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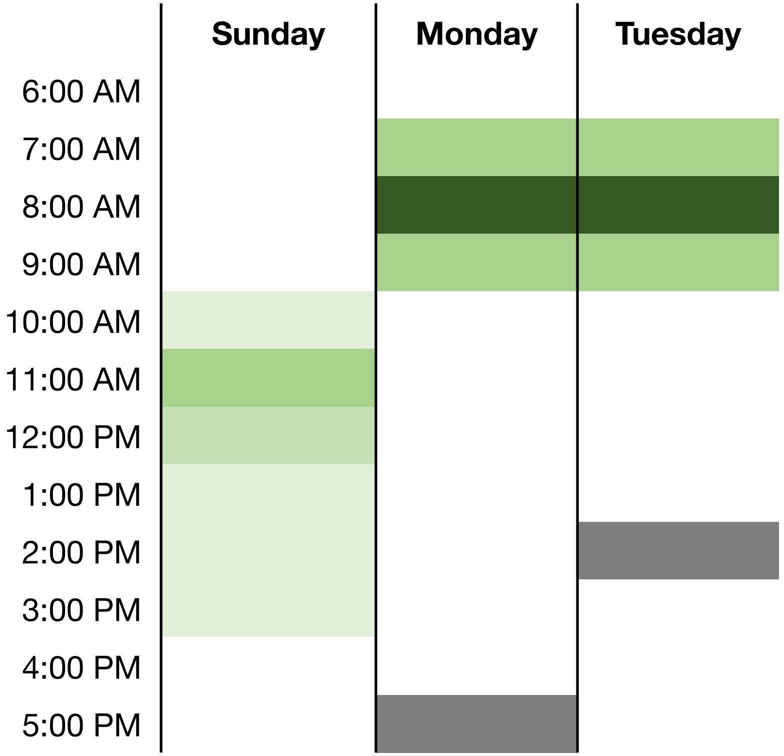
In short: we show the "shape" of customers' interactions matters!

Model

A Statistical Framework for Measuring Routineness

Model of Usage

From transaction data, we want to capture…



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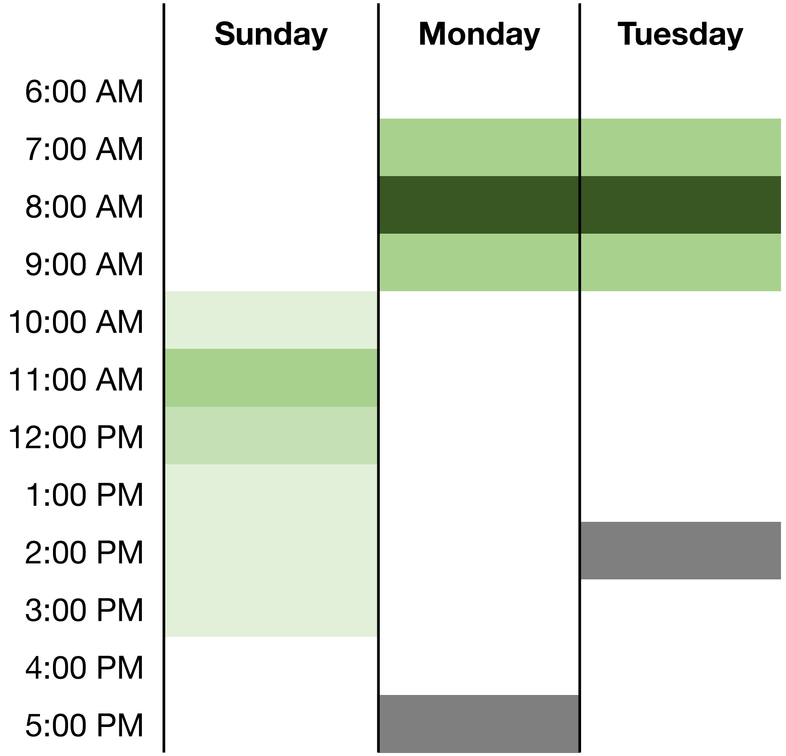

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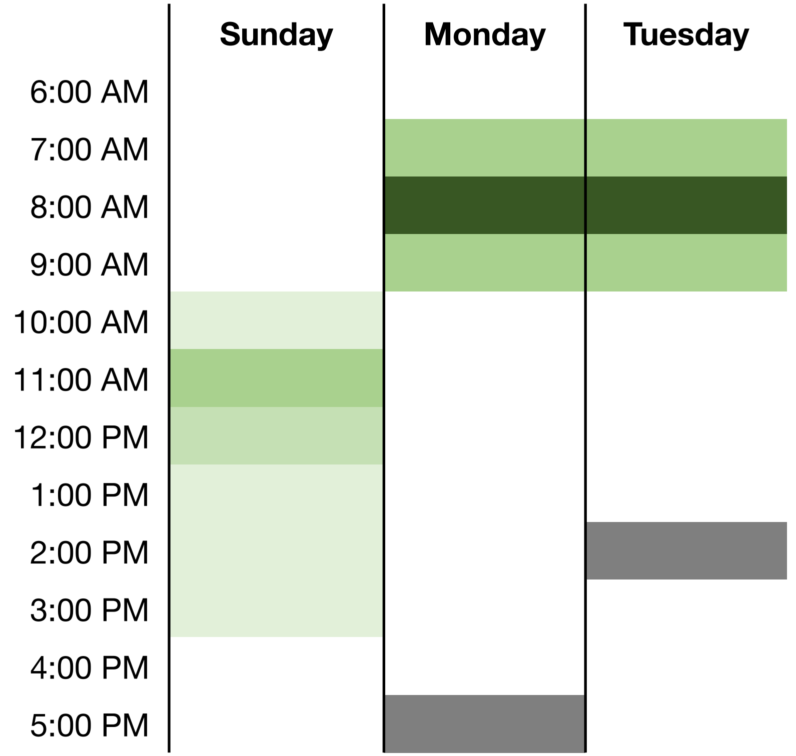

