Combining choice and response time data to analyse the ride-acceptance behaviour of ride-sourcing drivers

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Context

Ride-sourcing platforms

- have grown rapidly in recent years.
- are two-sided transportation markets.
- match passenger requests for on-demand transportation with available drivers.

Ride-sourcing drivers

- can accept or reject rides as they prefer.

Individual decision-making

- is central to ride-sourcing platforms.

Drivers' ride acceptance decisions

Request sent to driver.

$\Downarrow$

Driver sees ride features.

$\Downarrow$

Driver must decide within a few seconds whether to accept ride.

$\Downarrow$

Otherwise, ride is proposed to other drivers.

Motivation

- Efficiently match passenger and drivers to enhance platform performance
    - Reduce wait times, satisfy demand, maximise driver earnings, increase passenger and driver loyalty
    - Our case study: Drivers decline approx. 77% of ride requests.
- Incorporate driver preferences into matching algorithms to improve matching efficiency.
- Explain/predict drivers' ride-acceptance decisions to optimise ride-sourcing platforms.

Related work

Passenger behaviour

Driver behaviour

Empirical findings:

- Significant variation in ride-acceptance behaviour across socio-demographic variables, ride attributes, times of day, spatial attributes.

Methodology:

- Predominant focus on explaining/predicting outcomes.
- **Response times** have been ignored.

Our approach

Investigate ride-sourcing drivers' ride acceptance decisions considering both choice and response time data

- Formulate hierarchical drift-diffusion model to analyse ride-acceptance decisions
- Apply model to real-world data from a ride-sourcing platform

Background

Discrete choice models

- Outcome-oriented and static
- Predict decision outcomes under specified behavioural constraints (e.g. based on random utility theory)
- Widely adopted in transport and other applied economics disciplines to analyse complex decisions

Sequential sampling models

- Process-oriented and dynamic
- Decision-makers accumulate evidence regarding available options over time until a threshold is crossed.
- Used mostly in psychology to analyse simple perceptual decision-making tasks

Drift diffusion model (DDM)

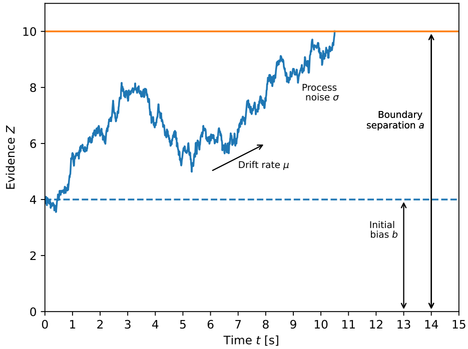
Evidence accumulation modelled as Wiener diffusion process:

$$Z(t_j) = Z(t_{j-1}) + \mu\Delta t + \sigma\Delta W(t_j)$$

with $\Delta t = t_j - t_{j-1}$, $\Delta W(t_j) \sim \mathcal{N}(0, \Delta t)$, $Z(0) = b$.

Key parameters:

- Threshold a: Response criterion, captures speed-accuracy trade-off.
- Bias ratio w: Initial bias towards upper or lower threshold ($b = wa$).
- Drift rate μ: Speed of evidence accumulation.
- Process noise σ: fixed to one for identification.



PDF and CDF of the DDM

Probability of absorption at lower boundary at time t:

$$f(t|\mu, a, w) = \frac{\pi}{a^2 \exp\left(-\mu a w - \frac{mu^2 t}{2}\right)} \times \sum_{k=1}^{\infty} k \sin(k\pi w) \exp\left[-\frac{1}{2}\left(\frac{k\pi}{a}\right)^2 t\right]$$

Probability of absorption at lower boundary until time t:

$$F(t|\mu, a, w) = P(\mu, a, w) - \frac{\pi}{a^2} \exp\left(-\mu a w - \frac{\mu^2 t}{2}\right) \times \sum_{k=1}^{\infty} \frac{2k \sin(k\pi w) \exp\left[-\frac{1}{2}\left(\frac{k\pi}{a}\right)^2 t\right]}{\mu^2 + k^2 \frac{\pi^2}{a^2}},$$

where $P(\mu, a, w) = \begin{cases} \frac{\exp(-2\mu a) - \exp(-2\mu a) - \exp(-2\mu a w)}{\exp(-2\mu a) - 1} & \mu \neq 0 \\ w & \mu = 0 \end{cases}$

Modelling ride-acceptance decisions under the go/no-go paradigm

- Drivers need to accept ride requests within 15 seconds, and do nothing to reject rides (= go/no-go decision).
- Let $z_{dr} = \begin{cases} (y_{dr}, t_{dr}) & \text{if } y_{dr} = 1 \\ y_{dr} & \text{if } y_{dr} = 0 \end{cases}$

Probability of accepting/rejecting ride request

$$P(z_{dr}|\mu_{dr}, a_{dr}, w_{dr}) = \begin{cases} f(t_{dr}| - \mu_{dr}, a_{dr}, 1 - w_{dr}) & \text{if ride is accepted} \\ 1 - F(t_{\text{end}}| - \mu_{dr}, a_{dr}, 1 - w_{dr}) & \text{if ride is rejected} \end{cases}$$

- Infinite sums approximated using efficient truncation approximations.
- DDM parameters depend on attributes of requests and drivers.
- Use MSL to accommodate random parameters $\rightarrow$ HDDM.

