Detecting Routines in Ride-sharing: Implications For Customer Management

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Yet, there are **no existing models** for identifying routines from transaction data!

Routines, Habits, and CRM

Behavioral Research

- Long history of research on habits, dating back to James (1890)
- *Habit:* Tendency to repeat behaviors without conscious thought (Wood et al., 2002)
- Habits are a primary driver of unsustainable transportation choices (White et al., 2019)
- Habit discontinuity: context changes can disrupt habits, and lead to deliberate consideration (Verplanken et al., 2008)

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Habits and CRM

- "Repeat buying habit": repeat brand purchases (Ehrenberg & Goodhardt, 1968)
- Shah et al. (2014): CRM with recurring behaviors like returns, purchasing on promotion, or purchasing low margin items
- "Habit stock" used to model smooth consumption over time (Dynan 2000)
- Customers who continue to transact out of habit may be negatively affected by outreach (Ascarza et al., 2016)
- Beyond RFM: clumpiness (Zhang et al., 2015), regularity (Platzer & Reutterer, 2016)

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This Project

1. Develop a novel, all-purpose model for identifying individual-level routines
2. Apply our model to a unique ride-sharing data set
3. Show that customers with a high level of routine usage **churn less**, and **spend more** in the long run
4. Explore how temporal routineness predicts and moderates other important customer outcomes, over and above: mere habit, routines in terms of "what," and other regularity metrics

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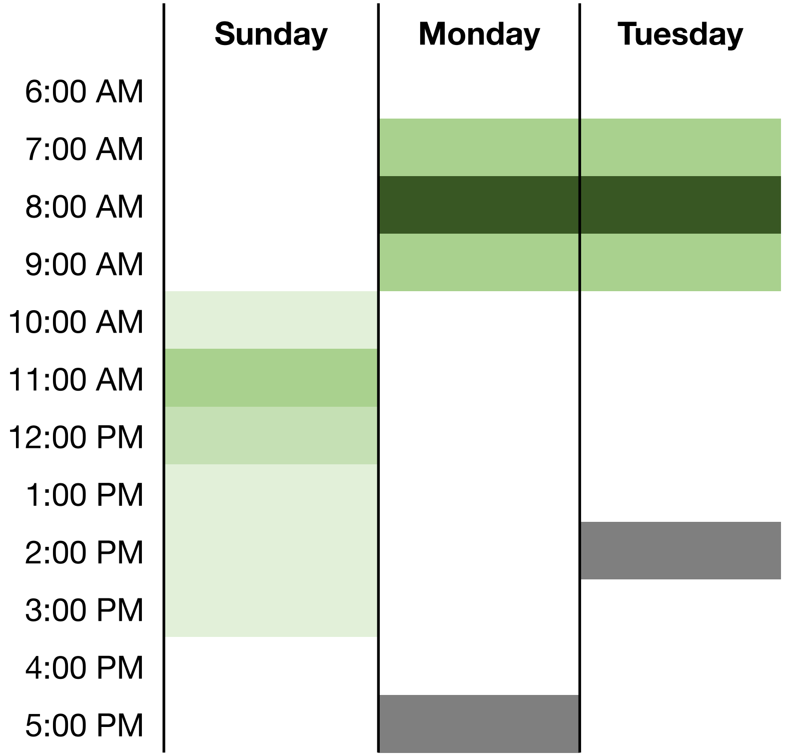
In short: we show the "shape" of customers' interactions matters!

Model

A Statistical Framework for Measuring Routineness

Model of Usage

From transaction data, we want to capture…



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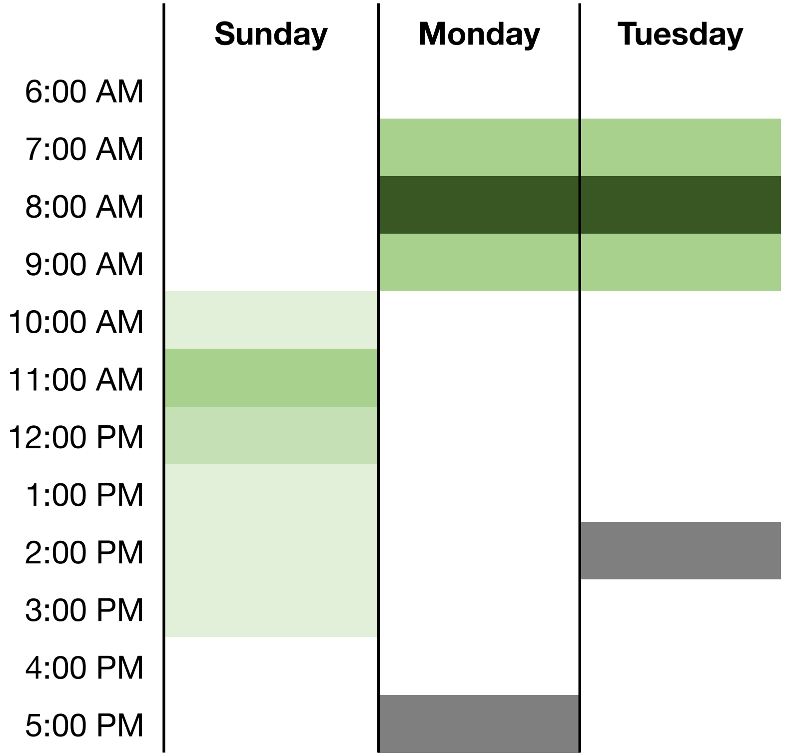

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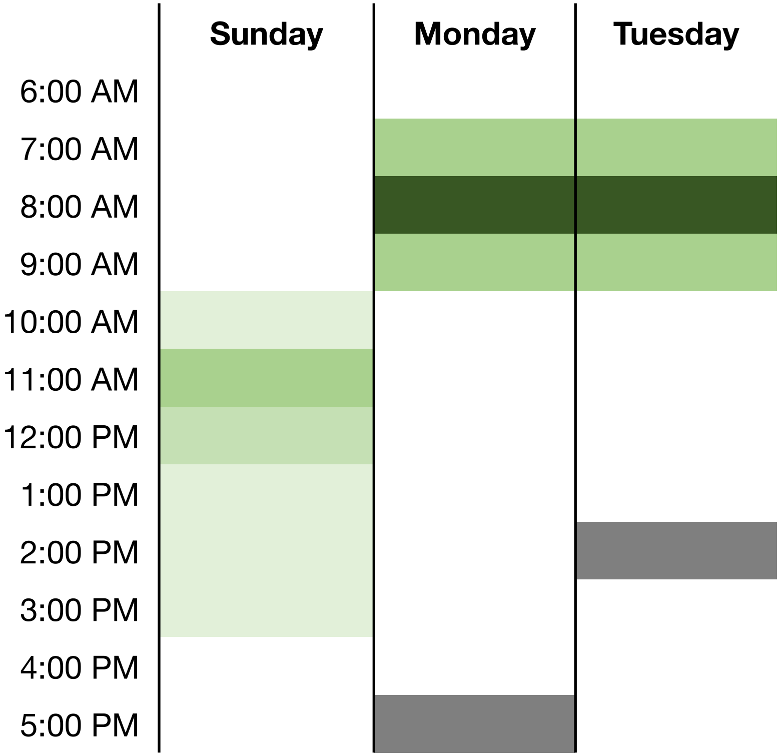