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Dependent variable: Usage (y)

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

Structured Decomposition:

$$E_{iw}^{\text{Routine}} = \sum_j \exp(\gamma_{iw} + \eta_{ij})$$

Specifying the Model Components

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"Scaling" – How active is this process in this week?

$$\alpha_{iw} \sim \mathcal{N}(\alpha_{iw-1}, \tau)$$

$$\gamma_i(w) \sim \mathcal{GP}(\gamma_0, k_{\text{SE}}(w, w'; \phi_\gamma))$$

"Random" depends just on prior week;
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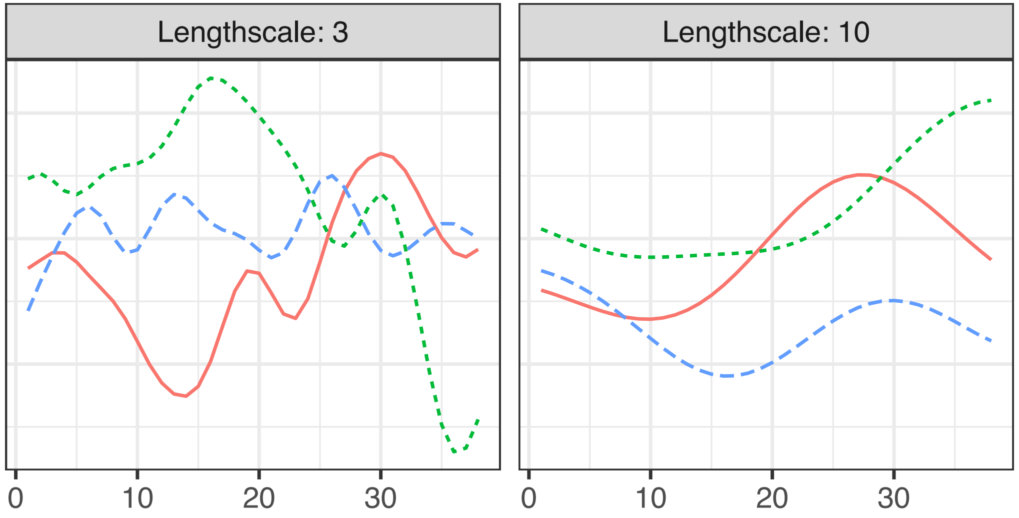

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“Day-Hour Rate” – When do we expect usage to occur?

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

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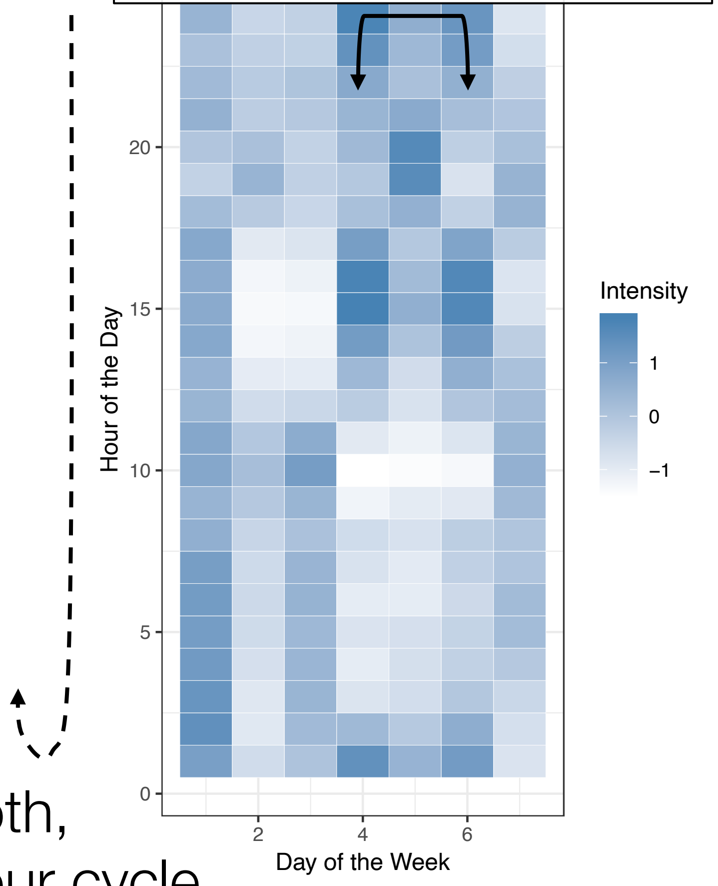
Linkages across days



