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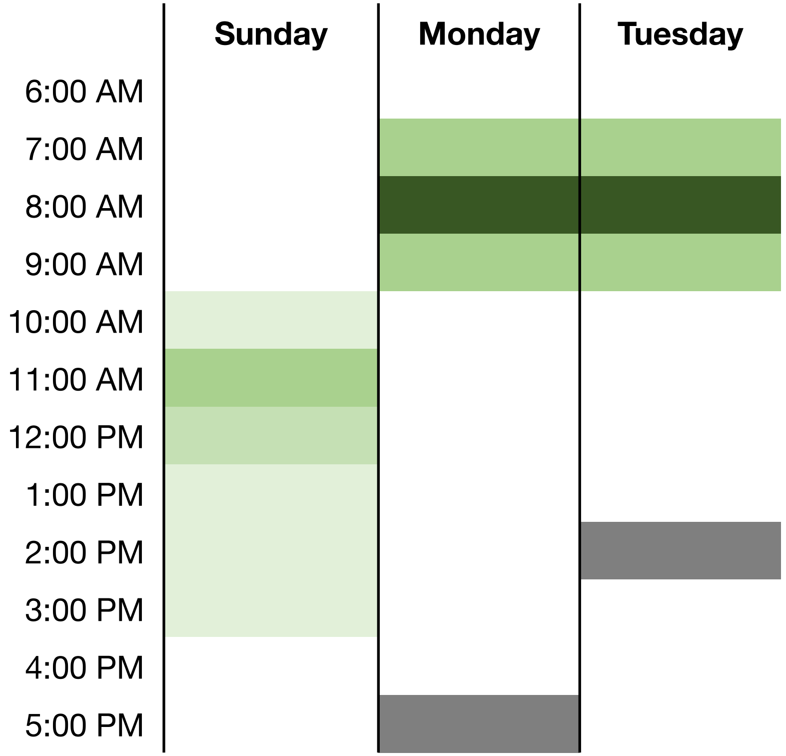
In short: we show the "shape" of customers' interactions matters!

Model

A Statistical Framework for Measuring Routineness

Model of Usage

From transaction data, we want to capture…



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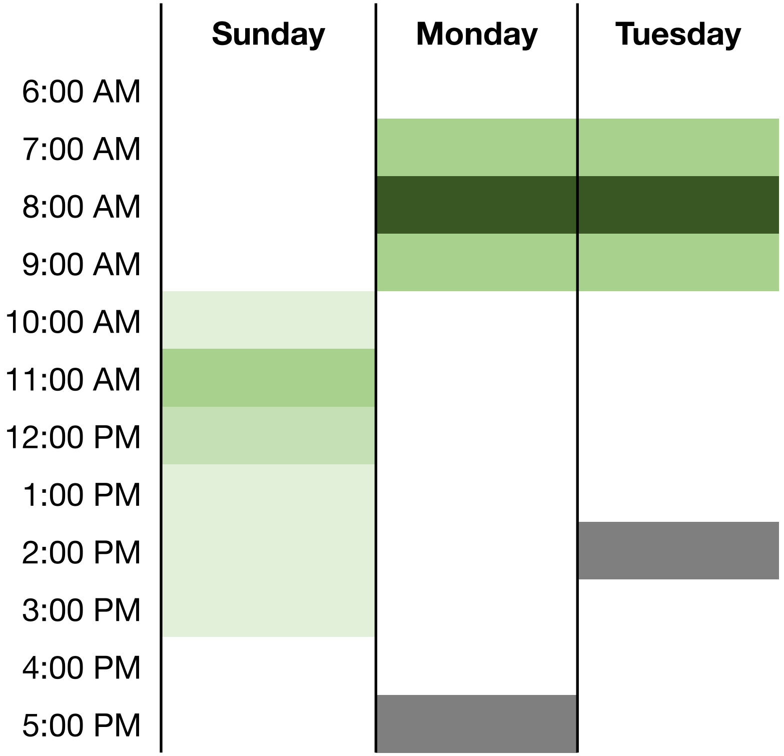

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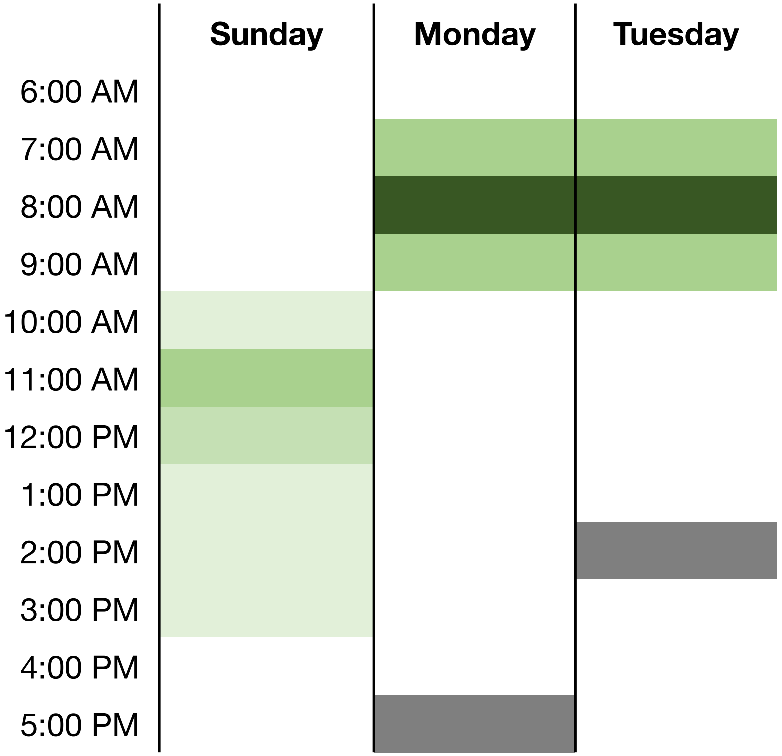

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Dependent variable: Usage (y)

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 $Y_A \sim \text{PP}(\lambda_A)$ and $Y_B \sim \text{PP}(\lambda_B)$,
then $Y_A + Y_B \sim \text{PP}(\lambda_A + \lambda_B)$.

Random requests:

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

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"Routineness"

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Gaussian process: a Bayesian nonparametric prior over a function space

Interlude: Gaussian processes

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Covariance function
"Kernel"

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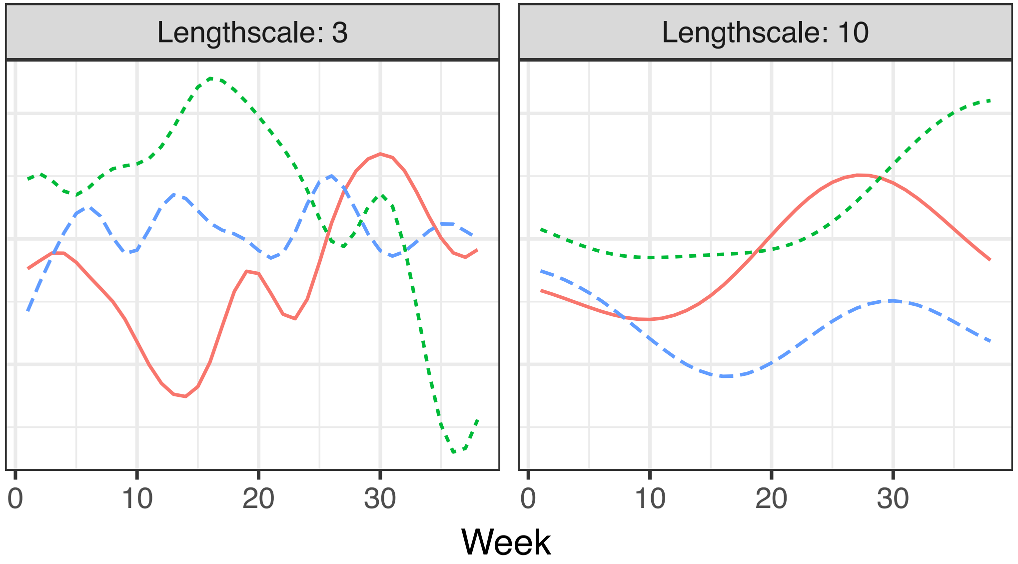

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Intuition: routines are by definition "sticky" over time