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Dependent variable: Usage (y)

Customer i, Week w, Day d, Hour h

Time $t = (w, d, h)$, Day-hour $j = (d, h)$

$$y_{it} \sim \text{Poisson}(\lambda_{it})$$

$$\lambda_{it} = \underbrace{\exp(\alpha_{iw} + \mu_j)}_{\text{Random usage}} + \underbrace{\exp(\gamma_{iw} + \eta_{ij})}_{\text{Routine usage}}$$

- α_{iw} and γ_{iw} – Individual- and week-specific scaling terms
- μ_j – Common day-hour rate
- η_{ij} – Individual-specific day-hour rate

These random and routine usage terms give us a **structured decomposition** of overall usage.

Model-based Decomposition

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Superposition of point processes:
If $Y_A \sim \mathrm{PP}(\lambda_A)$ and $Y_B \sim \mathrm{PP}(\lambda_B)$,
then $Y_A + Y_B \sim \mathrm{PP}(\lambda_A + \lambda_B)$.

Random requests:

$$E_{iw}^{\mathrm{Random}} = \sum_j \exp(\alpha_{iw} + \mu_j)$$

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Gaussian process: a Bayesian nonparametric prior over a function space

Interlude: Gaussian processes

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Mean function

Covariance function
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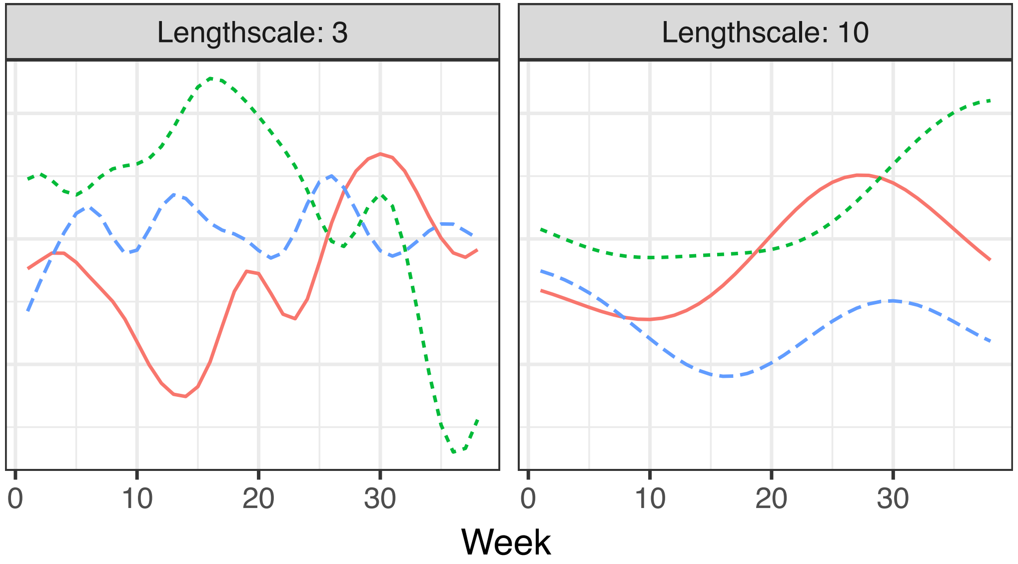

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Intuition: routines are by definition "sticky" over time

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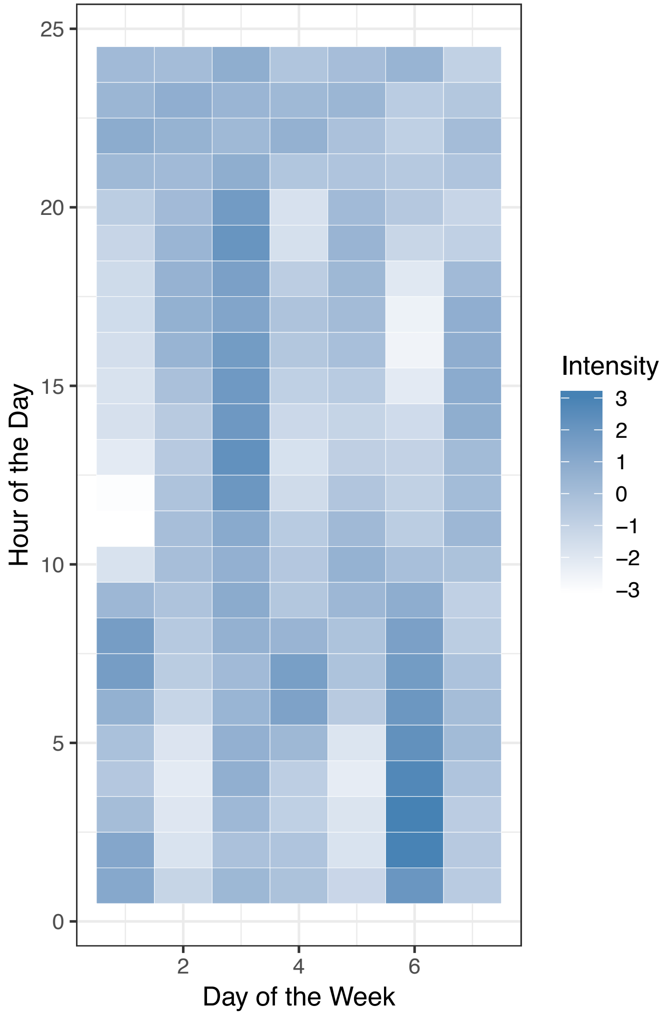

