AI: Strategy + Marketing (MGT 853)

AI and Customer Experience (Session 7)

Vineet Kumar

Yale School of Management

Spring 2024

Administrative Stuff

- Pop Quiz answers included in Slides for last session

Administrative Stuff

- Pop Quiz answers included in Slides for last session
- Next Class (April 20) is in Evans 2410

Administrative Stuff

- Pop Quiz answers included in Slides for last session
- Next Class (April 20) is in Evans 2410
- 4/23: Guest Speaker: James Lin (Head of AI/ML Innovation, Experian)

Administrative Stuff

- Pop Quiz answers included in Slides for last session
- Next Class (April 20) is in Evans 2410
- 4/23: Guest Speaker: James Lin (Head of AI/ML Innovation, Experian)
- Project Presentations in 2 sessions:

Administrative Stuff

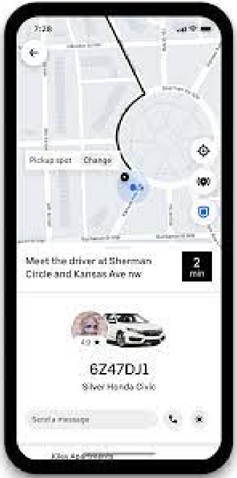
- Pop Quiz answers included in Slides for last session
- Next Class (April 20) is in Evans 2410
- 4/23: Guest Speaker: James Lin (Head of AI/ML Innovation, Experian)
- Project Presentations in 2 sessions:
  - May 2 (5-6 groups) / May 7 (3-4 groups)

Administrative Stuff

- Pop Quiz answers included in Slides for last session
- Next Class (April 20) is in Evans 2410
- 4/23: Guest Speaker: James Lin (Head of AI/ML Innovation, Experian)
- Project Presentations in 2 sessions:
  - May 2 (5-6 groups) / May 7 (3-4 groups)

Administrative Stuff

- Pop Quiz answers included in Slides for last session
- Next Class (April 20) is in Evans 2410
- 4/23: Guest Speaker: James Lin (Head of AI/ML Innovation, Experian)
- Project Presentations in 2 sessions:
  - May 2 (5-6 groups) / May 7 (3-4 groups)



Uber: Applying ML to Improve the Customer Pickup Experience

Uber Case Exhibits

Converting to Prediction Problems (In class exercise *if we have time*)

Let's try this in Groups

- Choose one of (1), (2) or (3). Tell the class what you have chosen before you get started.
  $\geq$ 2 groups for each.

3 Cases – Chose ONE

1) Social media (Instagram) – increase engagement
2) Content firm (Spotify) – recommend new content to its users
3) Apparel retailer – improve its product assortment

Let's try this in Groups

- Choose one of (1), (2) or (3). Tell the class what you have chosen before you get started.
  ≥ 2 groups for each.
- What is the business problem? How do you convert it to a prediction problem?

3 Cases – Chose ONE

1) Social media (Instagram) – increase engagement
2) Content firm (Spotify) – recommend new content to its users
3) Apparel retailer – improve its product assortment

Let's try this in Groups

- Choose one of (1), (2) or (3). Tell the class what you have chosen before you get started. $\geq$ 2 groups for each.
- What is the business problem? How do you convert it to a prediction problem?
- Suggest an (U)nsupervised, (S)upervised **and** (R)einforcement learning approach.

3 Cases – Chose ONE

1) Social media (Instagram) – increase engagement
2) Content firm (Spotify) – recommend new content to its users
3) Apparel retailer – improve its product assortment

Let's try this in Groups

- Choose one of (1), (2) or (3). Tell the class what you have chosen before you get started. ≥ 2 groups for each.
- What is the business problem? How do you convert it to a prediction problem?
- Suggest an (U)nsupervised, (S)upervised **and** (R)einforcement learning approach.
- What variables you will use as y and X?

3 Cases – Chose ONE

1) Social media (Instagram) – increase engagement
2) Content firm (Spotify) – recommend new content to its users
3) Apparel retailer – improve its product assortment

Let's try this in Groups

- Choose one of (1), (2) or (3). Tell the class what you have chosen before you get started.
  ≥ 2 groups for each.
- What is the business problem? How do you convert it to a prediction problem?
- Suggest an (U)nsupervised, (S)upervised **and** (R)einforcement learning approach.
- What variables you will use as y and X?
- Specify the actions (a), states (s), and reward (Π)

3 Cases – Chose ONE

1) Social media (Instagram) – increase engagement
2) Content firm (Spotify) – recommend new content to its users
3) Apparel retailer – improve its product assortment

Let's try this in Groups

- Choose one of (1), (2) or (3). Tell the class what you have chosen before you get started.
  ≥ 2 groups for each.
- What is the business problem? How do you convert it to a prediction problem?
- Suggest an (U)nsupervised, (S)upervised **and** (R)einforcement learning approach.
- What variables you will use as y and X?
- Specify the actions (a), states (s), and reward (Π)
- What business metric would you use to measure improvement?