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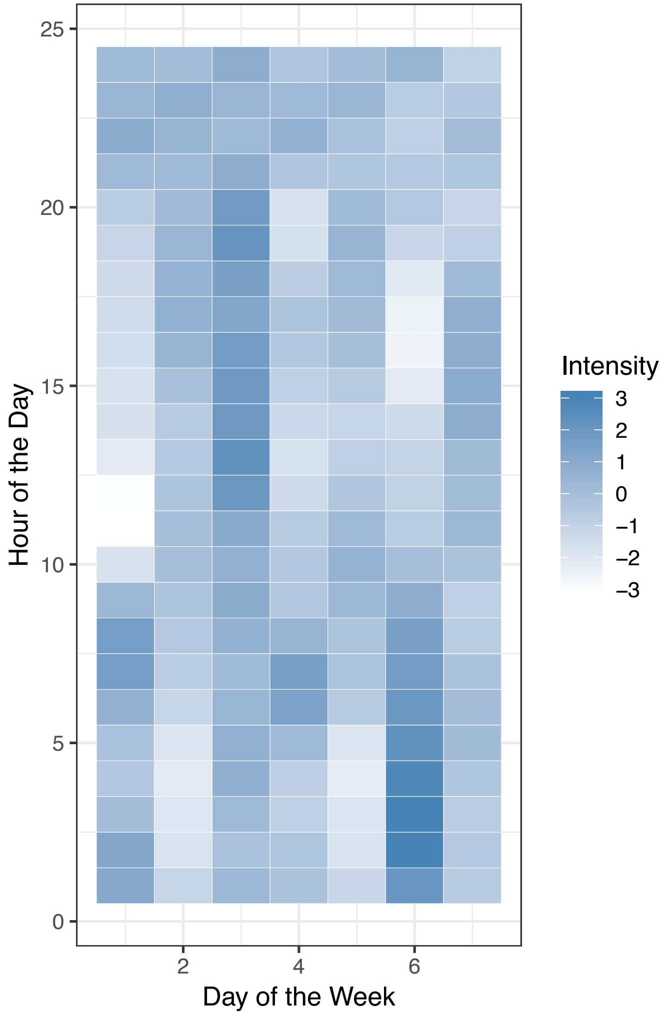

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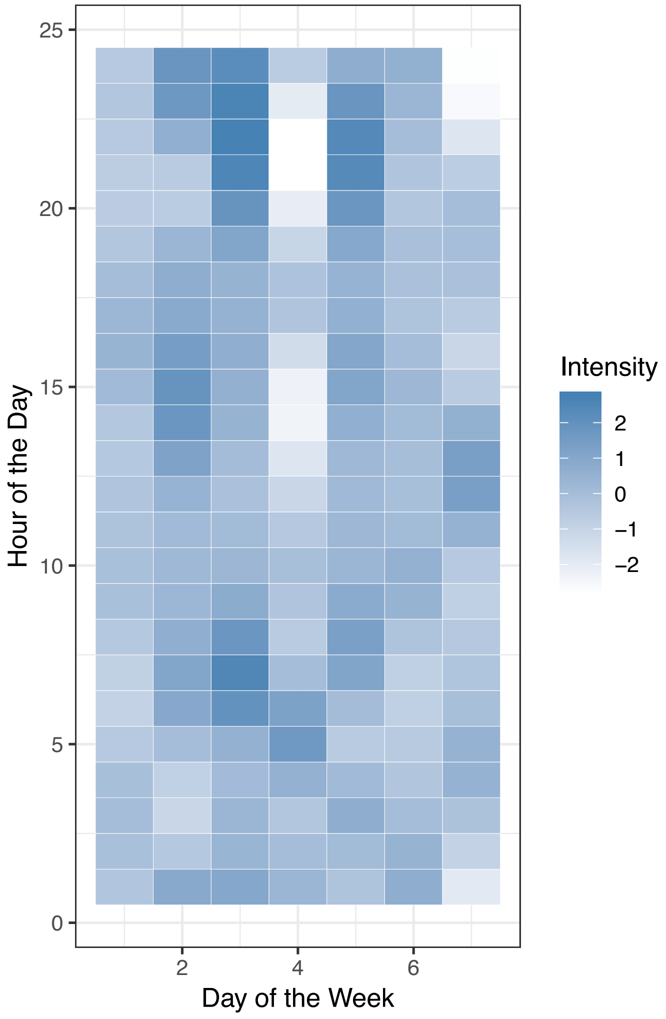

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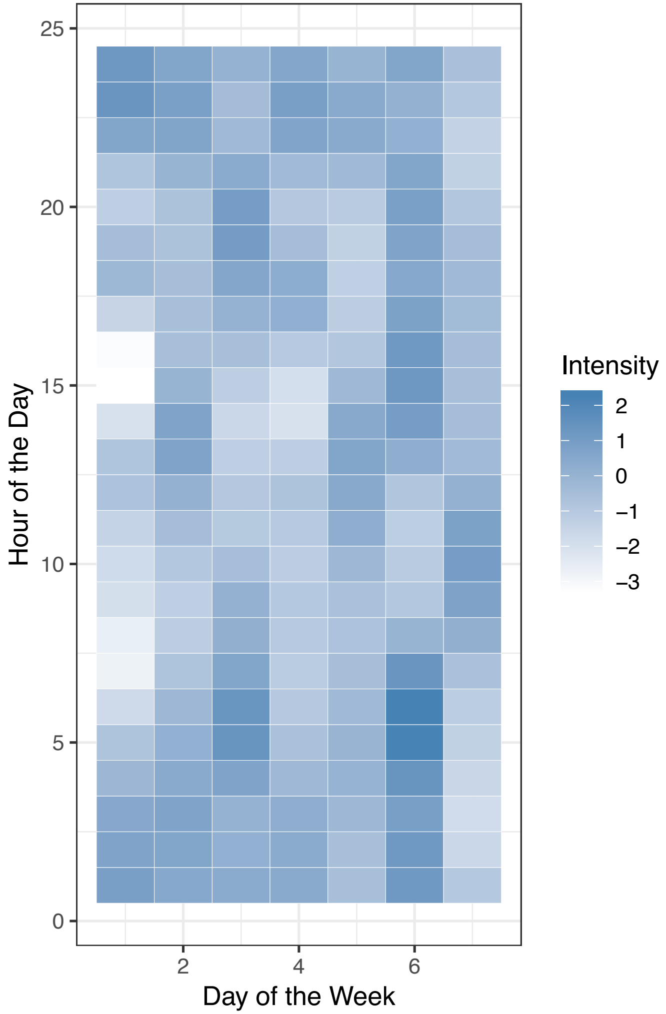

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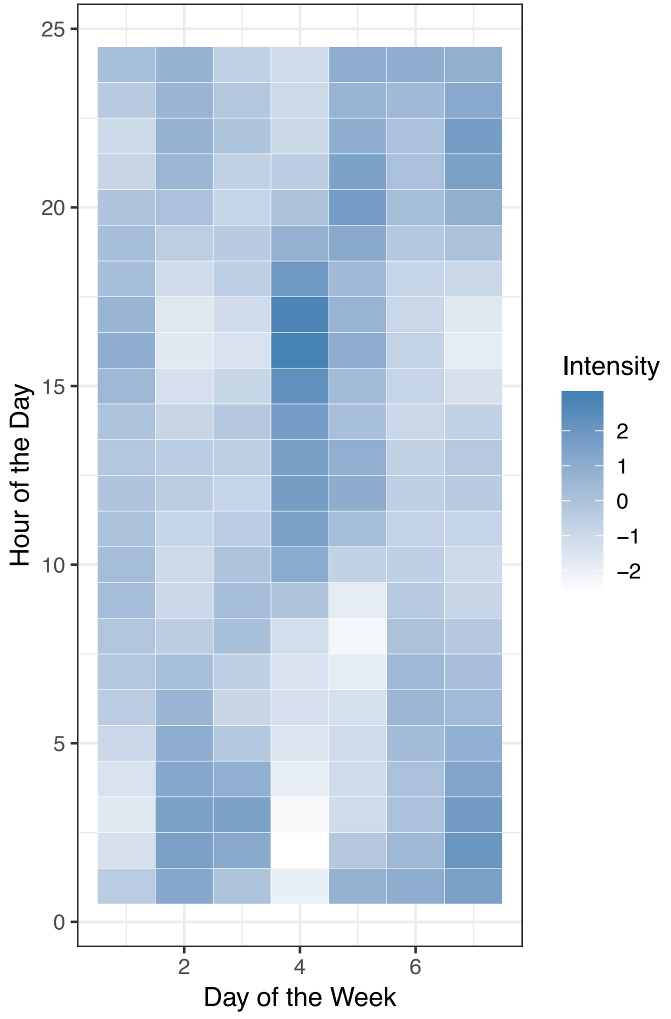