Smooth, 24-hour cycle

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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})

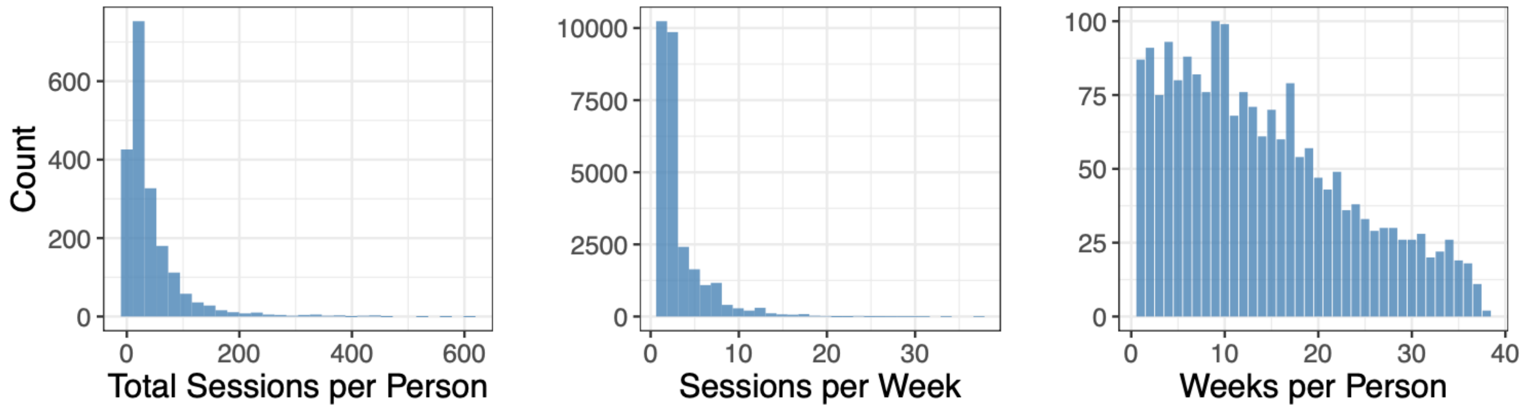
Results

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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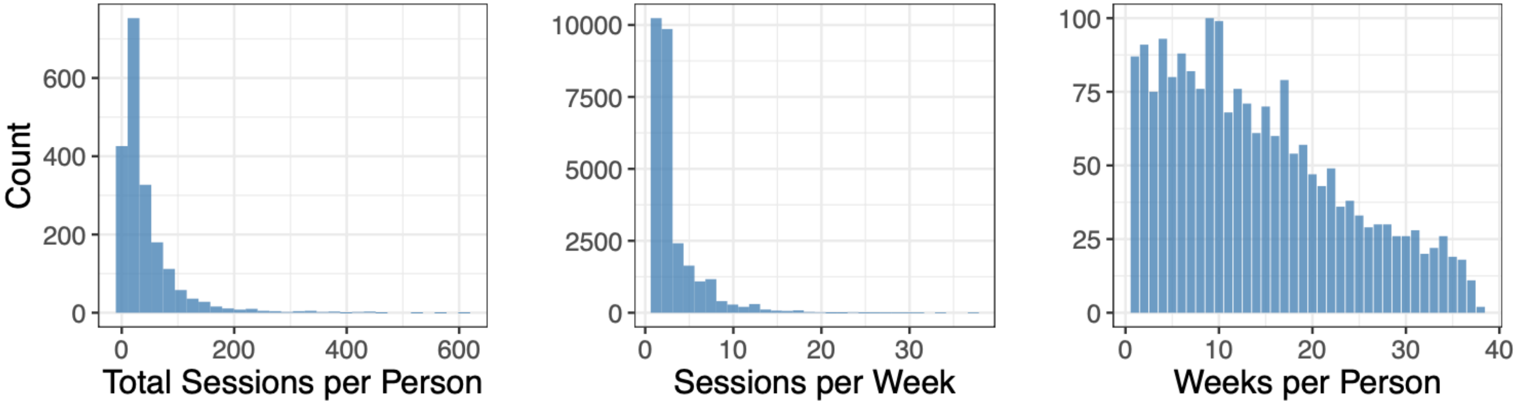