3 Cases – Chose ONE

1) Social media (Instagram) – increase engagement
2) Content firm (Spotify) – recommend new content to its users
3) Apparel retailer – improve its product assortment

Let's try this in Groups

- Choose one of (1), (2) or (3). Tell the class what you have chosen before you get started.
  $\geq$ 2 groups for each.
- What is the business problem? How do you convert it to a prediction problem?
- Suggest an (U)nsupervised, (S)upervised **and** (R)einforcement learning approach.
- What variables you will use as y and X?
- Specify the actions (a), states (s), and reward (Π)
- What business metric would you use to measure improvement?
- Role of Transparency, Interpretability and Explainability

3 Cases – Chose ONE

1) Social media (Instagram) – increase engagement
2) Content firm (Spotify) – recommend new content to its users
3) Apparel retailer – improve its product assortment

The End

Pop Quiz (0 Points)

Multiple choice: More than one option may be true

Q1

- You're working with an online retailer who has browsing and purchase data for users. They would like you to identify which consumers have been most responsive to their messaging promotions over the past year. Which of the following approaches could be helpful here?
  1. Unsupervised
  2. Supervised
  3. Reinforcement

Q2

- Which of these is an example of reducing model complexity?
    1. Deciding not to use certain features X in a prediction problem
    2. Including interaction terms $\boxed{y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_1 X_2}$
    3. Dropping out neurons in a neural network
    4. Penalizing models that have too many parameters

Q3

- Which of the following weather related problems would Unsupervised Learning *not* be suitable for?

  1. Identify features for inclusion in prediction problems
  2. Predict tomorrow's weather
  3. Determine which cities have similar weather patterns
  4. Discover a rule like "If it has rained today, and it is sunny now, we're likely to see a rainbow"

Q4

- Suppose we're predicting prices for cars based on visual features using images, in addition to characteristics like mpg, hp etc. You have annual data from 2010-2014. You split the data into training and test samples to predict prices and use Deep Learning to predict sales prices. Which options below are correct?
  1. Data splitting is not helpful because we are not leveraging all the data
  2. Data splitting is a good practice because of model complexity
  3. Data splitting is helpful because prediction on test data provides the best estimate
  4. There is data leakage when we split the data by years

Uber Discussion

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 $\implies$ 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 $\implies$ converts this to (S)upervised Learning problem
  - What exactly is this Proxy variable approach?
  - How do we validate this?

Uber Discussion – 3

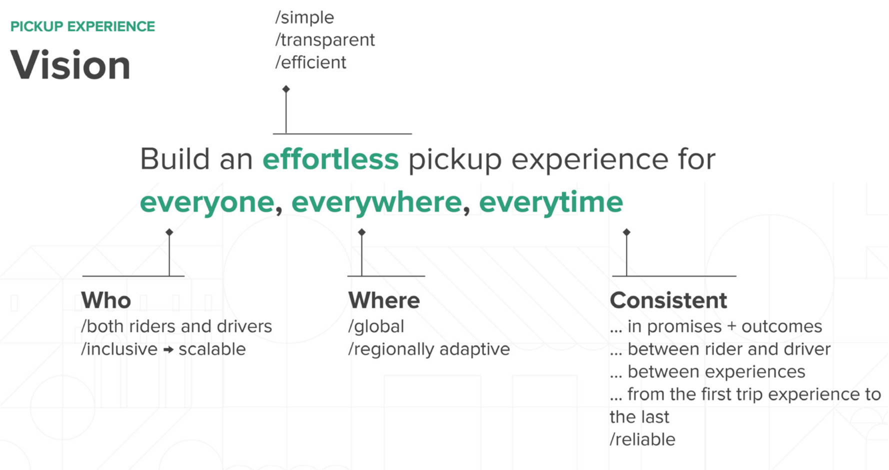
- What decisions / actions should Uber take to increase PQM? (Algorithm, Rider, Driver)
- How do we deal with Venue pickups?
  - Why do we care specifically about this?
  - What specific / additional challenges does this bring up?
  - How do we solve this?
- What data do we have for the X variables directly 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)

Uber Case Exhibits

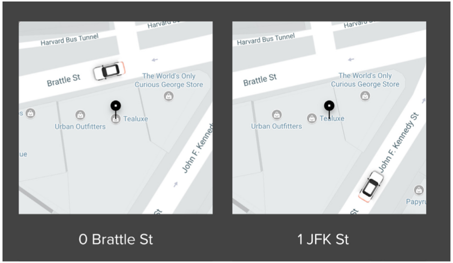
Figure 1: Uber's Pickup Experience Vision



Source: Uber.