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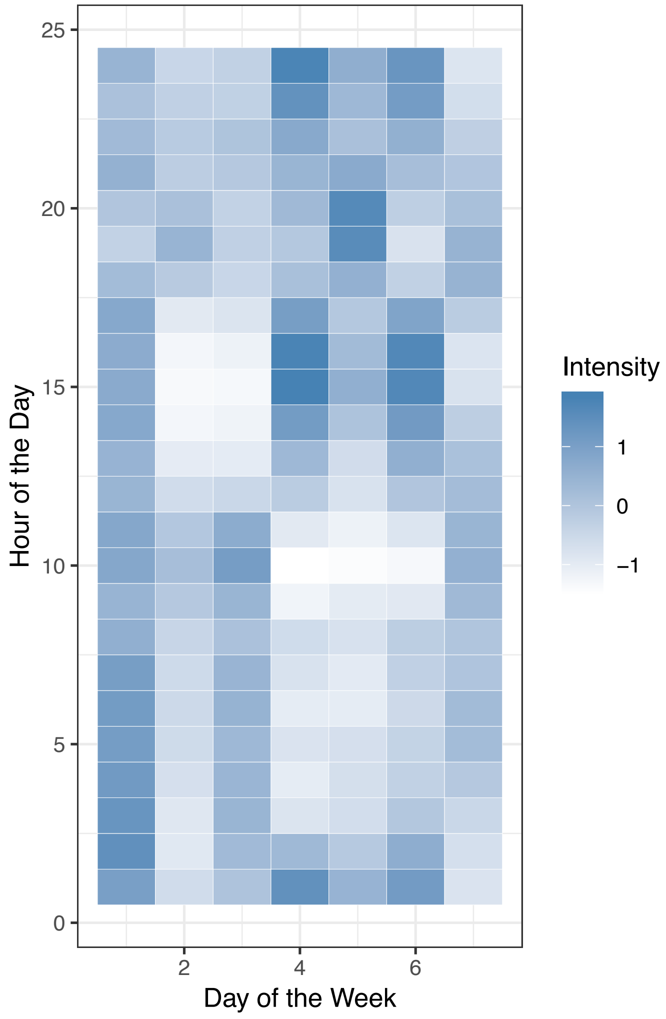

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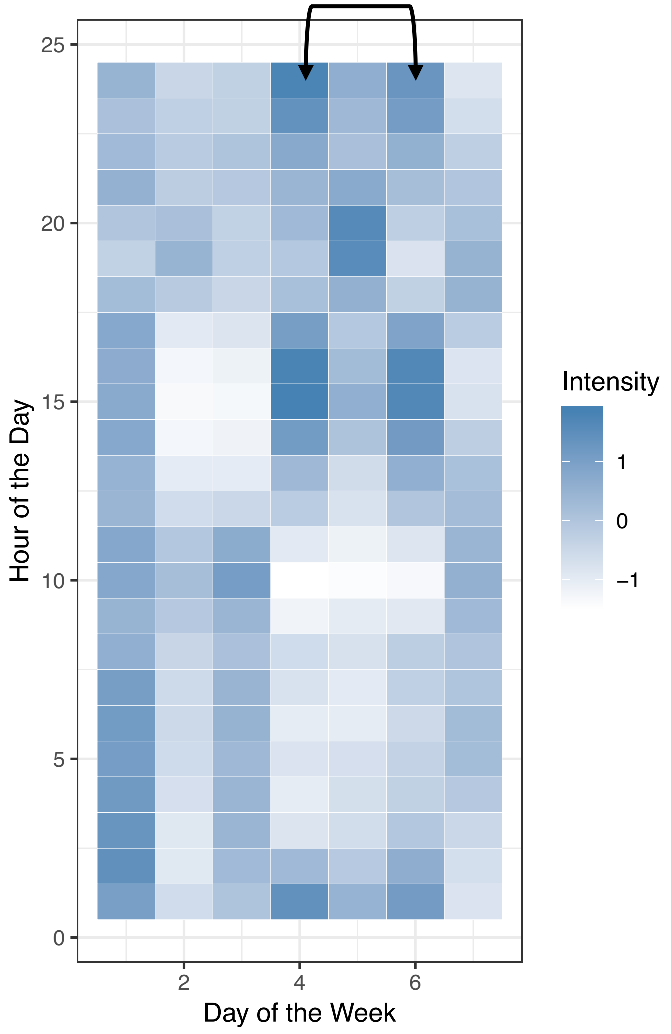

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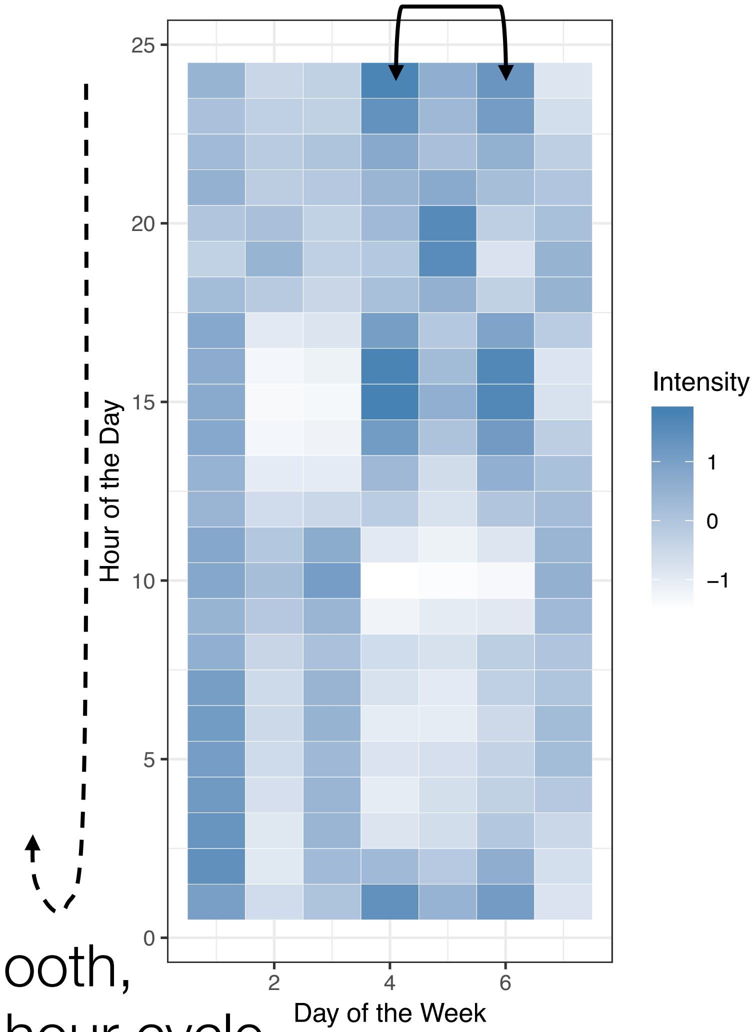

Smooth, 24-hour cycle

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Baselines for weekly variation:

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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

