AI: Strategy + Marketing (MGT 853)

AI and Customer Experience (Session 7)

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Yale School of Management

Spring 2025

Administrative Stuff

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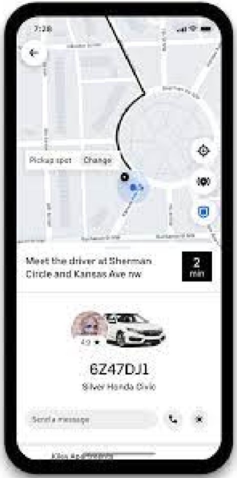

Uber: Applying ML to Improve the Customer Pickup Experience

Uber Discussion – 1

- What is Uber's business problem?
  - Why is this an important problem?
  - To start solving a business problem, we need the following components: (a) Define the problem (b) Identify metric (not accuracy) (c) Intervention and (d) Evidence of improvement ($\Delta \uparrow$)
- (How) can we do this without ML? (Can we just ask for pickup location? Address? Landmark?)
- Why do we think ML may help?
- We said that improving pickup happiness was the business goal. However, this depends on the type of person. The case mentions different Personas , let's do a deep dive into this idea of personas and (try) to identify what they care about. (Two sided Platform $\Longrightarrow$ need to worry about both riders and drivers.

Uber Discussion – 2

- What are the prediction problems that will help Uber solve business problem?
  - Persona – Multi-class classification problem (How do we validate?)
  - Pickup Location
    - What hypotheses could we have about the Pickup Location?
    - Do we have the y variable in the data? After the ride? Accurate?
  - Quality of Match between Rider (i) and Driver (j)
- What ML algorithms should we consider using?
- Do we observe happiness? No. So, should we use (U)nsupervised learning? Key Q is "Would it solve the business problem?"
- Proxy variable approach to solving this $\Longrightarrow$ converts this to (S)upervised Learning problem
  - What exactly is this Proxy variable approach?
  - How do we validate this?

Uber Discussion – 3

- What decisions / actions should Uber take to increase PQM? (Algorithm, Rider, Driver)
- How do we deal with Venue pickups?
  - Why do we care specifically about this?
  - What specific / additional challenges does this bring up?
  - How do we solve this?
- What data do we have for the X variables directly available?
- Which ones are not directly available in the data? Which can we feature engineer? Which do we have to obtain from third party sources? Which ones are passive versus active?

Uber Discussion – 4

- How do we measure value of the ML approach?
- Summarize the approach all the way from business problem to ML to back to business problem.
- Where have we used human judgment in Uber case?
- When should we use Semi-supervised Learning?
- How do we demonstrate value of ML in solving this problem?
  - Current approach (C), non-ML approach (T.A), ML approach (T.B)

Gaming in Learning (Adversarial Learning)

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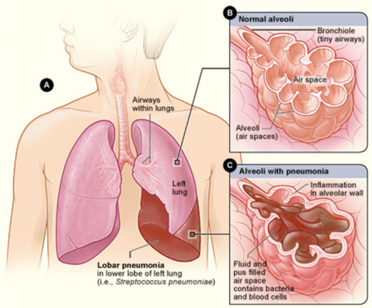

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So, what's the problem?

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  - What makes a good proxy? Can you prove it?

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  - Need to do a controlled experiment to demonstrate this link.