Behavioural indicators

Arc elasticity of probability of accepting until time t

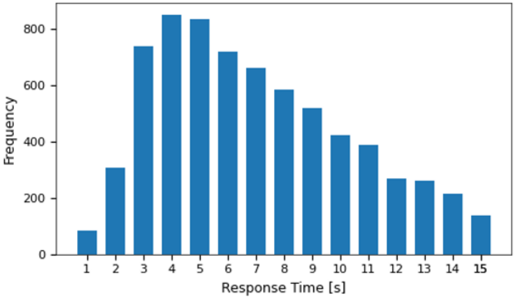
$$F(t|\mu, a, w)$$

Arc elasticity of expected response time t

$$\mathbb{E}(t|\mu, a, w) = \begin{cases} \frac{a}{\mu}\coth(a\mu) - \frac{aw}{\mu}\coth(aw\mu) & \mu \neq 0 \\ \frac{1}{3}a^2(1-w)^2 + \frac{2}{3}a^2 w(1-w) & \mu \to 0 \end{cases}$$

Real-world case study

- Accepted and rejected ride requests from a ride-sourcing platform operating in a city in south of Iran from Aug 2019 to Jan 2020.
- Extensive details regarding socio-demographic profiles of drivers and ride request attributes.
- Original dataset includes 8,062,050 records.
- Randomly select 20 records each from 1,000 drivers for model training and 200 drivers for out-of-sample validation.



Response time distribution across requests

Results: In- and out-of-sample predictive accuracy

Model	In-sample log.-lik.	Out-of-sample log.-lik.
Logit	-10302.524	-2062.653
Random parameter logit	-10177.815	-2046.691
DDM	-24766.444	-4946.175
HDDM	-24648.732	-4923.391

- Logit does not include response time because of complete separation.

Results: DDM/HDDM parameter estimates – threshold and bias

Variable	DDM	HDDM
Threshold		
Constant	-0.992^{***}	-1.156^{***}
Full-time Employment Status	0.185^{***}	0.254^{***}
Rainfall Volume	-1.886^{**}	-1.886^{**}
Time Since Last Proposed Request	0.579^{***}	0.575^{***}
Response for Last Proposed Request	0.327^{***}	0.298^{***}
Response for Before Last Proposed Request	0.409^{***}	0.380^{***}
Driver Ride Count	1.048^{***}	0.854^{***}
Number of Proposed Requests	-0.965^{***}	-0.824^{***}
Sigma of Random parameter		-0.365^{***}
Bias		
Constant	1.506^{***}	1.533^{***}
Driver Gender	-0.002	0.012
Driver Age	0.818^{***}	0.815^{***}
Rainfall Volume	0.43^{*}	0.391^{*}
Number of Rejection Since Last Ride	0.215^{*}	0.147^{*}
Experienced Driver	-0.059^{***}	-0.063^{***}

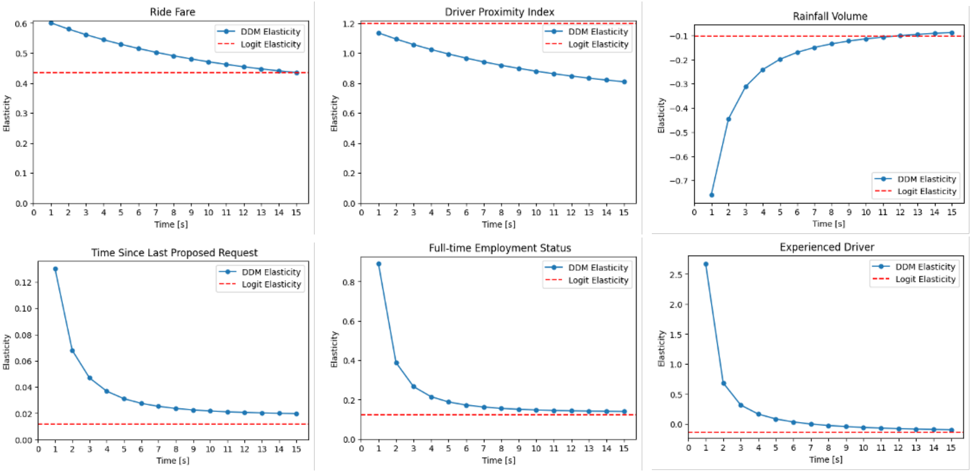
Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Results: DDM/HDDM parameter estimates – drift rate

Variable	DDM	HDDM
Drift rate		
Constant	-0.048	-0.023
Ride Fare	0.143^{***}	0.164^{***}
Price Per Distance	-0.553^{*}	-0.537^{***}
Driver Proximity Index	0.488^{***}	0.510^{***}
Log of Driver Proximity Index	-0.150^{***}	-0.159^{***}
Request Rejection Count	-0.115^{***}	-0.123^{***}
Experienced Driver	-0.038^{***}	-0.051^{***}
Distance Peak Interaction	0.370^{***}	0.447^{***}
Gender Price Interaction	-0.002	-0.017
Sigma of Random parameter		-0.090^{***}

Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Results: Elasticities of acceptance probability



Results: Elasticities of expected response times

Variable	DDM	HDDM
Rainfall Volume	0.394	0.357
Ride Fare	-0.097	-0.110
Ride Distance	-0.010	-0.018
Driver Proximity Index	-0.198	-0.202
Time Since Last Proposed Request	-0.071	-0.071
Full-time Employment Status	-0.016	-0.019
Experienced Driver	0.075	0.070

Conclusion

- Applied HDDM to real-world data from a ride-sourcing platform to analyse drivers' ride acceptance decisions.
- Stylised facts:
  - Proximity to requested ride's origin, higher ride fare, longer ride distance, full-time employment status $\rightarrow$ **faster** responses
  - Rain $\rightarrow$ **slower** responses
- Future research directions:
  - Explore other sequential sampling models
  - Integrate HDDM into matching algorithms

Thank you