Instructor: Jens Ludwig  
Time and Location: Mondays, 9:00-11:50am, Keller Center Room 0010  
Contact: jludwig@uchicago.edu  
Teaching Assistants: Gabriela Saade (gabysaade@uchicago.edu)

Course Description

It is hard to name a sector that will not be dramatically affected by artificial intelligence (or machine learning), from the private sector to government and nonprofits. There are many excellent courses that teach you the mechanics behind these innovations -- helping you develop an engineering skill set, like the R or Python programming skills required to build these algorithms.

This course takes a different approach. It is aimed at people who want to deploy these tools, whether that’s in a start-up company, a medium-sized NGO or a large government agency. While this requires some knowledge of how these tools work, that is only a small part of the equation, just as knowing how an engine works is a small part of understanding how to drive. What is really needed is an understanding of what these tools do well, and what they do badly. This course focuses on giving you a functional, rather than mechanistic, understanding. By the end, you should be an expert at identifying ideal (and problematic) use-cases and thereby should be well-placed to create new policy or other applications that use artificial intelligence.

Objectives and Goals

This course aims to equip students with a functional, rather than a mechanical, understanding of AI. Through a series of interactive lessons students will develop a better intuition for AI applications, helping students become expert at identifying ideal use-cases and thereby well-placed to create new products, businesses and policies that use artificial intelligence.

Our goal is to make students smarter consumers of AI. The class is intended as a complement to, not substitute for, standard machine learning classes that focus on the nuts and bolts of how to be an algorithm producer (‘what’s the advantage of a support vector machine over a gradient-boosted decision tree?’ or ‘how do I program this up in Python?’) But there is a distinct set of intuitions that are under-developed in standard machine learning classes, and perhaps under-appreciated even by people who engage in industrial-strength machine learning as their profession. We hope that by the end of the quarter each of you will be positioned to tell even a sophisticated private-sector user of AI like Netflix, with their giant team of data scientists, something that they currently only dimly understand -- or if they understand it, they and their C-suite executives do not fully appreciate how critical it is to the company’s entire future as a business (or similarly for, say, the office of a big-city chief information officer).

More generally by the end of the course, students will have:
• A functional framework for thinking about what AI does.
• The ability to ask questions to determine whether a potential idea is actually a feasible AI project, especially understanding the hidden risks.
• How to evaluate whether an AI system is doing the job you imagine it is.
• How a strategic thinker (rather than an engineer) can help build AI systems
• An improved ability to find new opportunities to apply AI that are actually feasible

Students should also know that this course will NOT teach:

• How to code AI algorithms
• How to estimate data models
• The mathematical formalisms behind AI or machine learning algorithms
• A nitty-gritty understanding of the kinds of specific algorithmic classes out there (e.g. model architectures in convolutional neural networks, etc.).

The class, therefore, does not require a background in programming. It does, however, require enough understanding of key statistical concepts such as mean, variance, sampling, correlation and regression. The course is set up to avoid heavy mathematical notation and formalism; thus imposing a heavy demand for critical thinking.

Prerequisites and Auditing

There are no formal prerequisites for this class although we assume students have familiarity with basic concepts in statistics and regression analysis.

As we are trying to keep the class small, we will not be allowing auditors.

Format

We will rely on:

1. Offline lectures. Videos for each lecture will be posted a week in advance. Watch these early. Please note any questions you have and include them in your homework submissions.
2. In-person class meetings
   a. The first part will be to answer your submitted questions. The goal is to clarify what was unclear in the lecture. Or expand on any points you wanted clarified. **This part will only be as good as the question you submit.**
   b. The second part will be a series of group discussions including smaller breakout groups. The goal will be to reinforce what you have learned in the video lectures.
3. Readings. These will be assigned each week.
Assignments and Grading

There will be no exams. Students will complete two big projects:

- **Explain** *(15 points)*. A great way to learn something is to teach it (make whatever inference you wish about why this class is being taught). The goal of this project is to pick one of the concepts from class and to teach it. Specifically, you will put together either a slide deck or essay:
  - A slide deck (with voice over written-out). This will be as if you were giving a 10-15-minute presentation to teach this concept to fellow students.
  - An essay. This will be a 2000-word essay again as if you were putting together a good Medium-post. The audience is again people with your level of knowledge.
  - This will be due the day of the final class - **March 7 by 9PM**.
  - You will be graded on: (i) accuracy, (ii) clarity and (iii) the effort you put into making the concept your own. At a minimum, you should not use any examples or explanations we used.
  - This is a solo assignment. We encourage you to practice your talk in groups or circulate your essays for feedback. But every part of what you submit is meant to be entirely yours.