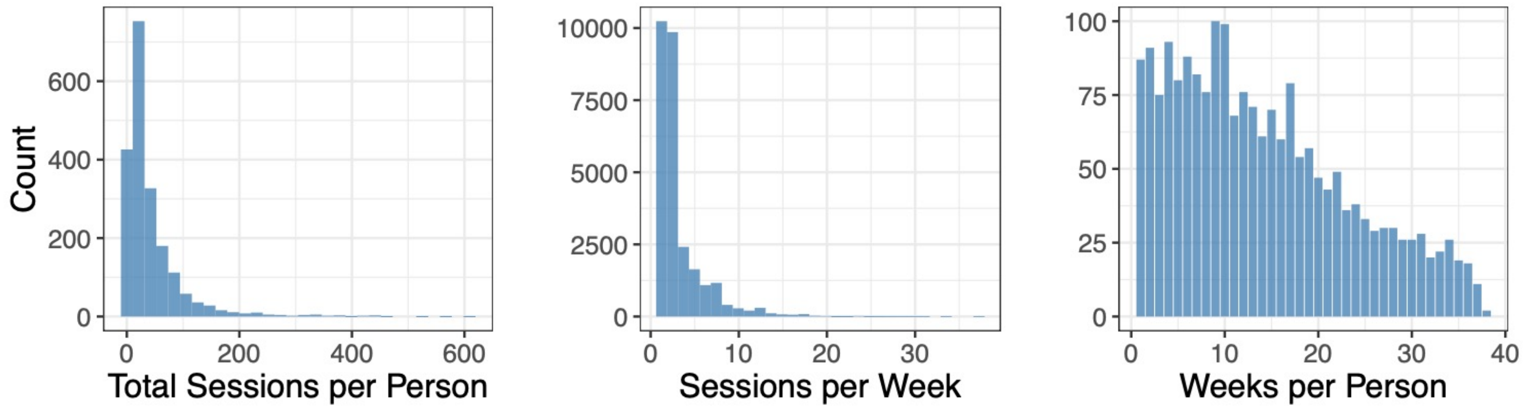
Results

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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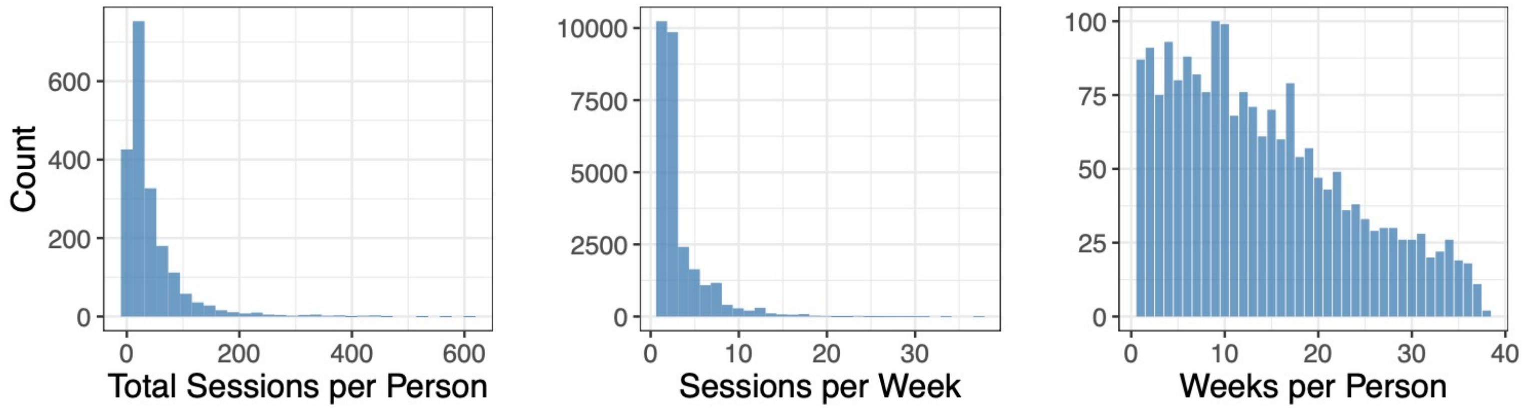

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Basic unit of analysis:
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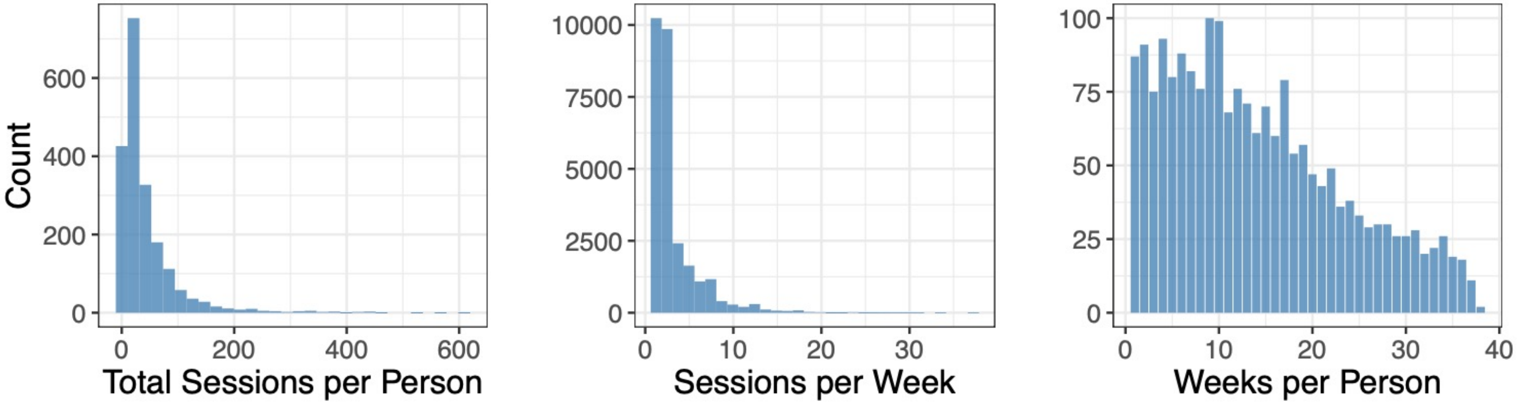

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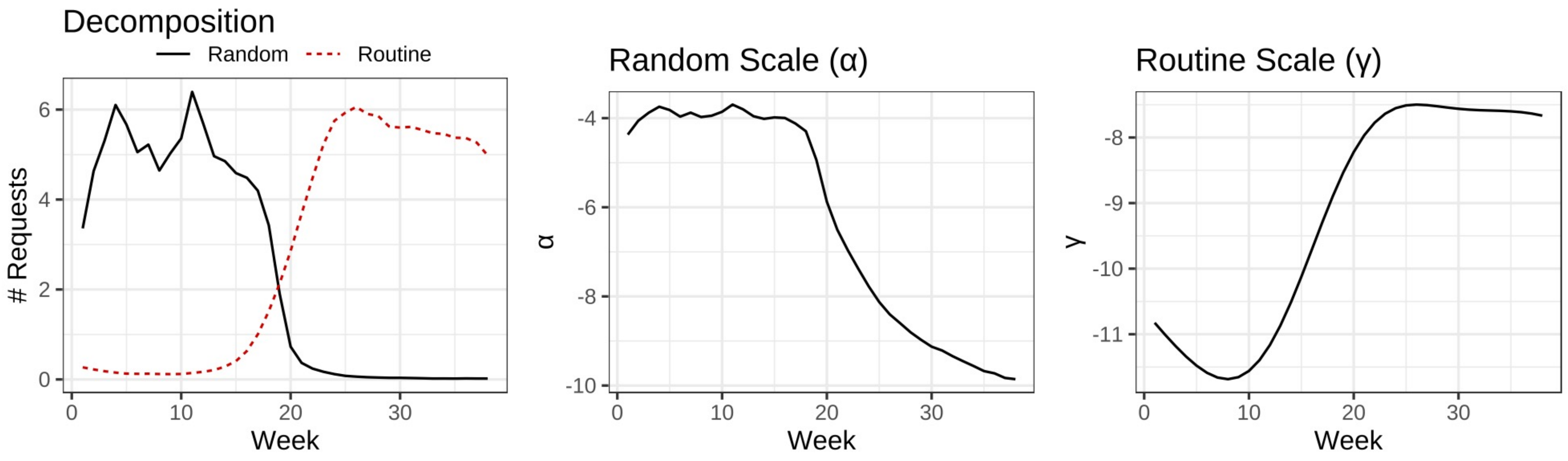

