Detecting Routines in Ride-sharing: Implications For Customer Management

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HARVARD BUSINESS SCHOOL

Columbia Business School AT THE VERY CENTER OF BUSINESS™

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

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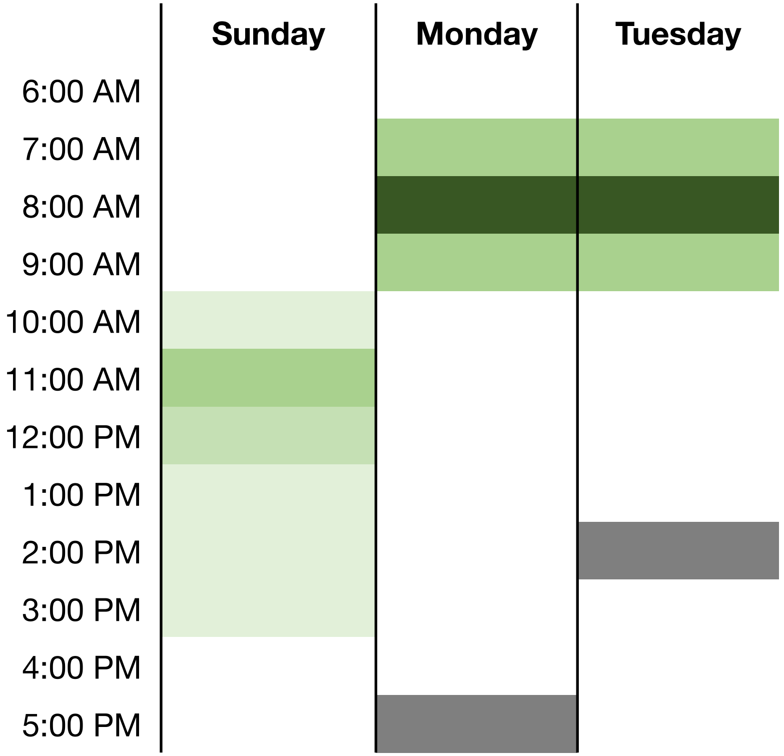
In short: we show the "shape" of customers' interactions matters!

Model

A Statistical Framework for Measuring Routineness

Model of Usage

From transaction data, we want to capture…



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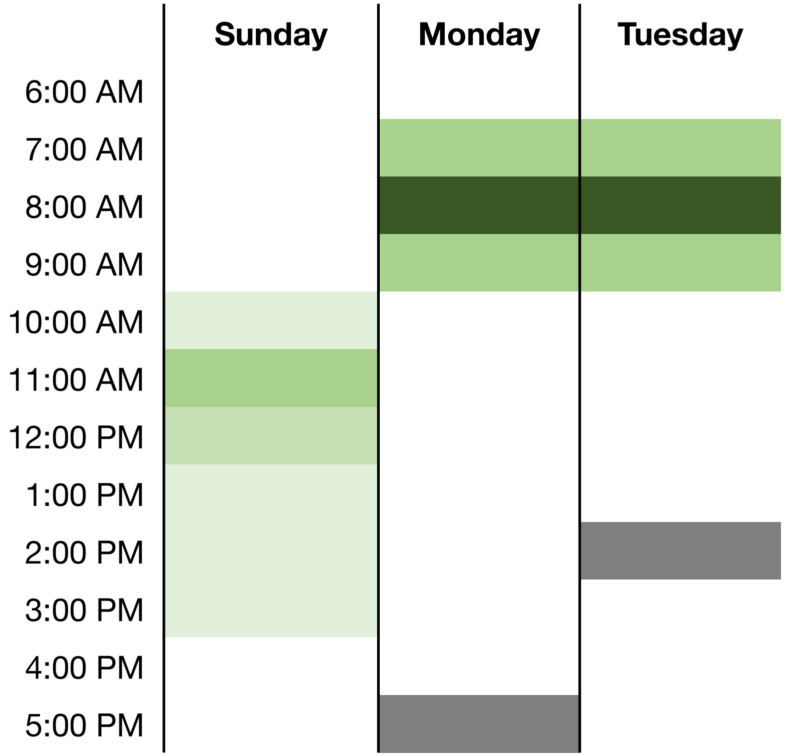