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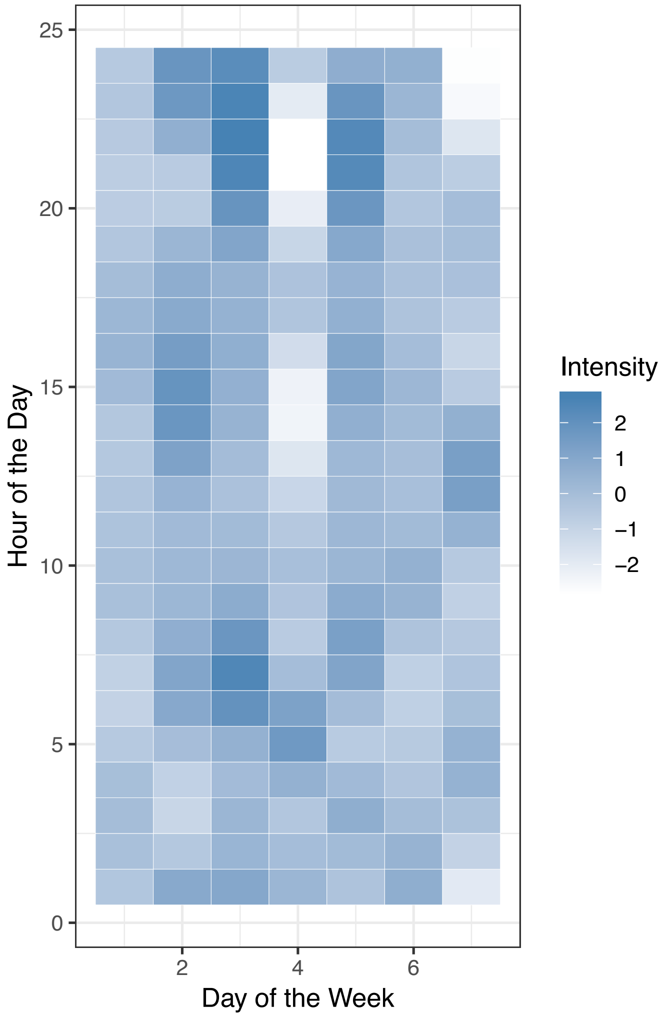

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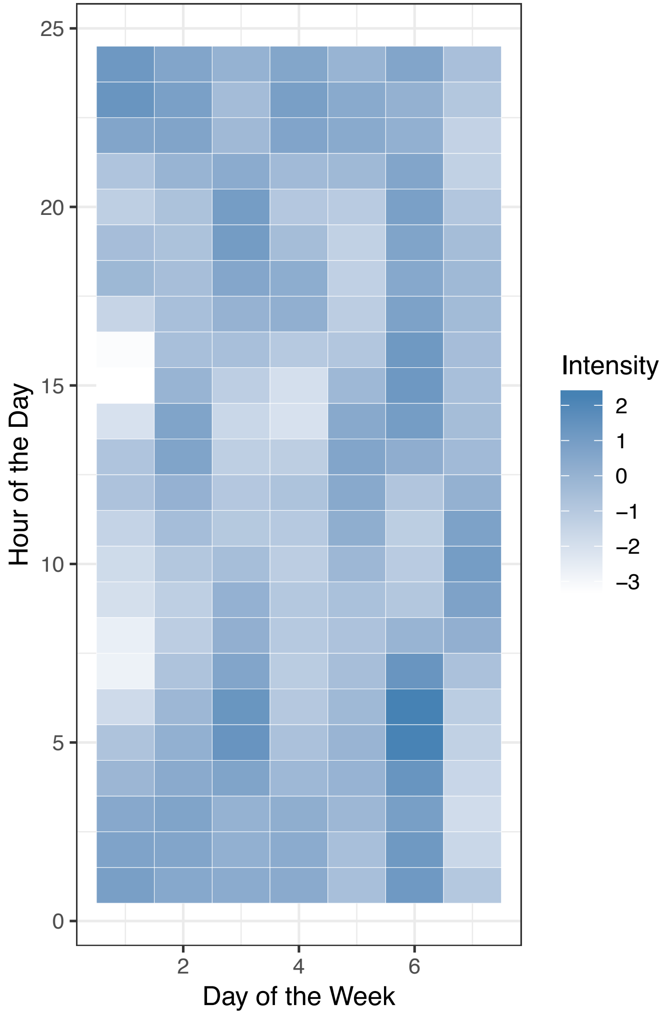

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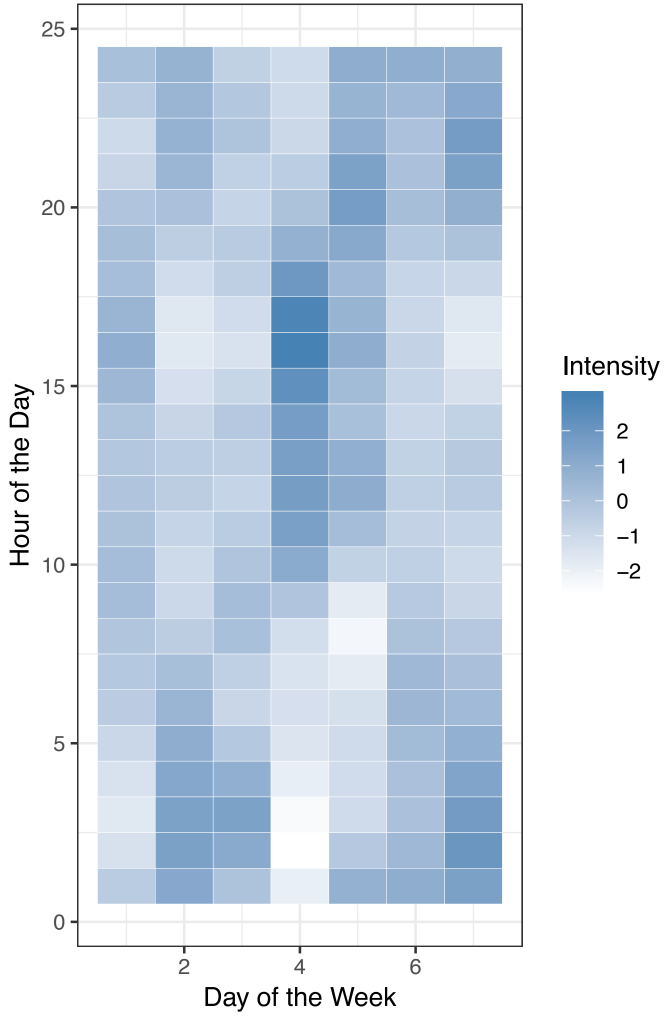

