - Computation: Value function iteration, approximation techniques
   - Estimation: Nested Fixed-Point algorithm (Rust, 1987), conditional choice probabilities (Hotz & Miller, 1993)

I encourage students from other departments in Kellogg or outside the business school to enroll. Background in microeconomics and econometrics is definitely helpful, but students with even limited experience in these subjects have done well in the course. In these cases, a strong math background is especially important. Feel free to contact me if you have questions about whether your background is suitable for the class.
Grading

Your grade depends on

- Class participation (20%)
- Research presentation (10%)
- Homework assignments (70%)

There is no final exam.

Class Participation

Each of you is expected to contribute to class discussions. You should actively listen and think critically about the concepts and issues. Don’t be passive. Ask questions—this is an important part of being a good researcher. Good researchers like to discuss research.

In some sessions, there will be required papers that you should read prior to class. These papers can be found at the end of this syllabus, along with other recommended readings. You are only required to read those papers marked as [REQUIRED]. All other readings are optional.

Research Presentation

You will have an opportunity to present someone else’s paper to the class. In addition to letting you learn deeply about another paper, you will also practice your presentation skills.

There are two sessions in which you will have the chance to present: session 6 or session 10. I will provide more details and expectations during class.

Homework Assignments

As the assignments represent the bulk of your grade, I expect you to allocate significant effort to them. The goal of the coding assignments is to translate models into code. This involves getting comfortable with the coding language, the mathematical objects, testing, debugging, and structuring your code. Hence, you should code the model itself (e.g., the log-likelihood or objective function), but not necessarily the nuts and bolts such as the optimization routine. For instance, when you implement the multinomial logit, you cannot use the R function \texttt{mlogit}, but you can use the functions \texttt{optim} or \texttt{nlm} to optimize the log-likelihood.

Grading. I have high expectations for your work. As a PhD-level class, I assume you’re equally serious about learning the material and putting the appropriate effort into the assignments. I will grade the assignments using the following scale:

- High Pass (HP) - Vastly exceeded my expectations.
- Pass (P) - Met my expectations.
- Low Pass (LP) - Significantly below my expectations.
- Fail (F) - The majority of the assignment was incomplete or you did not turn in anything.

To receive an “A” in the course, it is not necessary to receive an HP on each of the assignments. However, you will definitely not receive an “A” if you earn P’s on all your assignments.

Due Dates. All assignments are due on Tuesdays just before class, to be submitted electronically.

Deliverables. To get credit for an assignment, you must submit (1) a PDF with your estimation results, discussion, and the output of your code and (2) a soft copy of the code. Make sure your code is clearly annotated/comments so that I can understand the logical flow, key components, main computations, etc. You may also be asked to explain your code in class, so you should come prepared to discuss your code’s logic and your design choices.

On Cooperation. I strongly encourage you to read the papers on your own to the best of your ability and then to discuss them with other students prior to class. On coding assignments, you should do these alone,
but you can ask your classmates questions, just not for code. Do not borrow code—not from a classmate and not from anywhere else. The point of the coding assignments is for you to become comfortable with translating models into estimation routines. Not only is it academically dishonest to use another student’s code, you rob yourself of this critical skill. Stealing code will result in a failing grade. If you are uncertain what would constitute stealing, ask me.

**Software**

**Coding**

I recommend implementing all the assignments in R and using RStudio as your development environment. Please let me know if you prefer an alternative, such as Matlab, Python or Julia. You are not allowed to use “high-level” statistical software (e.g., Stata, SAS, SPSS) for any part of any of the assignments.

I highly recommend that you use the tidyverse set of packages. This includes dplyr for manipulating data frames and ggplot2 for creating plots. These will serve you well in the long-run.

Some useful R links:

- R for Data Science.
- An online version of the book “Advanced R”.
- Advice on efficient R programming

**Homework Assignments**

I will not accept any homework assignments written up in Word, Excel, plain text, or similar. You have three options:

1. Use R Markdown. This has become quite popular in recent years as it lets you weave together Markdown, Latex, and R code/output. You can even create slides in R Markdown, and some Latex content is rendered immediately in the document (such as equations). Personally, I find this to be an extremely convenient tool. You should submit the source and compiled output.

2. Use Latex. If you don’t already know Latex, now is a good time to learn. You should submit the source “.tex” and the compiled PDF files. On Macs, you need MacTex. On Windows, I recommend MikTex. There are numerous Latex editors (e.g., TeXstudio, TeXnicCenter, WinEdit).

3. Use a WYSIWYG editor such as Lyx. I learned Latex before using Lyx and am grateful for that experience. Lyx is helpful in some ways (you can see equations rendered immediately) but some aspects of it are clunky. Submit both the lyx and PDF. (You still need install Latex to use Lyx.)

**Textbooks**

There is no required textbook for the course. However, I recommend looking at:


The book is available for free in the link above. I will reference some of its chapters in the session schedule. I also recommend checking out NBER Summer Institute Econometric Lectures, which sometimes have slides, extended notes, and videos (!):

- All lectures
- Imbens and Wooldridge covering various topics in econometrics
## Schedule

<table>
<thead>
<tr>
<th>Session</th>
<th>Topics</th>
<th>Due</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Jan 8</td>
<td>Descriptive vs. Structural Modeling, Multinomial Choice</td>
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<tr>
<td>2. Jan 15</td>
<td>Nested Logit, Unobserved Heterogeneity</td>
<td>HW 1</td>
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<tr>
<td>3. Jan 22</td>
<td>State Dependence I</td>
<td></td>
</tr>
<tr>
<td>5. Feb 5</td>
<td>Aggregate Discrete-Choice Models II</td>
<td>HW 3</td>
</tr>
<tr>
<td>6. Feb 12</td>
<td>Aggregate Discrete-Choice Models III, Presentations</td>
<td></td>
</tr>
<tr>
<td>10. Mar 12</td>
<td>Presentations, Buffer Time</td>
<td>HW 6</td>
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</tbody>
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<th>HW</th>
<th>Description</th>
<th>Due</th>
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<td>HW1</td>
<td>Multinomial Logit</td>
<td>Apr 10</td>
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<tr>
<td>HW2</td>
<td>Mixed Logit / Brand Loyalty</td>
<td>Apr 24</td>
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<tr>
<td>HW3</td>
<td>Homogeneous Aggregate Logit</td>
<td>May 1</td>
<td>10%</td>
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<tr>
<td>HW4</td>
<td>Heterogeneous Aggregate Logit</td>
<td>May 15</td>
<td>15%</td>
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<tr>
<td>HW5</td>
<td>Dynamic Programming I</td>
<td>May 22</td>
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<tr>
<td>HW6</td>
<td>Dynamic Programming II</td>
<td>June 5</td>
<td>10%</td>
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## Readings

### Session 1


- Train, K. (2009), Chapters 2 and 3. (background on logit choice models)


### Session 2

- Train, K. (2009), Chapters 4 and 6. (nested logit and mixed logit)


• Train, K. (2009), Chapters 14 (EM algorithm).

**Session 3**


**Background**


**Session 4**


Session 5


Session 6


Session 7

- Stokey & Lucas, Chapters 1- 4. (Posted on Canvas. The models are mostly from macroeconomics, but the background content could be helpful)

Session 8


Session 9


Session 10

Buffer time: we will finish up dynamics and/or I will talk about recent research.