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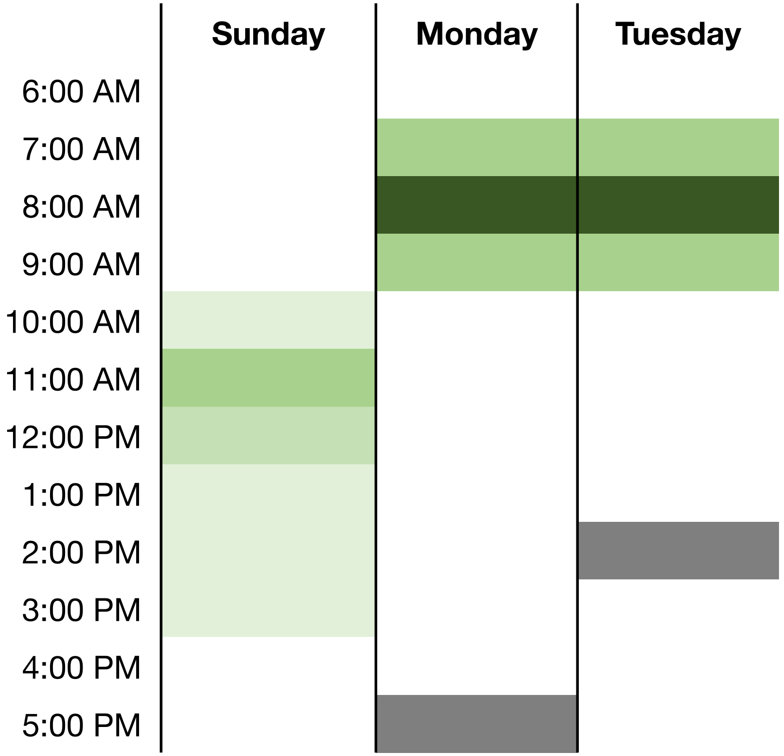

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Dependent variable: Usage (y)

Customer i, Week w, Day d, Hour h

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

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

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

- 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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Scaling terms for weekly variation:

$$\alpha_{iw} \sim \mathcal{N}(\alpha_{iw-1}, \tau)$$
$$\gamma_i(w) \sim \mathcal{GP}(\gamma_0, k_{\mathrm{SE}}(w, w'; \phi_\gamma))$$

Rate terms for day-hour variation:

$$\mu(d, h) \sim \mathcal{GP}\left(0, k_{\mathrm{DH}}(d, h; \phi_\mu)\right)$$
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Gaussian process: a Bayesian nonparametric prior over a function space

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Squared exponential kernel with fixed smoothness

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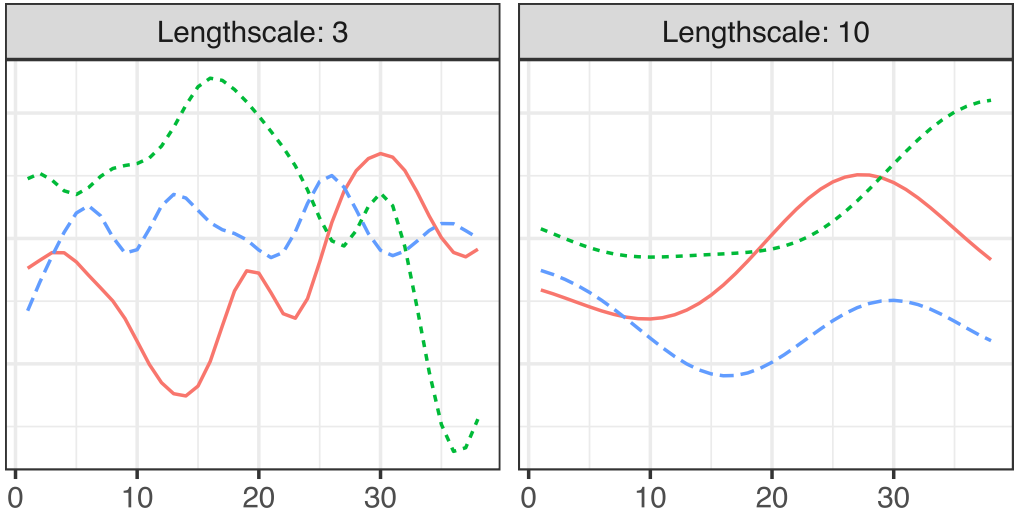