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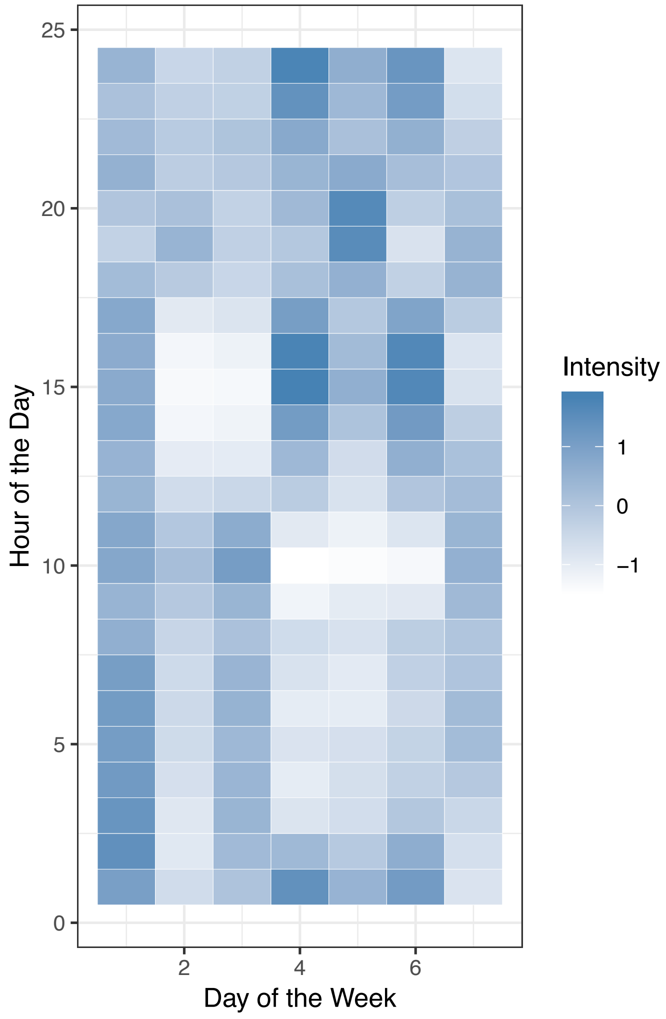

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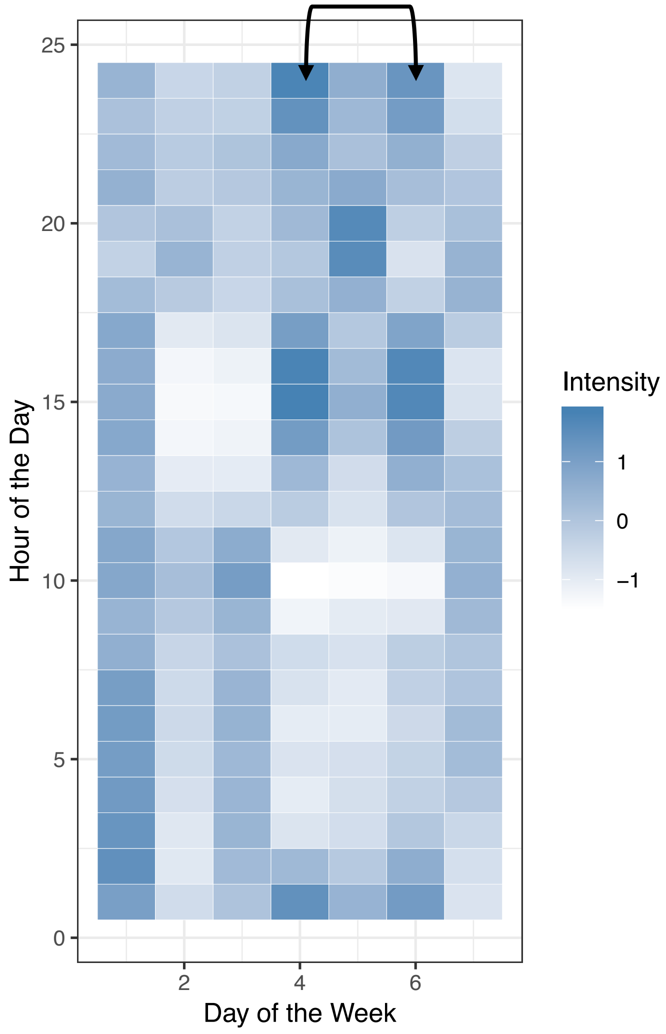

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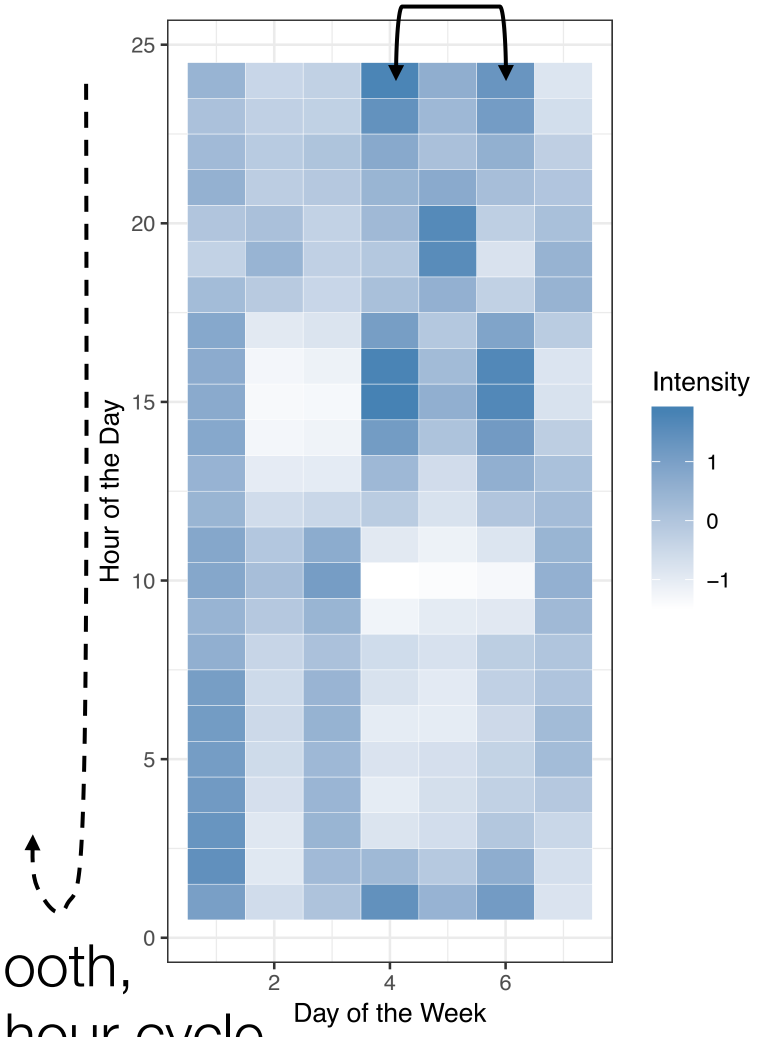

Smooth,
24-hour cycle

How do we specify those intensity functions?