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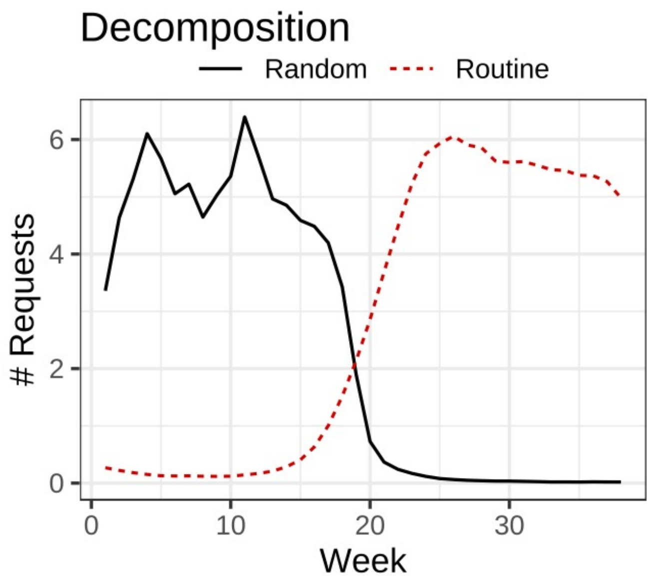
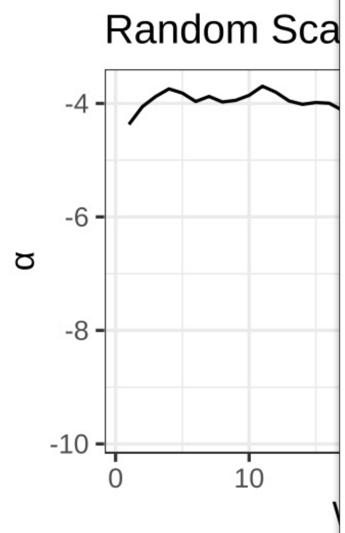
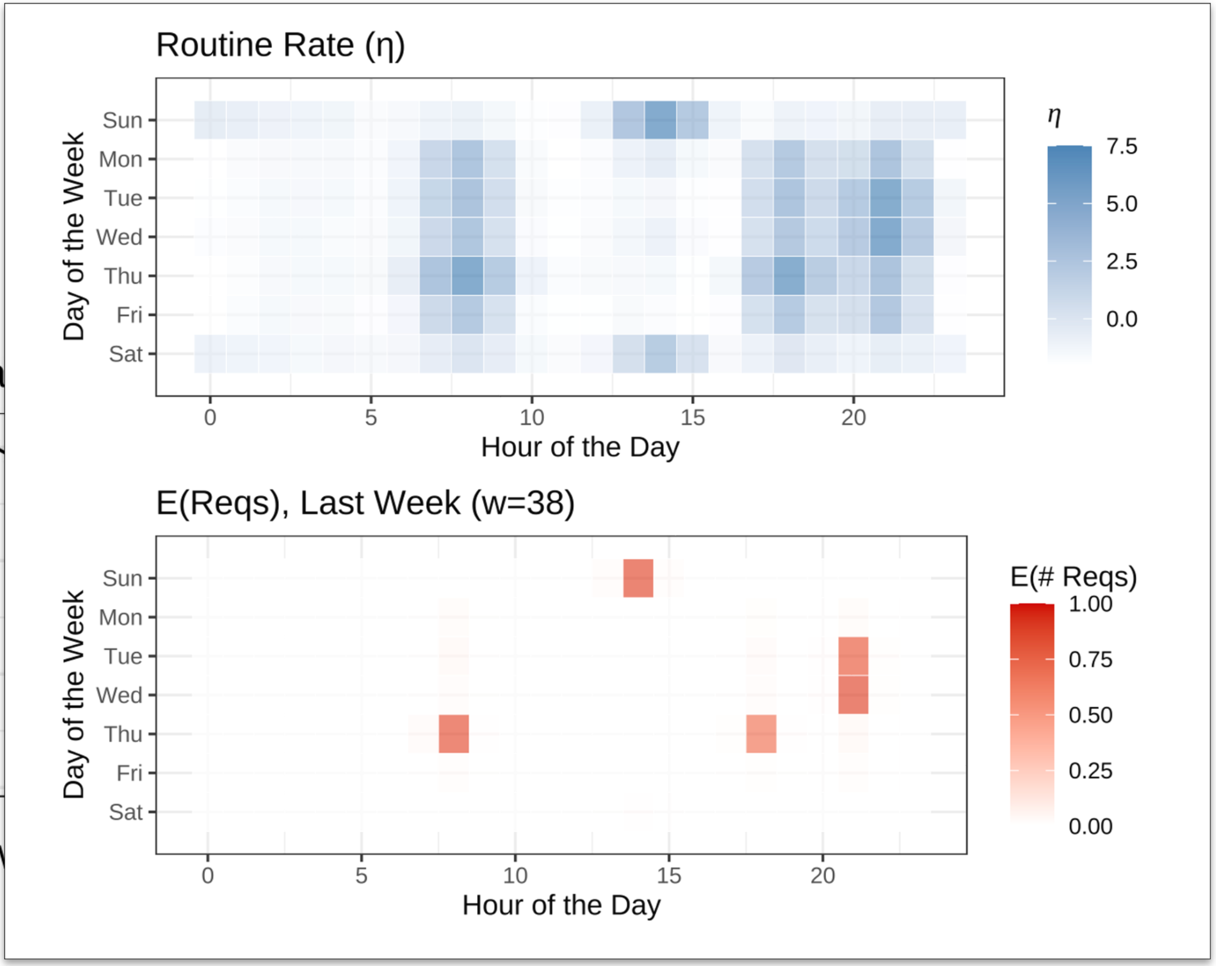
Case 1: Random then Routine







“Quasi-simulation”

- 500 real customers + 15 fake customers with specific usage patterns

Case 2: Routine then Churn

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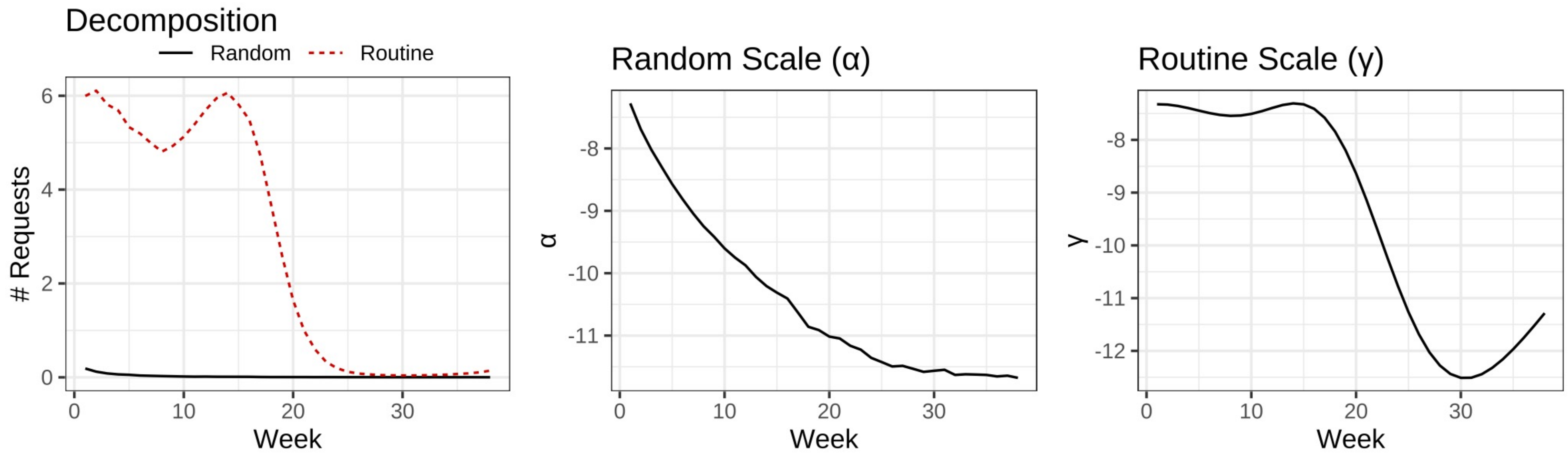