Key Assumption

The routine scale, $\gamma_i(w)$ evolves <u>slowly</u> over weeks

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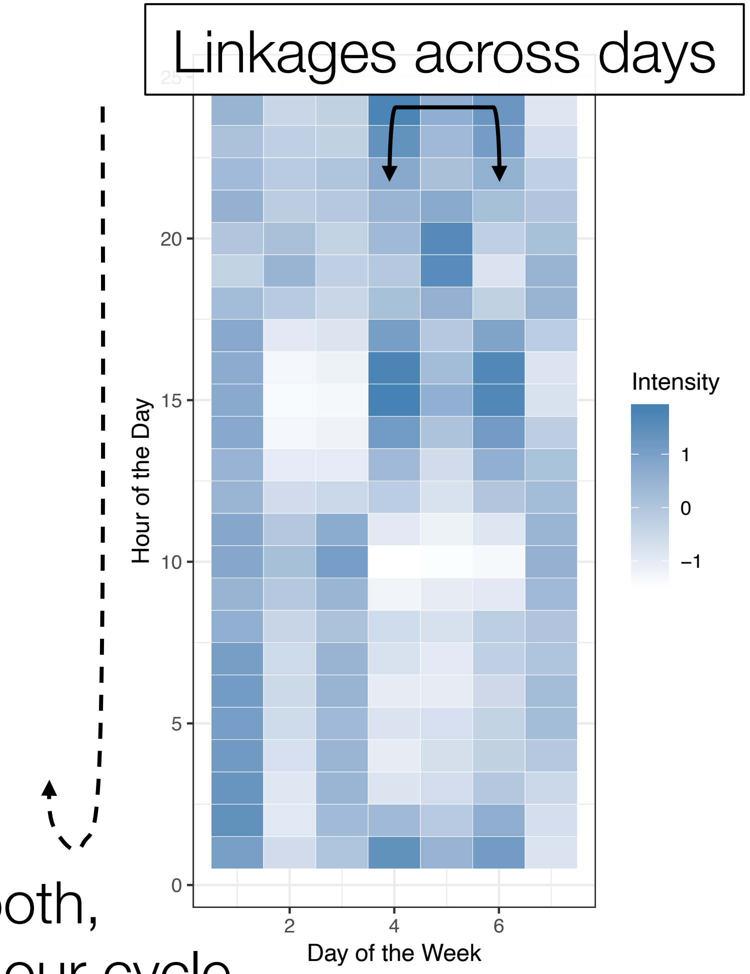
Novel day-hour kernel



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})