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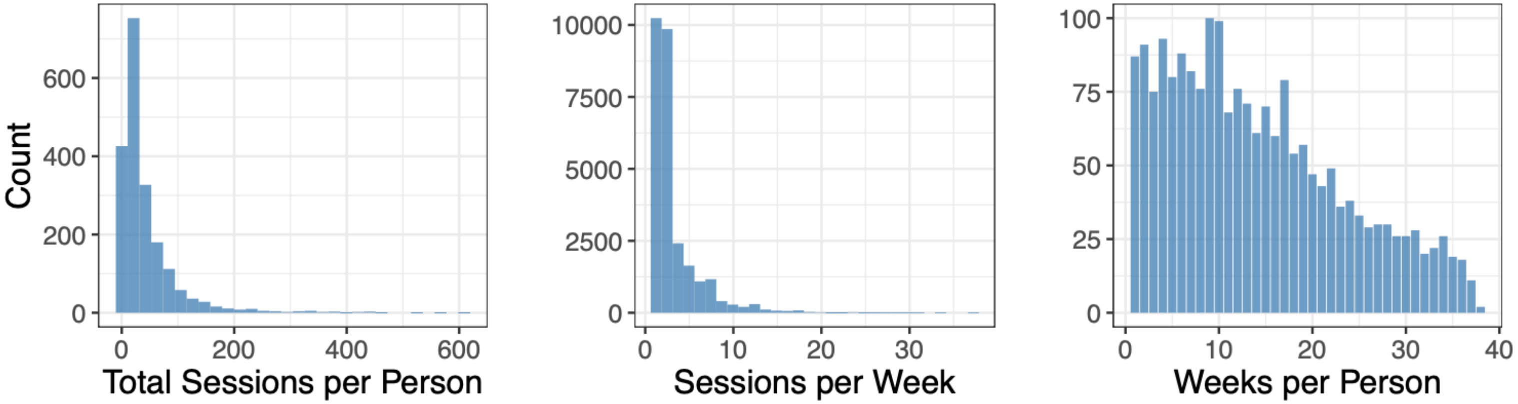
Basic unit of analysis: a "session"



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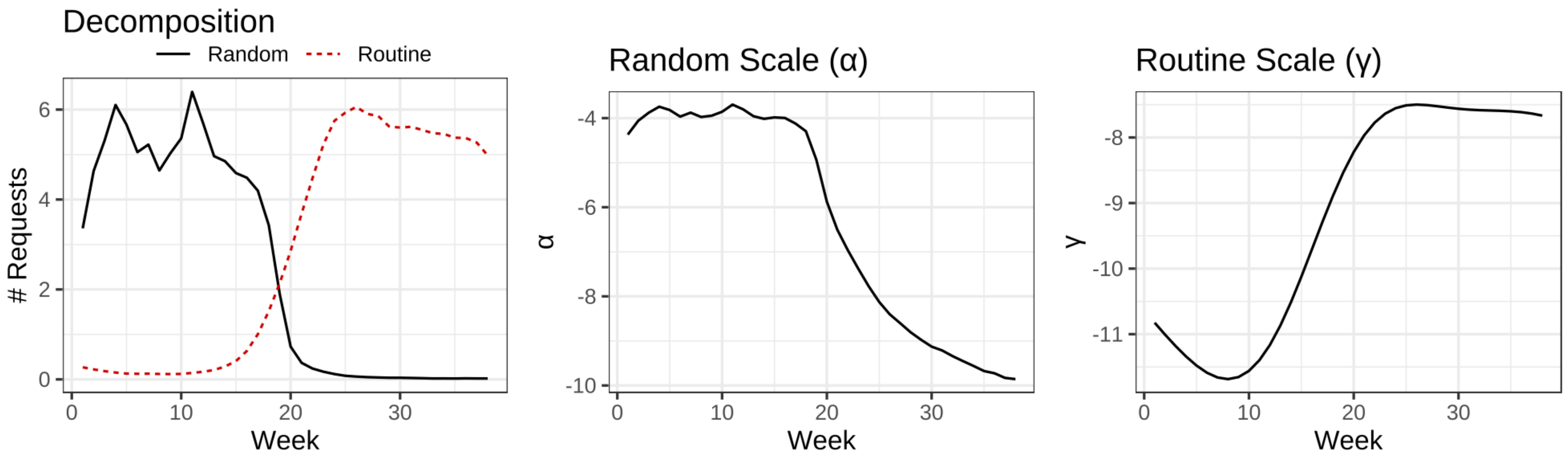