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Baselines for weekly variation:

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Squared exponential kernel with fixed smoothness

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This structure basically buys us two things:

1. A decomposition of total usage into “random” and “routine”

2. An individual-level estimate of what that routine is (η_{ij})

$$\eta_i(d,h) \sim \mathcal{GP}\left(0, \boxed{k_{\mathrm{DH}}(d,h;\phi_\eta)}\right)$$

Novel day-hour kernel

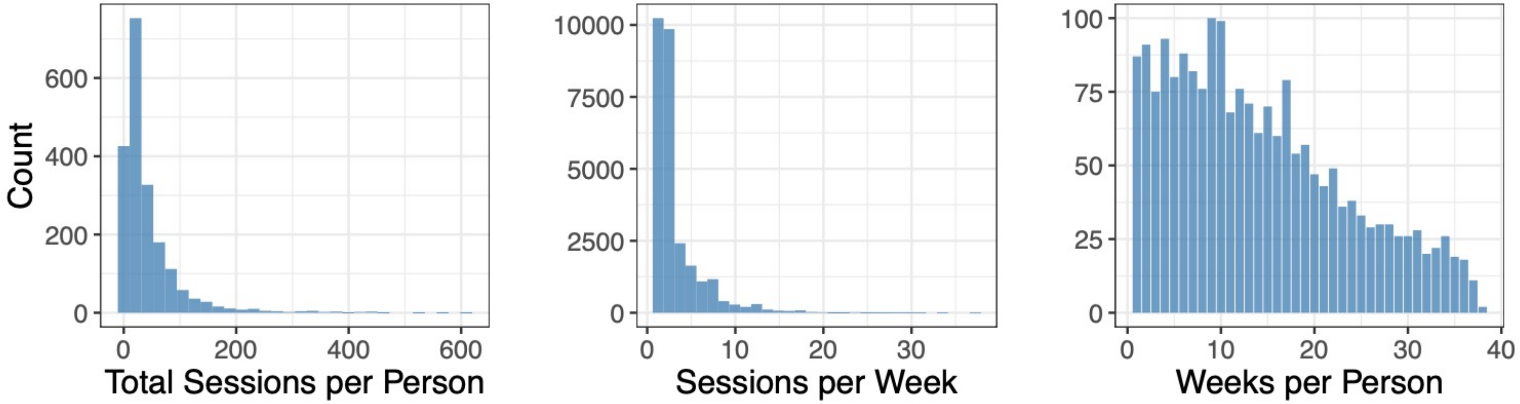
Results

Application to Ride-sharing Data

Ride-sharing Data

- Collaboration with a NYC-based ride-sharing company

Total Customers	2,000
Total Weeks (Training)	38
Total Weeks (Holdout)	10
Number of Sessions	86,952
Sessions / Customer	43.48
Sessions / Customer / Week	3.10
Weeks in Data / Customer	14.02



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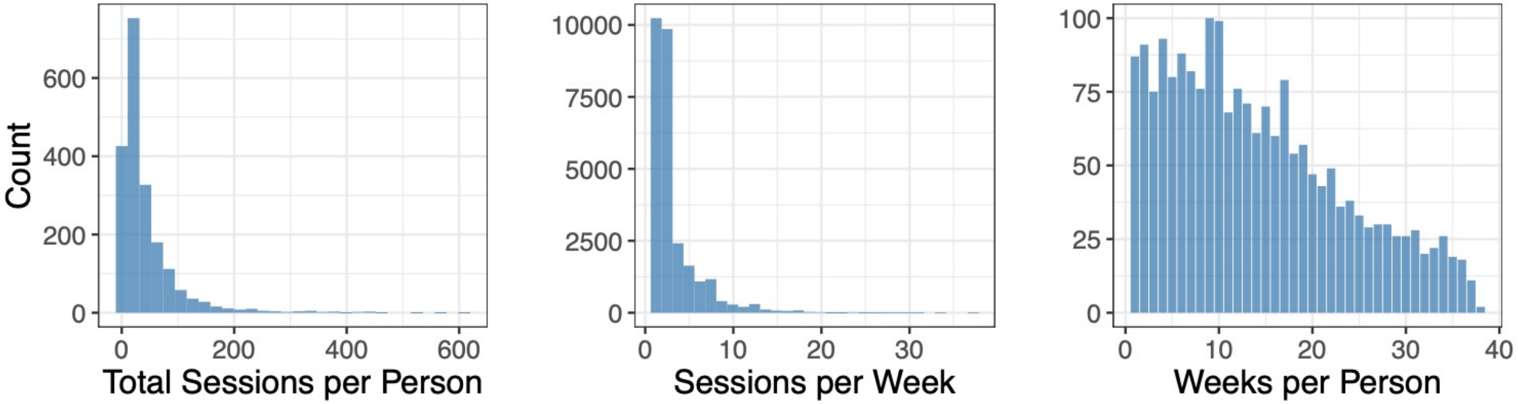