Figure 2: Examples of Challenges in Using GPS Signal to Predict a Rider's Location

Multiple Interpretations of GPS: Wrong Street



Multiple Interpretations of GPS: Ambiguous Location

Which address is right?

- P.F. Chang's
- CambridgeSide Galleria
- 100 Cambridgeside Pl
- 100 Cambridgeside Pl Ste C101

Exhibit 4: Meet Toolkit

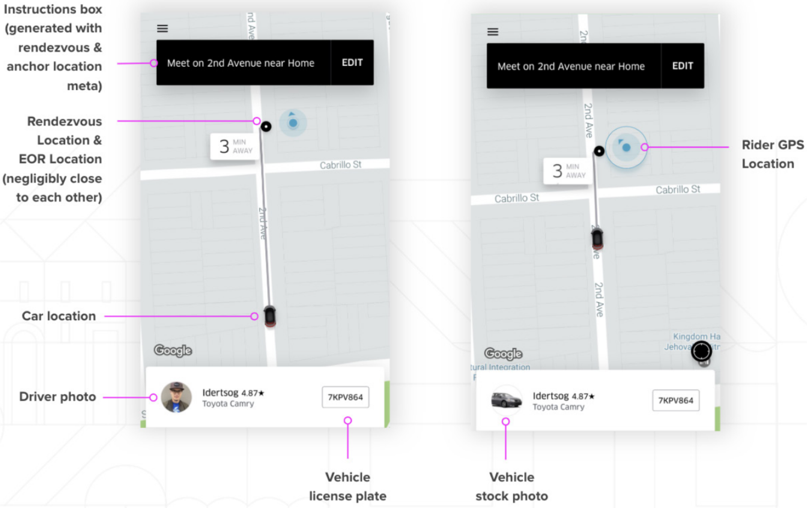


Exhibit 6: Potential Features to Define a Pickup Quality Metric

Environment Related

- Congestion along a potential hot spot or pickup (real-time pruning)
- Event-based pruning around a hot spot (e.g., detecting lane closure, construction, sidewalk construction)

Behavioral

- Sensor Inferences
- User Generated Feedback Cards
- Support Tickets opened
- UX Research

Passive (Sensors)

- Location scoring during uncertainty
- Driver loops around rendezvous
- Driver ETA jumps within last 300 meters of pickup
- ETA versus ATA (estimated time of arrival versus actual time of arrival)
- Number of steps walked by riders
- Number of heading changes for driver
- Number of heading changes for rider
- Driver idle time (seconds)

Exhibit 6: Potential Features to Define a Pickup Quality Metric

Environment Related

- Congestion along a potential hot spot or pickup (real-time pruning)
- Event-based pruning around a hot spot (e.g., detecting lane closure, construction, sidewalk construction)

Behavioral

- Sensor Inferences
- User Generated Feedback Cards
- Support Tickets opened
- UX Research

Passive (Sensors)

- Location scoring during uncertainty
- Driver loops around rendezvous
- Driver ETA jumps within last 300 meters of pickup
- ETA versus ATA (estimated time of arrival versus actual time of arrival)
- Number of steps walked by riders
- Number of heading changes for driver
- Number of heading changes for rider
- Driver idle time (seconds)

User Signal

- Cancellation Rate (by driver or rider)
- Rider/driver Contact Rate
- PLE

Location Related

- X-axis, z-axis confidence swings

Mobile Events / Behavioral Indicators

- Number of taps until request
- Time spent in pin edit

Exhibit 7: Steps in Creating a Machine Learning Model

Business Analyst Leads

Define the business problem to be solved.

- What is the business problem?
- Why is it an important problem?
- How will the solution benefit customers and the company?

Evaluate if Machine Learning is appropriate.

- Access to enough volume of data
- Accuracy and bias of data
- Cost of collecting data
- Latency of decisions
- Structured decision problem

Gather & label data.

- Data from product instrumentation
- Data from proxy signals
- Data provided by customers
- Data from third-party sources

Data Scientist Leads

Preprocess data & define features.