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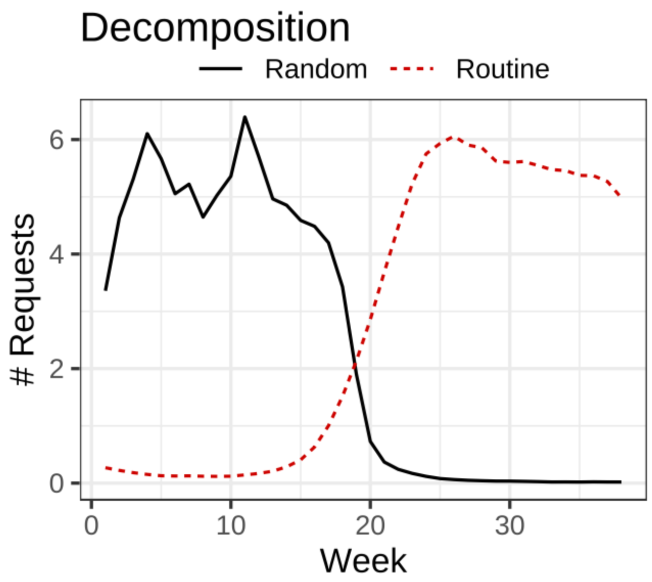
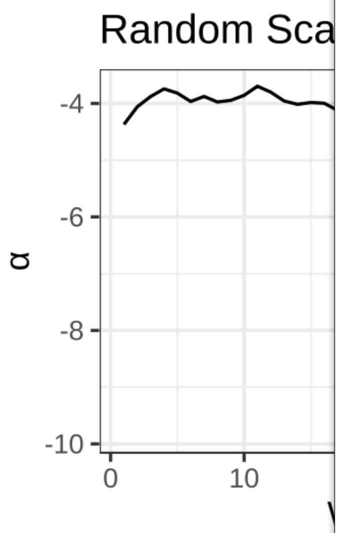
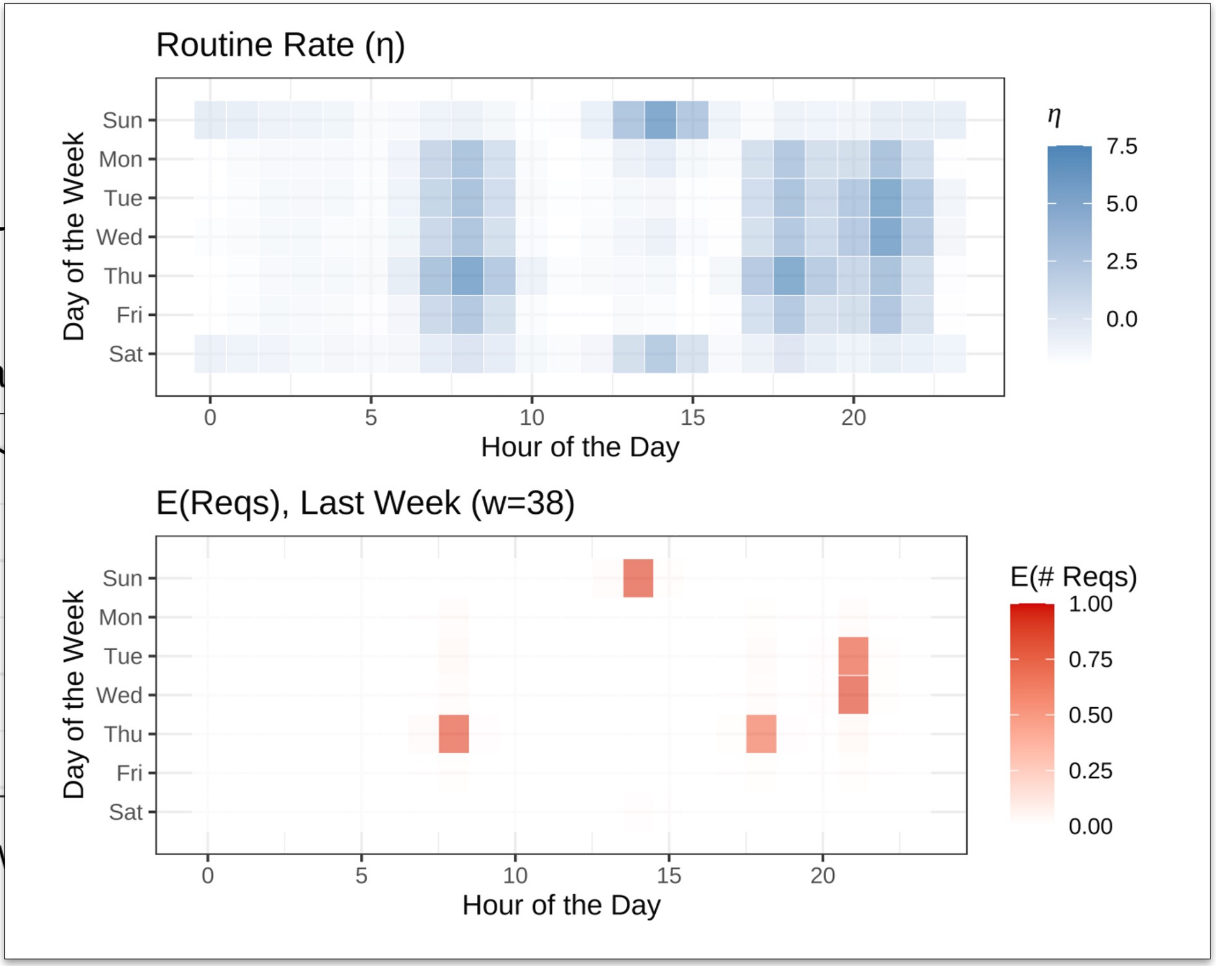
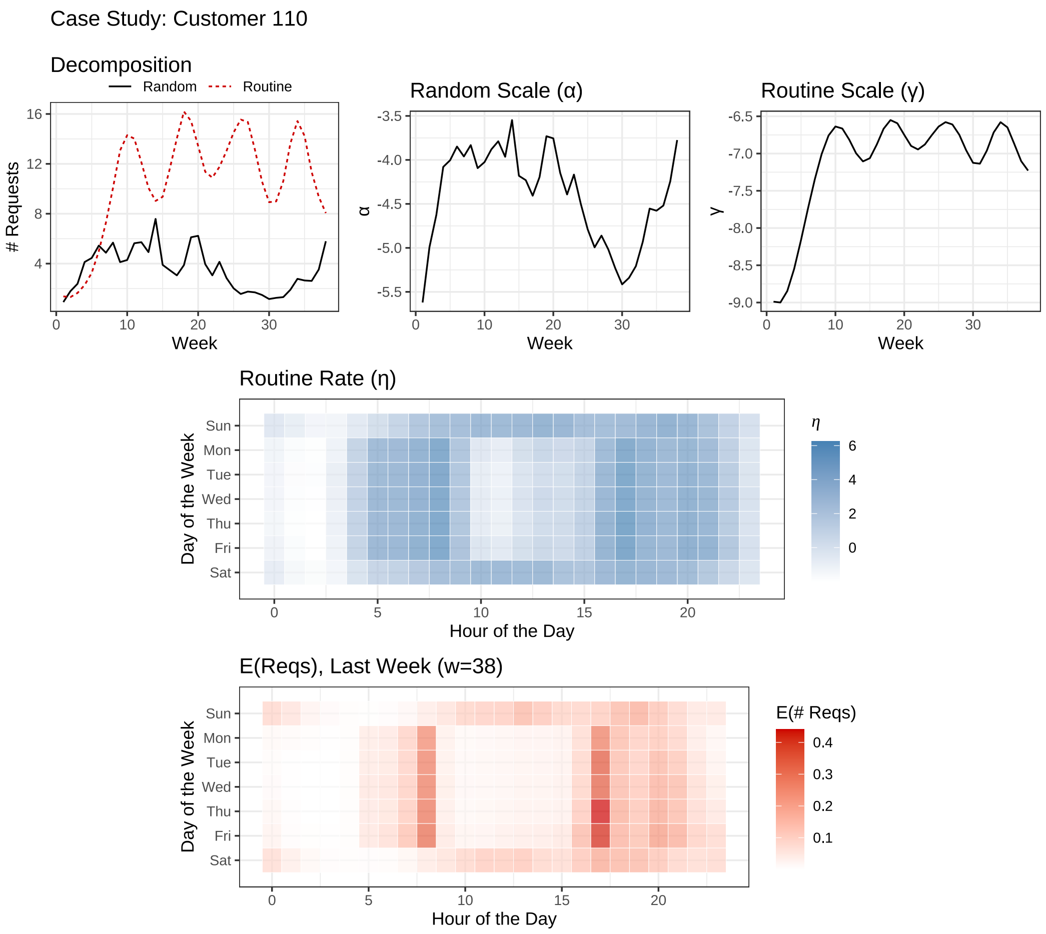