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Basic unit of analysis:
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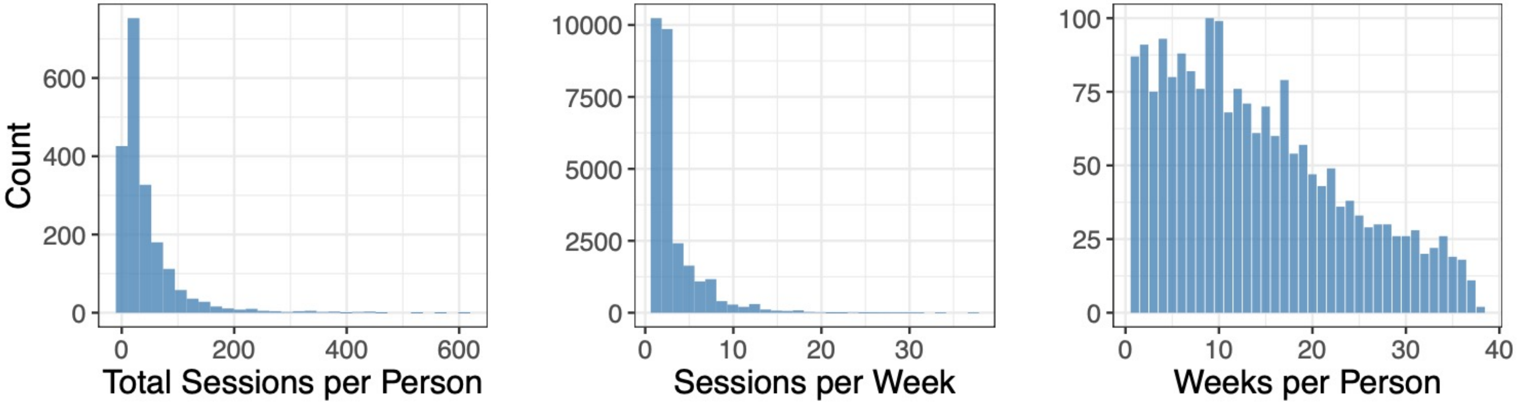
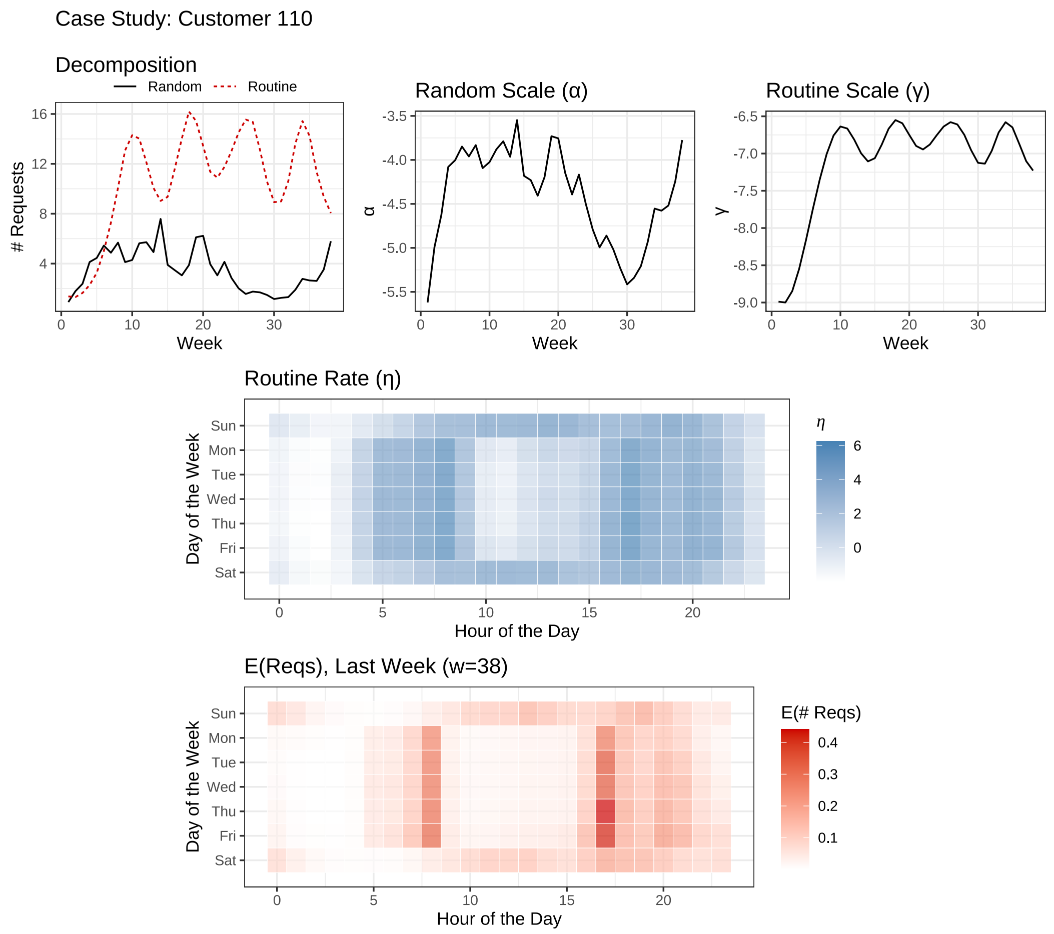
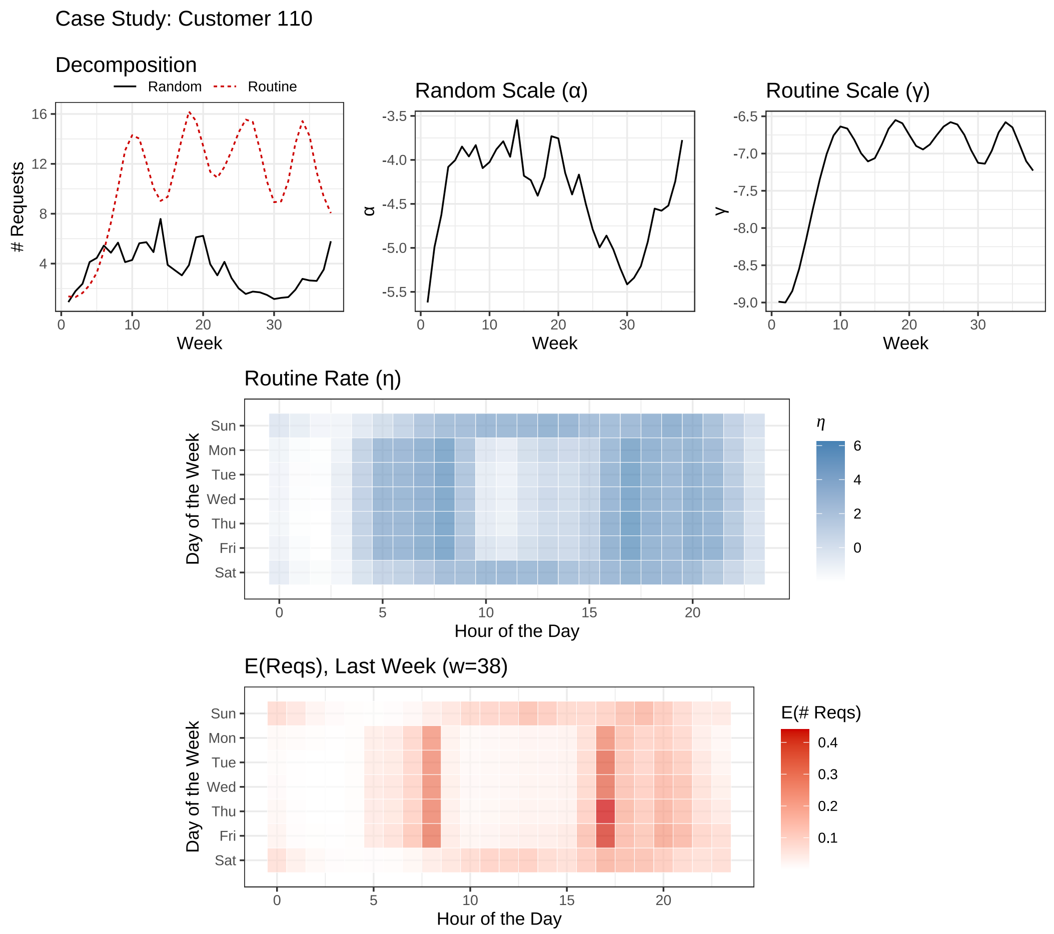
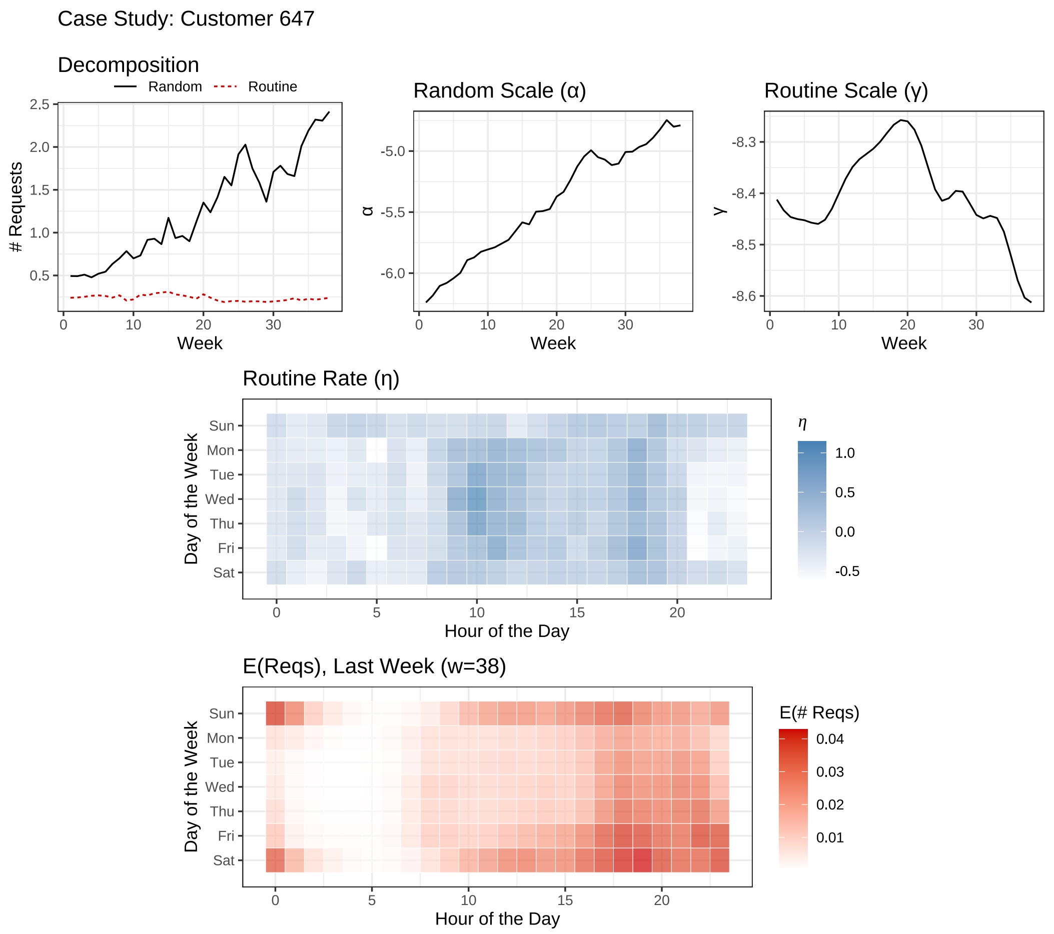