- Ingest data from sensors, users and third parties.
- Clean data
- Define features for ML model
- Define objective function

Select ML approach & algorithms.

- Choose among supervised, unsupervised, or reinforcement learning
- Assess different algorithms within chosen type of ML approach
- Choose best performing algorithms

Engineer features & improve model.

- Brainstorm possible features
- Check how features work in the model
- Conduct feature engineering
- Use ensemble methods to improve model performance

UX Leads

Make decisions & design user experience.

- Trigger UX messages to customers
- Trigger messages to employees or partners
- Automatically update UI dashboards based on model outputs

Uber Case Takeaways

Takeaways from Uber Case - 1

- First, understand the business problem before thinking through prediction / ML problem. Develop a plan to: (a) solve the business challenge, and (b) demonstrate that the plan worked

Takeaways from Uber Case - 1

- First, understand the business problem before thinking through prediction / ML problem. Develop a plan to: (a) solve the business challenge, and (b) demonstrate that the plan worked
- Evaluate whether ML is the right approach. Consider non-ML approaches and see if ML has critical advantages. Need to understand the value of ML approach.

Takeaways from Uber Case - 1

- First, understand the business problem before thinking through prediction / ML problem. Develop a plan to: (a) solve the business challenge, and (b) demonstrate that the plan worked
- Evaluate whether ML is the right approach. Consider non-ML approaches and see if ML has critical advantages. Need to understand the value of ML approach.
- Supervised approach may not be easy. Consider using a Proxy variable in place.

Takeaways from Uber Case - 1

- First, understand the business problem before thinking through prediction / ML problem. Develop a plan to: (a) solve the business challenge, and (b) demonstrate that the plan worked
- Evaluate whether ML is the right approach. Consider non-ML approaches and see if ML has critical advantages. Need to understand the value of ML approach.
- Supervised approach may not be easy. Consider using a Proxy variable in place.
    - Why make this judgment call? Can we not use Unsupervised?

Takeaways from Uber Case - 1

- First, understand the business problem before thinking through prediction / ML problem. Develop a plan to: (a) solve the business challenge, and (b) demonstrate that the plan worked
- Evaluate whether ML is the right approach. Consider non-ML approaches and see if ML has critical advantages. Need to understand the value of ML approach.
- Supervised approach may not be easy. Consider using a Proxy variable in place.
  - Why make this judgment call? Can we not use Unsupervised?
  - What makes a good proxy? Can you prove it?

Takeaways from Uber Case - 2

- Semi-supervised learning can be a viable approach in many situations. Can validate the proxy connects to the immediate business objective by acquiring some data (often 5-10% may suffice)

Takeaways from Uber Case - 2

- Semi-supervised learning can be a viable approach in many situations. Can validate the proxy connects to the immediate business objective by acquiring some data (often 5-10% may suffice)
- Understand customer heterogeneity (personas or segments) and ensure that ML is working well for all

Takeaways from Uber Case - 2

- Semi-supervised learning can be a viable approach in many situations. Can validate the proxy connects to the immediate business objective by acquiring some data (often 5-10% may suffice)
- Understand customer heterogeneity (personas or segments) and ensure that ML is working well for all
  - Does a rider always have a single persona? What about driver?

Takeaways from Uber Case - 2

- Semi-supervised learning can be a viable approach in many situations. Can validate the proxy connects to the immediate business objective by acquiring some data (often 5-10% may suffice)
- Understand customer heterogeneity (personas or segments) and ensure that ML is working well for all
  - Does a rider always have a single persona? What about driver?
  - And *not* making things worse for some segments

Takeaways from Uber Case - 2

- Semi-supervised learning can be a viable approach in many situations. Can validate the proxy connects to the immediate business objective by acquiring some data (often 5-10% may suffice)
- Understand customer heterogeneity (personas or segments) and ensure that ML is working well for all
  - Does a rider always have a single persona? What about driver?
  - And *not* making things worse for some segments
- Even after all this, link between business objective (pickup happiness) and ultimate top (R) or bottom line (Π) may be unclear.

Takeaways from Uber Case - 2

- Semi-supervised learning can be a viable approach in many situations. Can validate the proxy connects to the immediate business objective by acquiring some data (often 5-10% may suffice)
- Understand customer heterogeneity (personas or segments) and ensure that ML is working well for all
  - Does a rider always have a single persona? What about driver?
  - And *not* making things worse for some segments
- Even after all this, link between business objective (pickup happiness) and ultimate top (R) or bottom line (Π) may be unclear.
  - Might need to do a controlled experiment to demonstrate this link.