Real Case Studies



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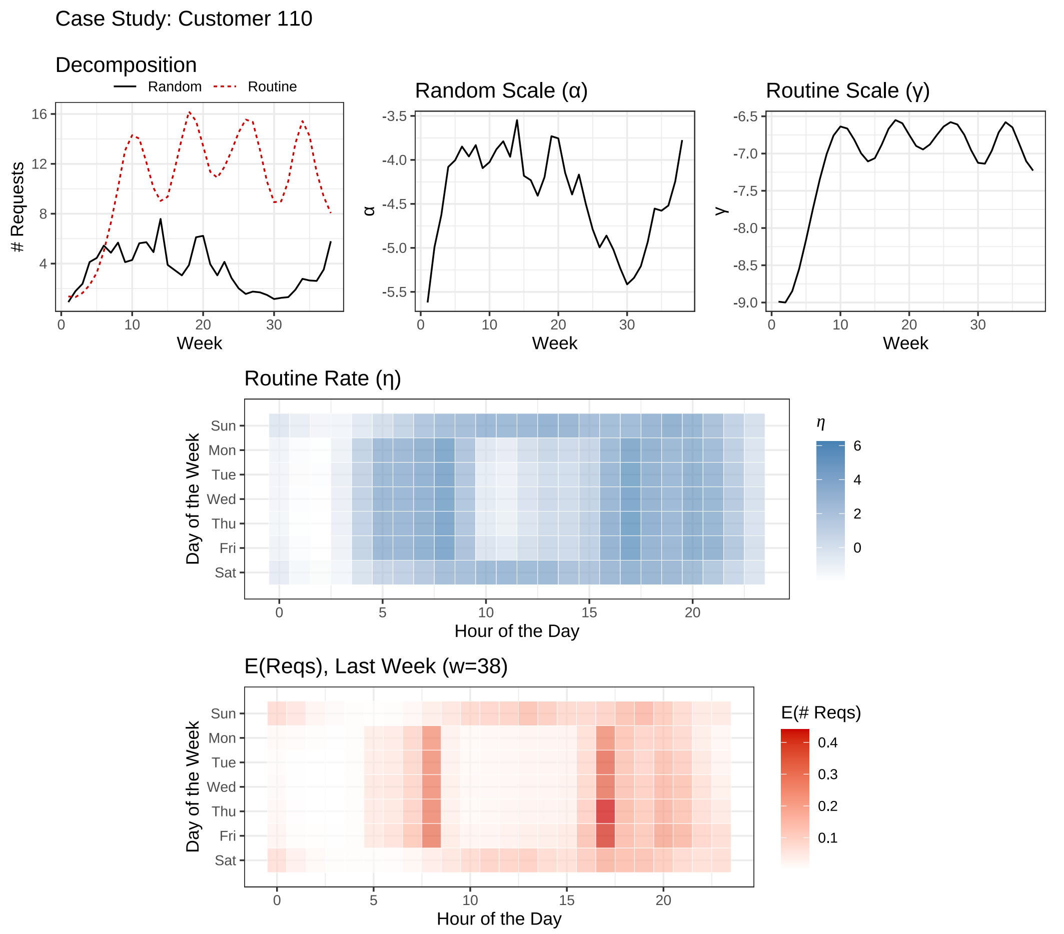