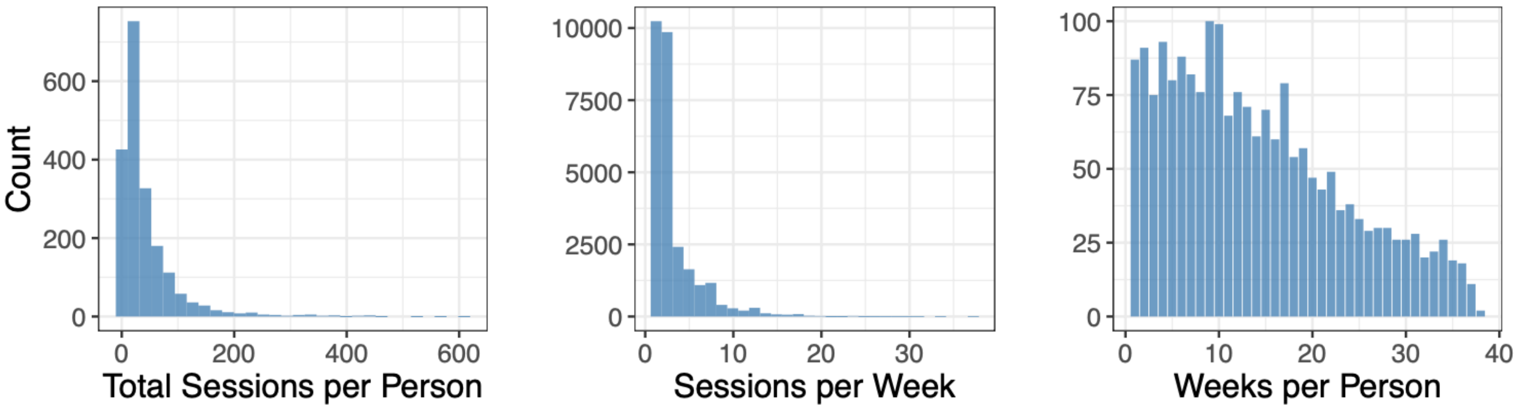
Results

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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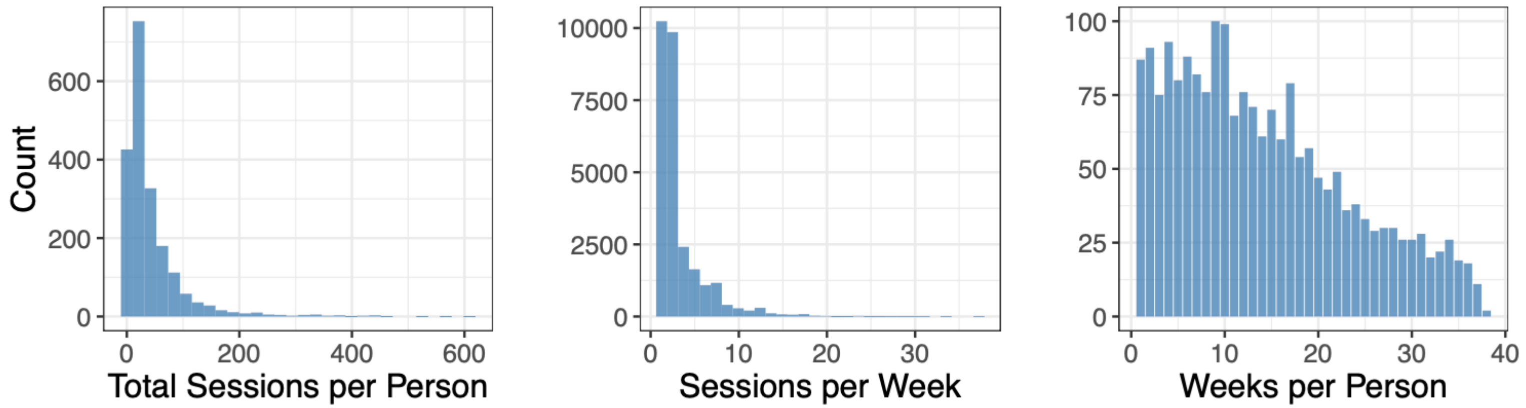

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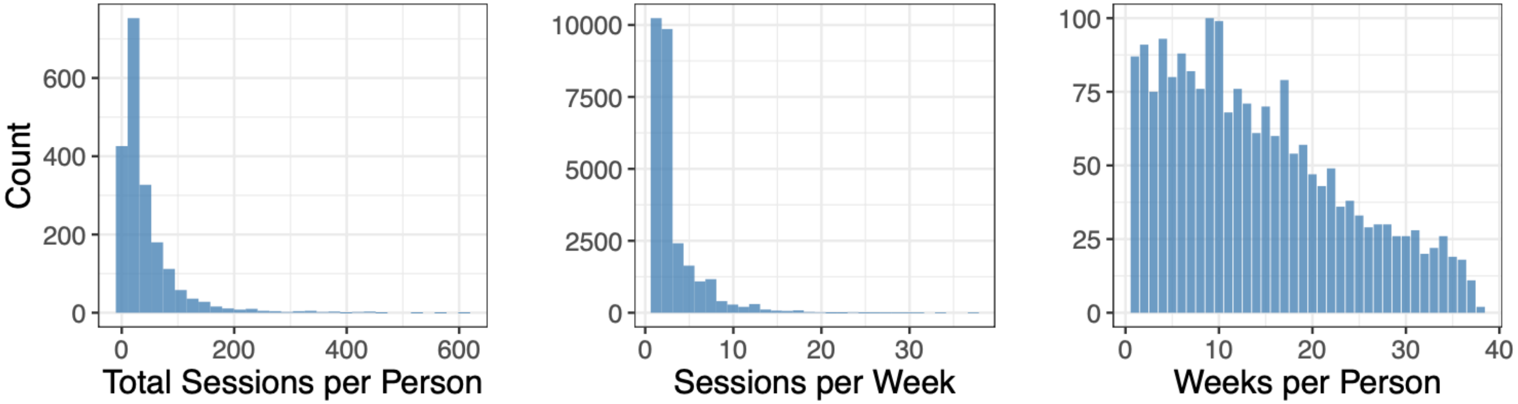
Basic unit of analysis:
a "session"