Real Case Studies

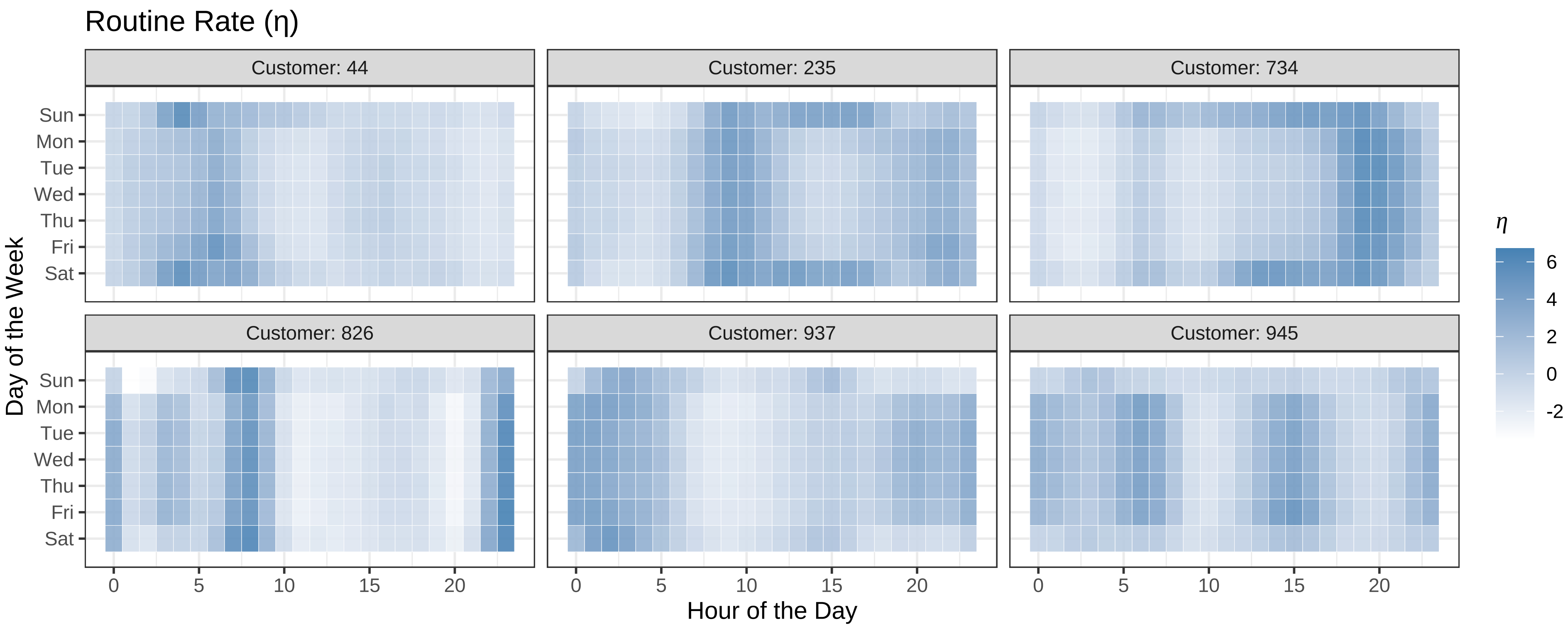


Real Case Studies





Many types of routines



Many types of routines

"Night owls"

Many types of routines

"Morning and night"

Validation

Can we trust these results?