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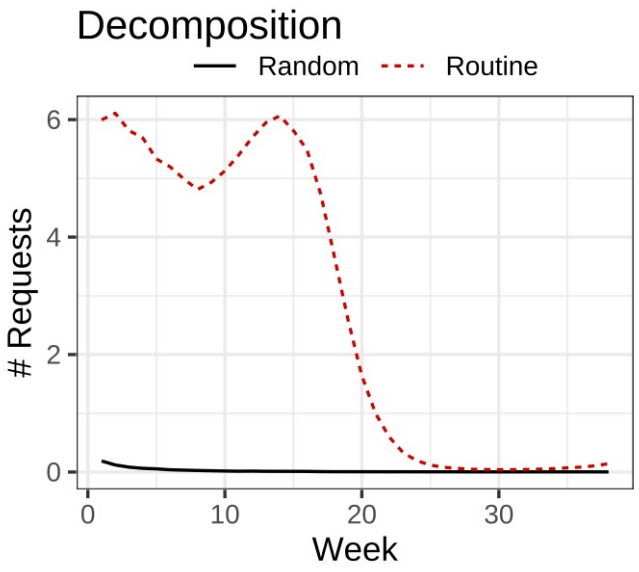
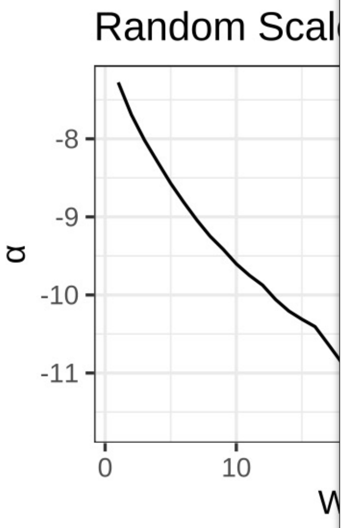
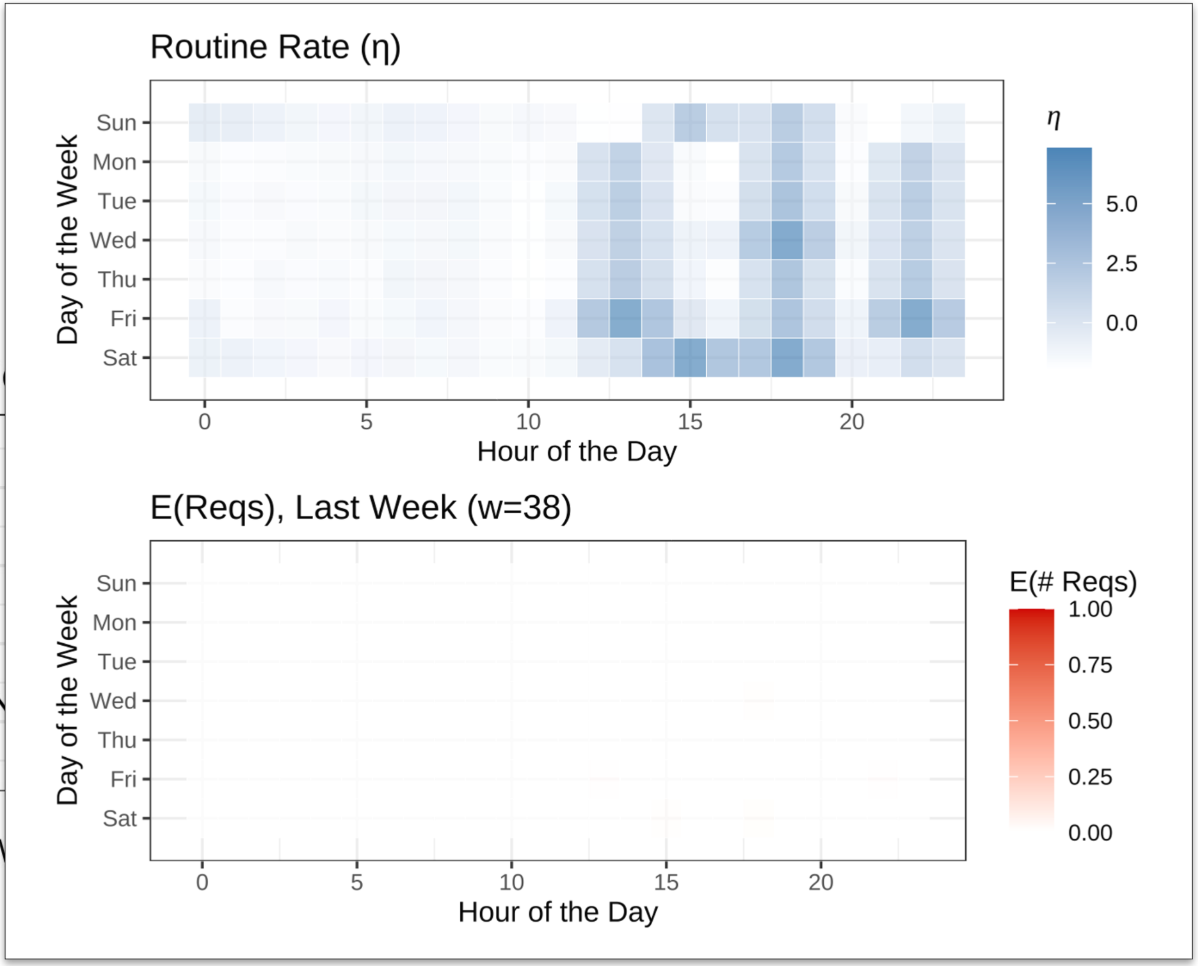
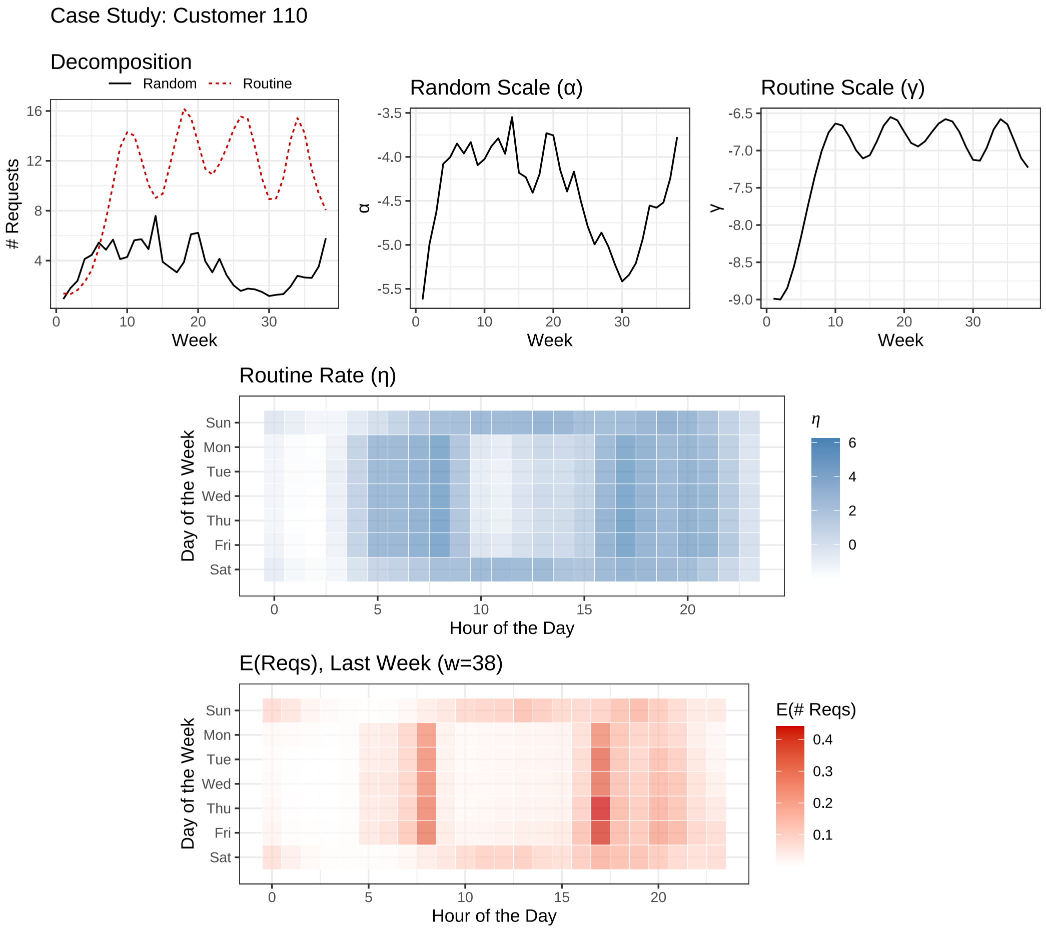