“Quasi-simulation”

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

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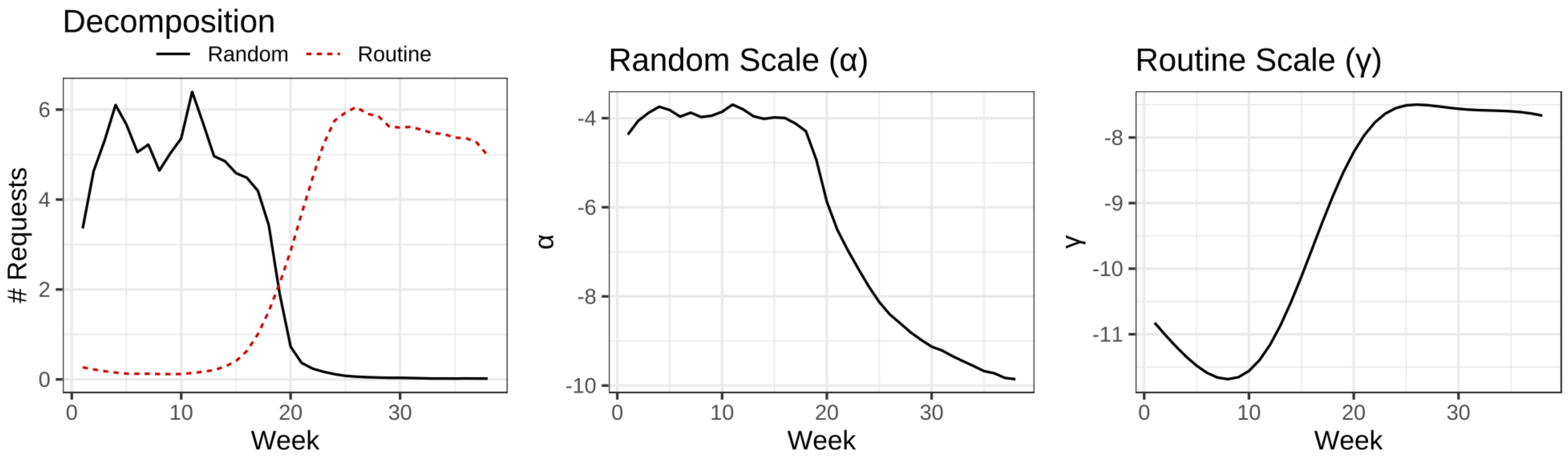

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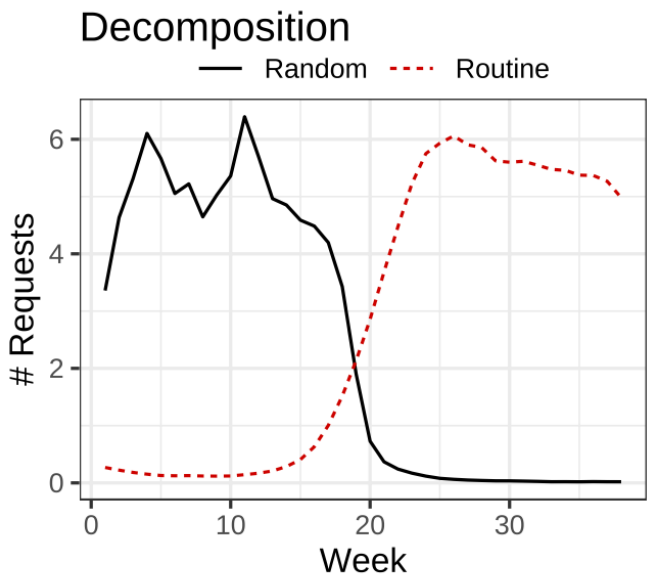