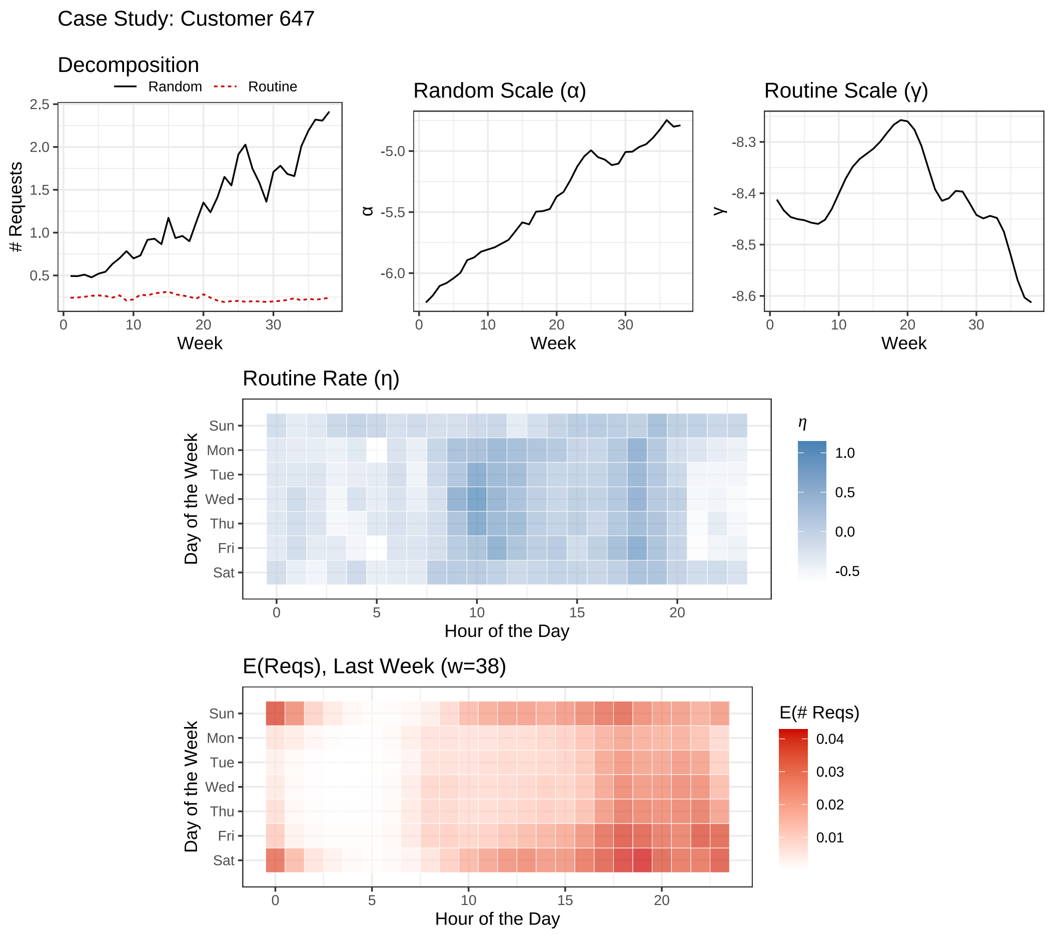

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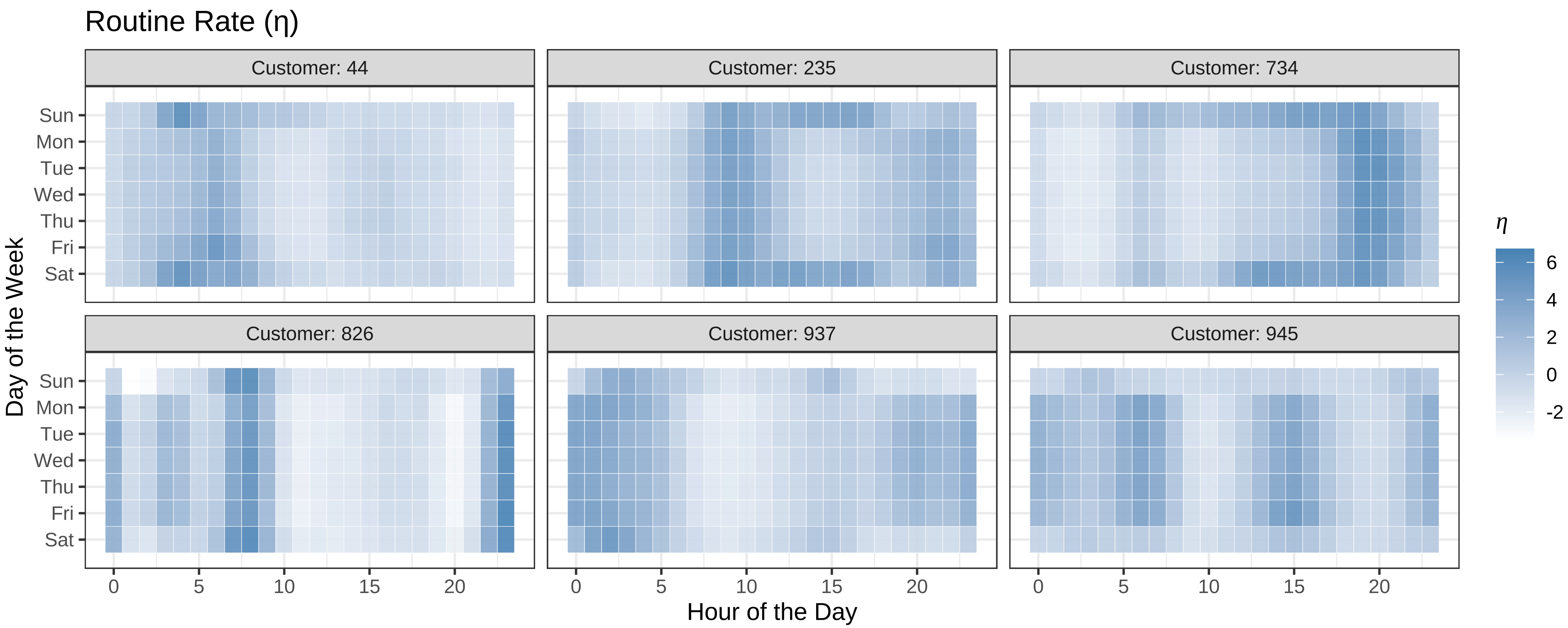

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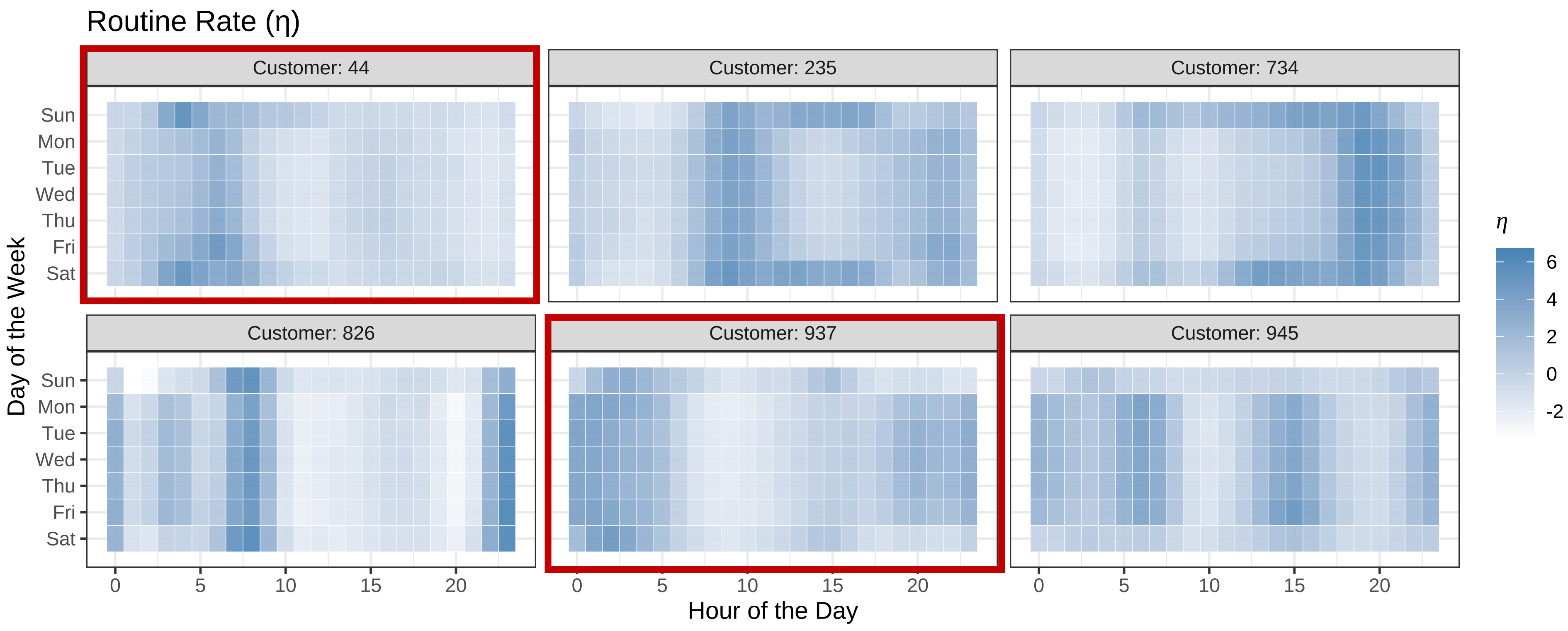

“Night owls”

Many types of routines

"Morning and night"

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
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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.**

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Are routine customers better in other ways?

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- Two metrics of location dispersion:
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After controlling for timing routineness, location dispersion is **not significantly linked** to future activity.

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