Real Case Studies



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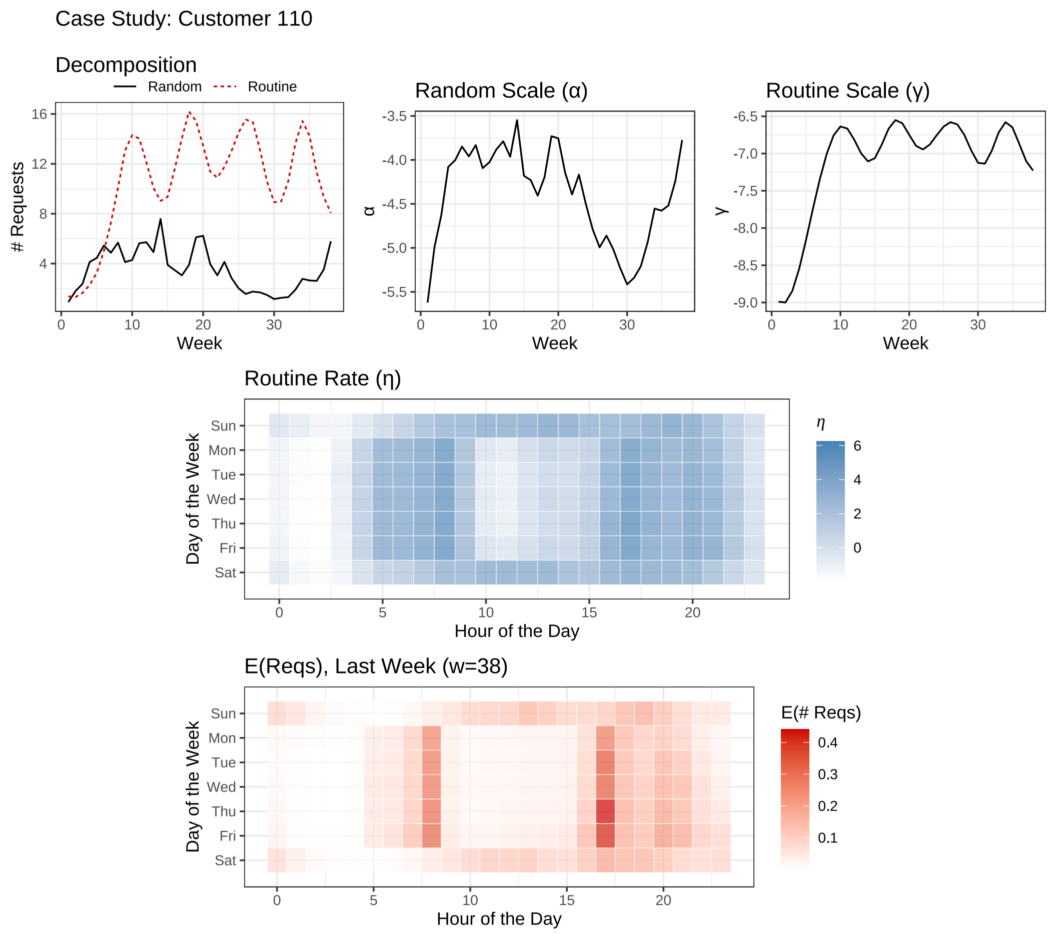
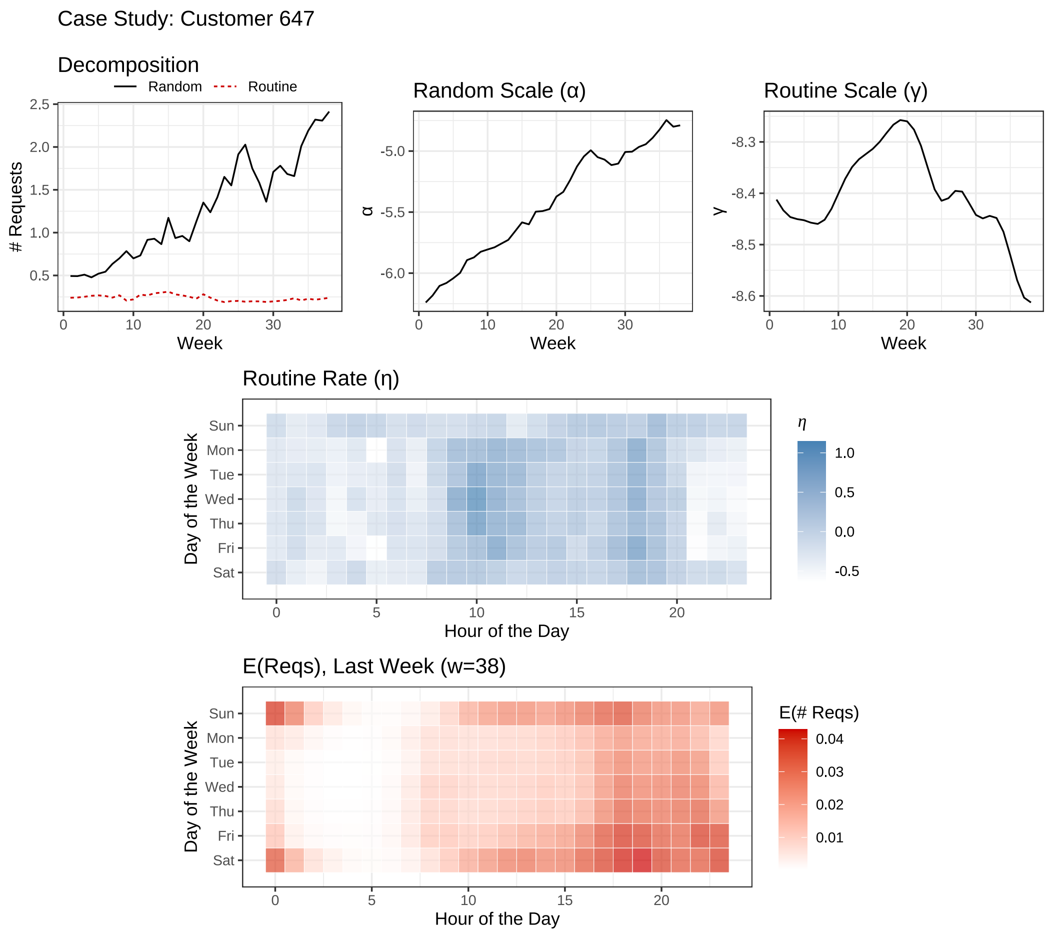
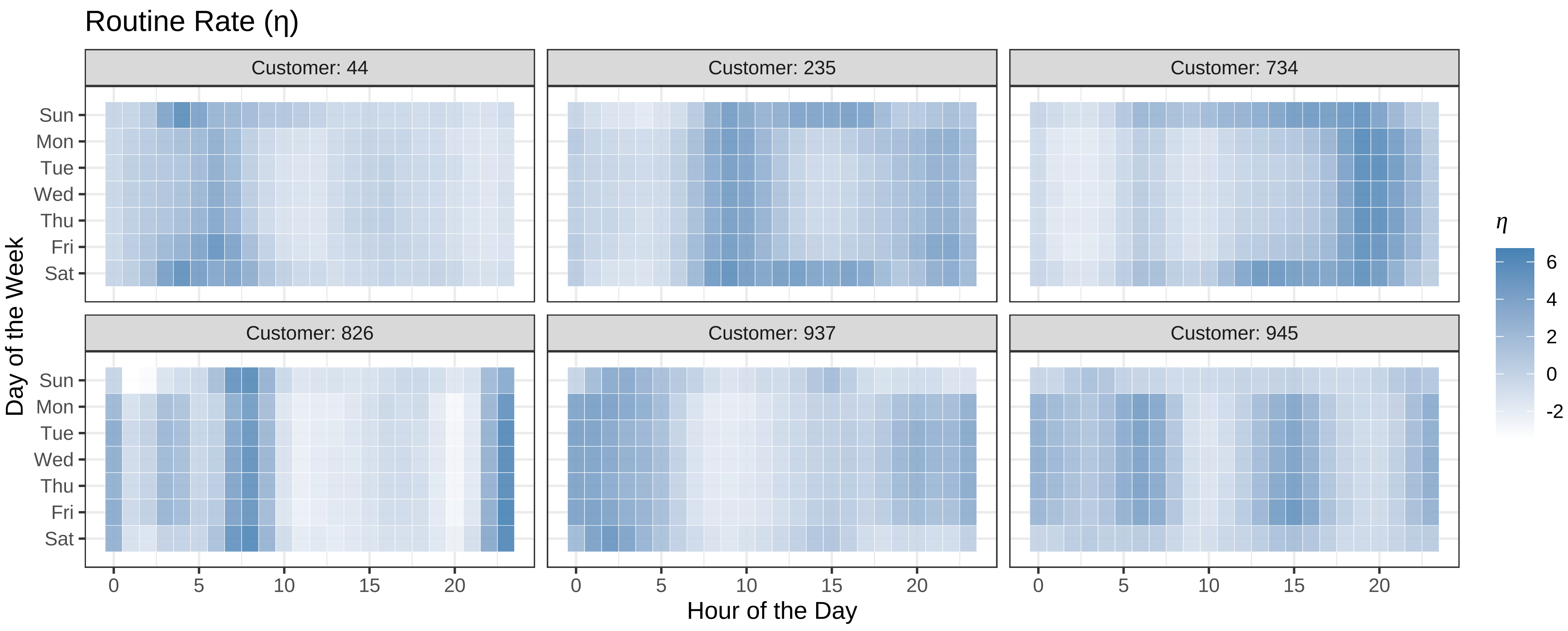