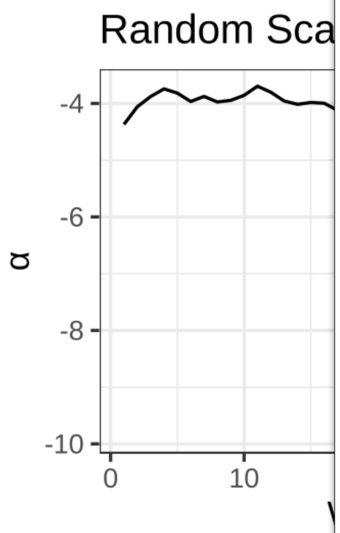

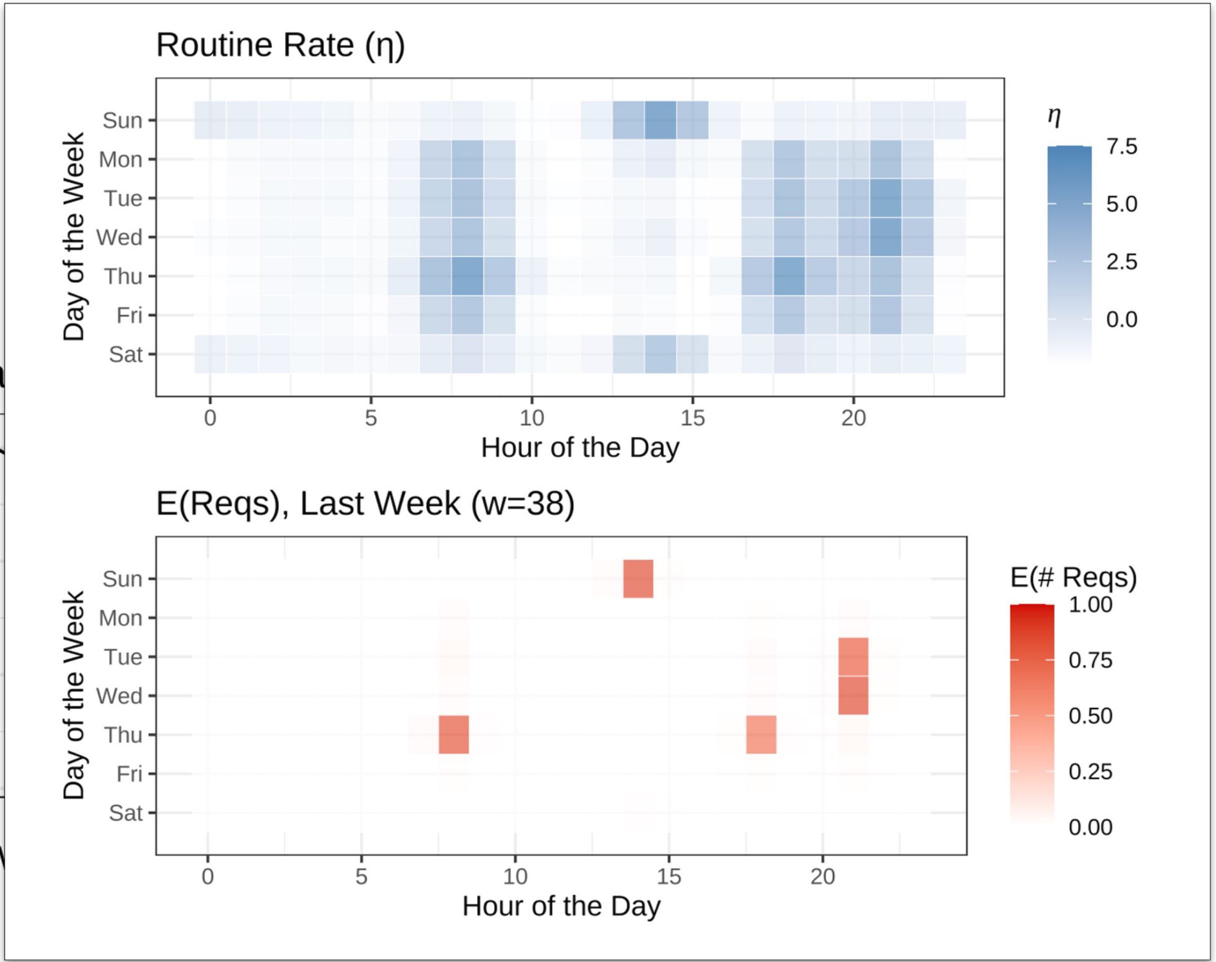