- **Apply** *(25 points)*. Another great way to learn something is to apply it. Both as consumers and from your jobs you have a wealth of experience. Use it and find an AI application. The application must be feasible. We will grade first and foremost on feasibility and the thought you have put into how you would build it. Within that constraint, you are obviously looking for lucrative and impactful applications.
  - The final output will be a memo describing the application. It should spell out the basic idea, the potential flaws, how will you address them and your strategy for building it out. You can spend some time on the value but that is not the central point – this is not a strategy, pitching or market-sizing exercise. It is an AI-build exercise. This will be due by **March 14th by 5pm**.
  - The final output is also a solo assignment just as with the “Explain” assignment. But we realize that brain-storming is hard so we’ll encourage you to work in groups of 4-6 (if you have trouble finding a group contact a TA). The groups are solely for finding and generating ideas. They are not meant for the homework assignments and vetting of ideas.

- **Submitted questions**
  - These will be submitted by Sunday at 5PM along with your homework below.

- **Homework assignments** *(60 points)*.
  - Each one is due by **Sunday at 5PM**
  - Each homework will be addressing a question for the lecture you just saw and we discussed.
  - If you are confused about something submit a question – otherwise you will do badly on the homework associated with that lecture.
  - There will be 6 homeworks, each graded on a 10-point scale
● Grading of homeworks:
  o If you misunderstood something, how we penalize you depends on whether you asked a question about it.
  o If you did ask a question about the thing you got wrong, then you will be penalized less: obviously I failed to explain it well
  o If you didn’t ask a question, you will be penalized heavily.

*Late assignments are not accepted* and will simply receive a 0.
Course Outline

Below you will find a short overview of the topics and order in which we will cover them. **Guesses** for how many topics each lecture will take are in brackets.

<table>
<thead>
<tr>
<th>Date</th>
<th>Lecture</th>
<th>Key Takeaways</th>
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<tbody>
<tr>
<td>Jan 3</td>
<td>Introduction</td>
<td>• The enormous potential of AI but also its perils</td>
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<td></td>
<td>• Introduce the architect’s perspective on AI</td>
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<td>• What you will and will not learn in this class</td>
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<td>• Scope the kinds of AI we will not focus on in this class</td>
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<td>• Supervised Learning: what is it?</td>
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<td>Jan 10</td>
<td>Factory Tour &amp; Blueprints</td>
<td>• A framework for AI building that we will use in the rest of the class.</td>
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<td>• Introduce blueprints and their key elements</td>
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<td>• See how one company does it – Look Deep</td>
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<td>Jan 17</td>
<td>No class</td>
<td>(MLK Day)</td>
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<td>Jan 24</td>
<td>Data-ification</td>
<td>• Where you can add most of your value: Dataification.</td>
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<td>• How you datafy</td>
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<td>• A useful distinction: Automation vs prediction</td>
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<td>Jan 31</td>
<td>Finding Opportunities and When ML is the wrong choice</td>
<td>• A set of heuristics for finding impactful AI opportunities</td>
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<td>• New kinds of data</td>
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<td>• Algorithms can see things we cannot.</td>
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<td>• Integration into workflow</td>
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<td>• Causality vs prediction</td>
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<td>Feb 7</td>
<td>Bad data and how to fix it</td>
<td>• AI algorithms failed because their data failed them</td>
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<td>• Two problems: Wrong label and wrong distribution</td>
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<td>• Polling errors as an example of these two problems</td>
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<td>• Ways to get a bad label and what to do about it</td>
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<td>• Ways to get a bad distribution and what to do about it</td>
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<td>Date</td>
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| Feb 14  | Bad data and how to evaluate it (cont’d). and Evaluating the algorithm | • Passing familiarity with existing evaluation metrics  
• Common pitfalls in evaluation – both statistical and organizational. |
| Feb 21  | Common issues with ML algorithms                                      | • Algorithmic bias  
• Spurious correlation  
• Spam problems |
| Feb 28  | Our favorite applications and Conclusion                             | • Walk through the bail application  
• Talk through some of the ideas we’re most excited about  
• Review class takeaways |