Many types of routines



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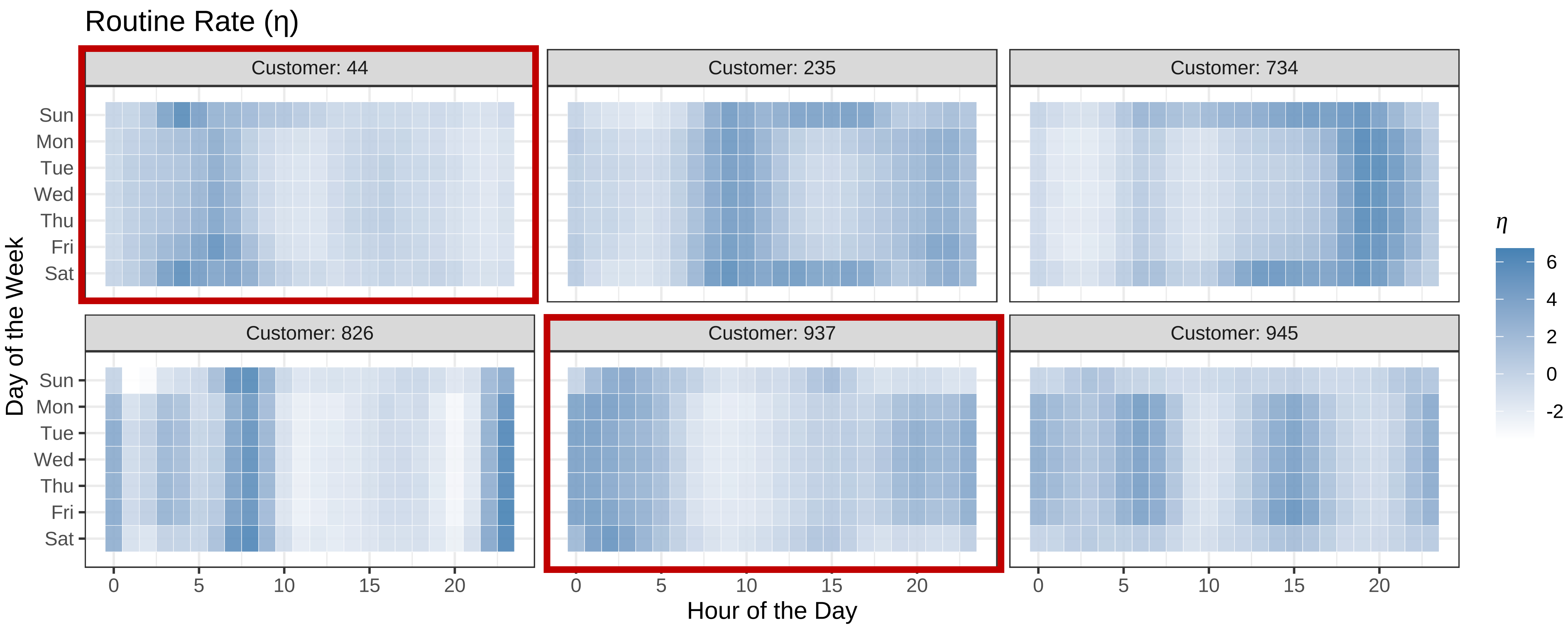


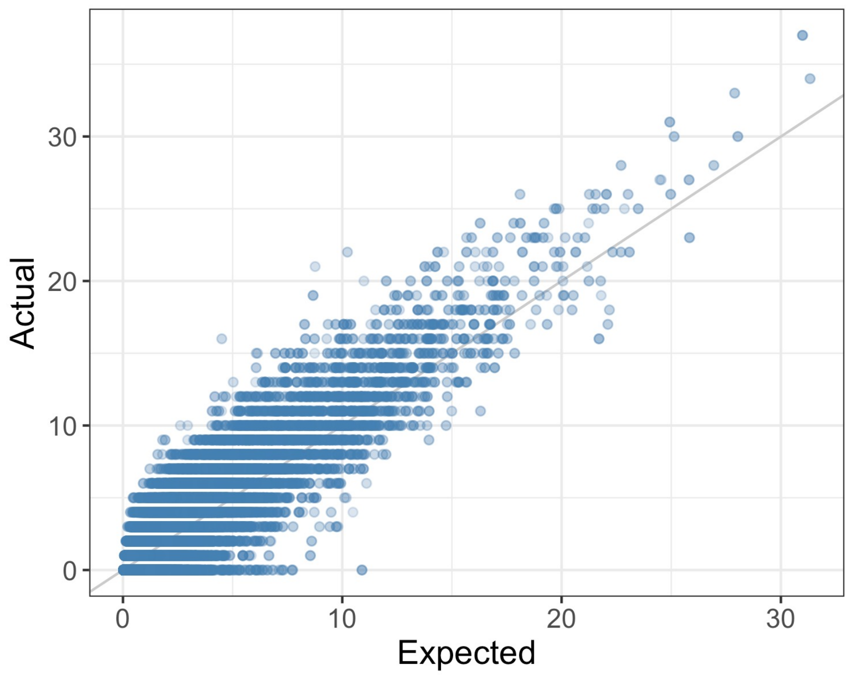
“Night owls”

Many types of routines

“Morning and night”

Validation

Can we trust these results?



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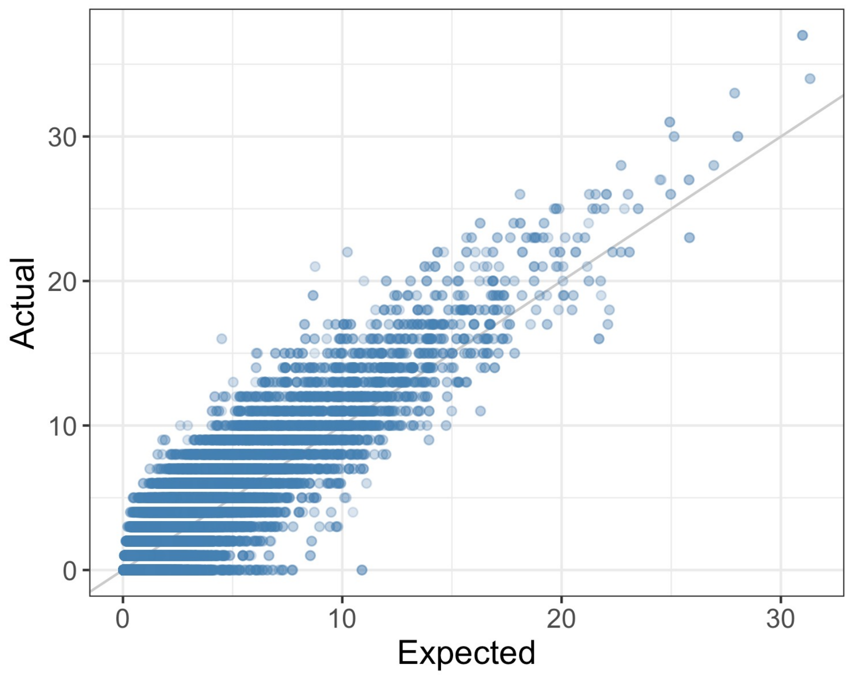

Prediction of transaction times:

- Predict timing of <u>routine</u> rides
- 100+% improvement over "universal" routine

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

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More to the story…

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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)

Main effect

Moderating effects

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- In ride-sharing: are people routine in *where* people are going, in addition to *when* they're going?
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Entropy: given the empirical distribution $\boldsymbol{p}$ of locations, $\ell = 1, \ldots, L$:

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

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

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

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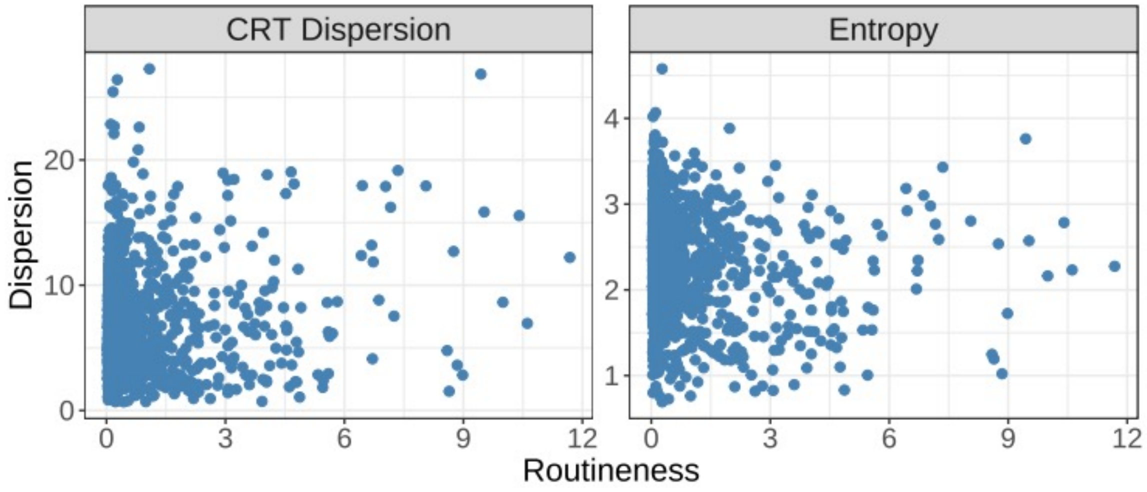

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Summary

- **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?

ryandew@wharton.upenn.edu

Working paper available at www.rtdew.com