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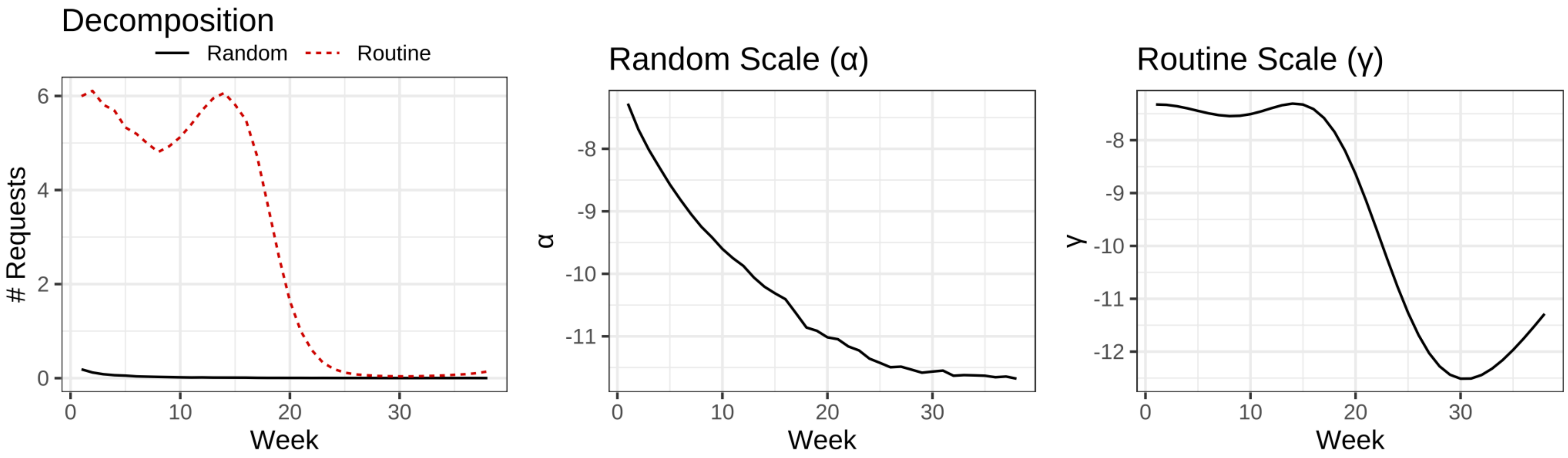