Implications

Why should we care about routines?

Are routine customers more valuable?

	Dependent variable:			
	# Sessions		Activity	
	OLS		*Logistic*	
	Full Holdout	Last 5 Weeks	Full Holdout	Last 5 Weeks
	(1)	(2)	(3)	(4)
Requests $(w = 38)$	2.224***	0.597***	0.383***	0.180**
	(0.223)	(0.141)	(0.108)	(0.057)
Recency	−0.189***	−0.106***	−0.140***	−0.124***
	(0.042)	(0.026)	(0.010)	(0.010)
Frequency	0.095***	0.049***	−0.00002	0.004*
	(0.007)	(0.004)	(0.002)	(0.002)
Routine $(w = 38)$	5.750***	3.284***	1.110**	0.307*
	(0.436)	(0.275)	(0.385)	(0.147)
Observations	2,000	2,000	2,000	2,000
R^2	0.567	0.425		

Note: *p<0.05; **p<0.01; ***p<0.001
Intercept omitted for clarity.

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Model-based Routineness
(Week 38)

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Total Requests
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Key result: The number of rides *coming from a routine* is a significant predictor of **short- and long-run usage and retention.**

More to the story…

Are routine customers better in other ways?

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	Dependent variable:	
	Accept Proposal	Request Again
	(1)	(2)
Routineness	0.084***	0.208***
# Requests (Week 38)	−0.021*	0.321***
Price	−0.031***	−0.052**
Driver ETA	−0.050***	−0.002
ETA Destination	−0.012***	−0.017
Speed	0.074***	−0.034
Pickup Walking Dist.	−0.041***	−0.006
# Passengers Req.	−0.003	0.025
Routineness x Price	−0.001	0.037**
Routineness x Driver ETA	0.009***	0.005
Routineness x ETA Destination	−0.0002	−0.009
Routineness x Speed	0.162***	−0.089
Routineness x Pickup Walking Dist.	−0.008***	−0.0002
Routineness x # Passengers Req.	−0.001	0.019
Pickup Delay		−0.027***
Dropoff Delay		−0.010
Dropoff Walking Dist.		−0.012
# On-board (Pickup)		−0.015
# On-board (Dropoff)		0.002
Max On-board		0.012
Routineness x Pickup Delay		0.018**
Routineness x Dropoff Delay		0.007
Routineness x Dropoff Walking Dist.		0.005
Routineness x # On-board (Pickup)		0.013
Routineness x # On-board (Dropoff)		0.001
Routineness x Max On-board		−0.011
Other Controls	Yes	Yes
Observations	38,166	14,704
R^2	0.052	0.068
Note:		*p<0.1; **p<0.05; ***p<0.01

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- More likely to accept ride proposals and request again

Main effect

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More to the story…

Are routine customers better in other ways?

In ride-sharing, we find highly routine customers are…

- More likely to accept ride proposals and request again
- Less price sensitive
- Somewhat more picky about the rides they take
- Somewhat less sensitive to bad service (pickup delay)

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Entropy: given the empirical distribution $\boldsymbol{p}$ of locations, $\ell = 1, \dots, L$:

$$\text{Entropy} = -\sum_{\ell=1}^{L} p_k \log p_k$$

CRT Dispersion: given L unique locations in K total trips:

$$\text{CRT Disp.} = \frac{L}{\log K}$$

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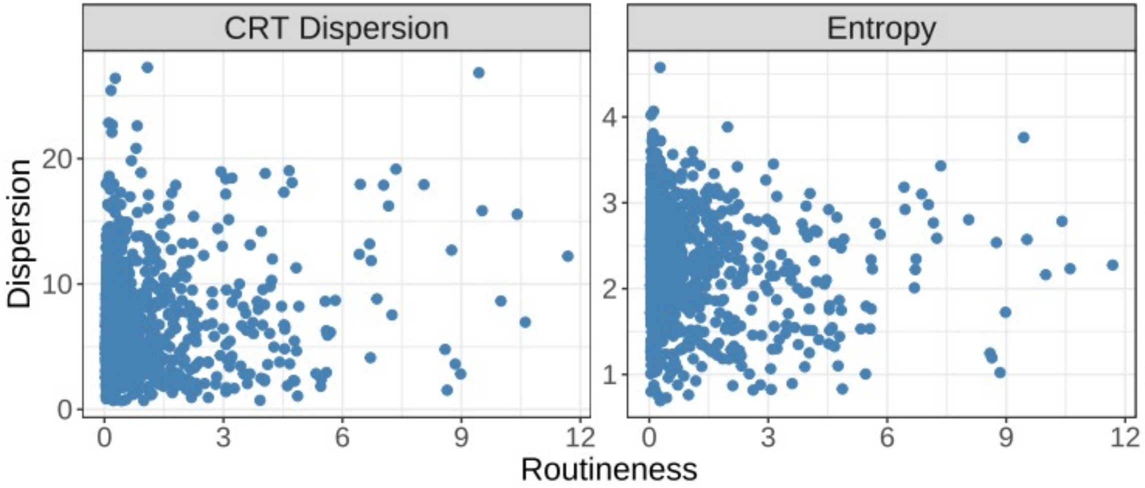

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Summary

- **Methodological:** Our model decomposes transaction histories into routine and random components
  - Gaussian process with novel day-hour kernel allows for precise individual-level routine estimates
  - Nesting GP in an inhomogeneous Poisson process → structured decomposition of usage
  - The result: a novel routineness metric

- **Substantive:** The shape of a customer's transaction history matters!
  - Additional evidence for the role of habit, and specifically routines, for CRM
  - A new "KPI" for predicting customer value: higher routineness = higher value
  - Routine customers are also better in other ways: price sensitivity, resilience to disruptions
  - Temporal routines are distinct from "what" (or "where") routines

Thank you!

Questions / comments?

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Working paper available at www.rtdew.com