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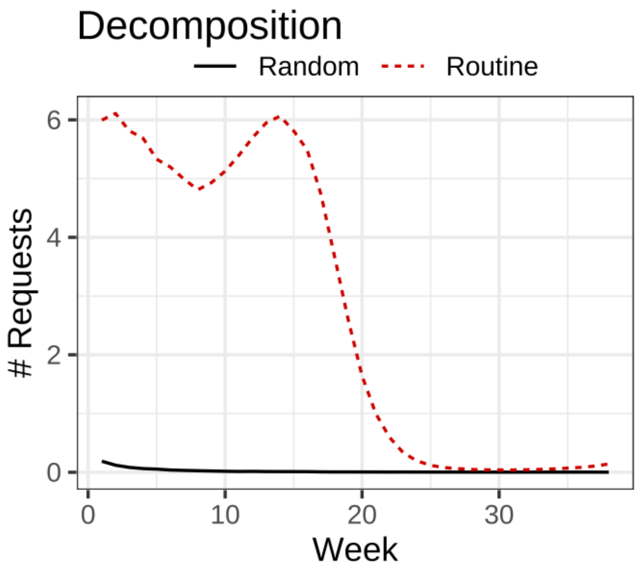
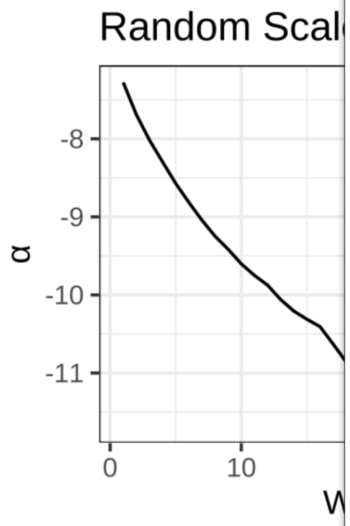
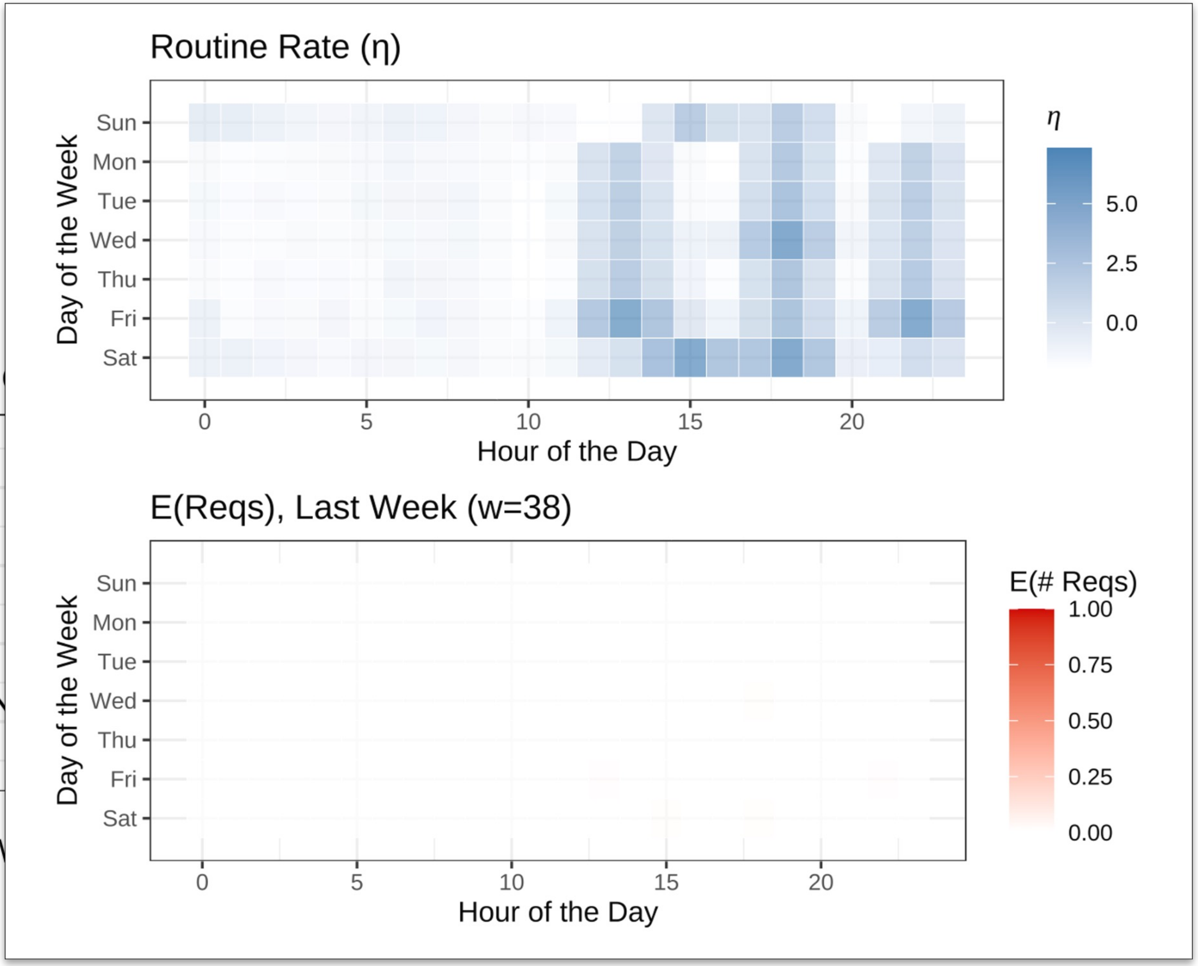
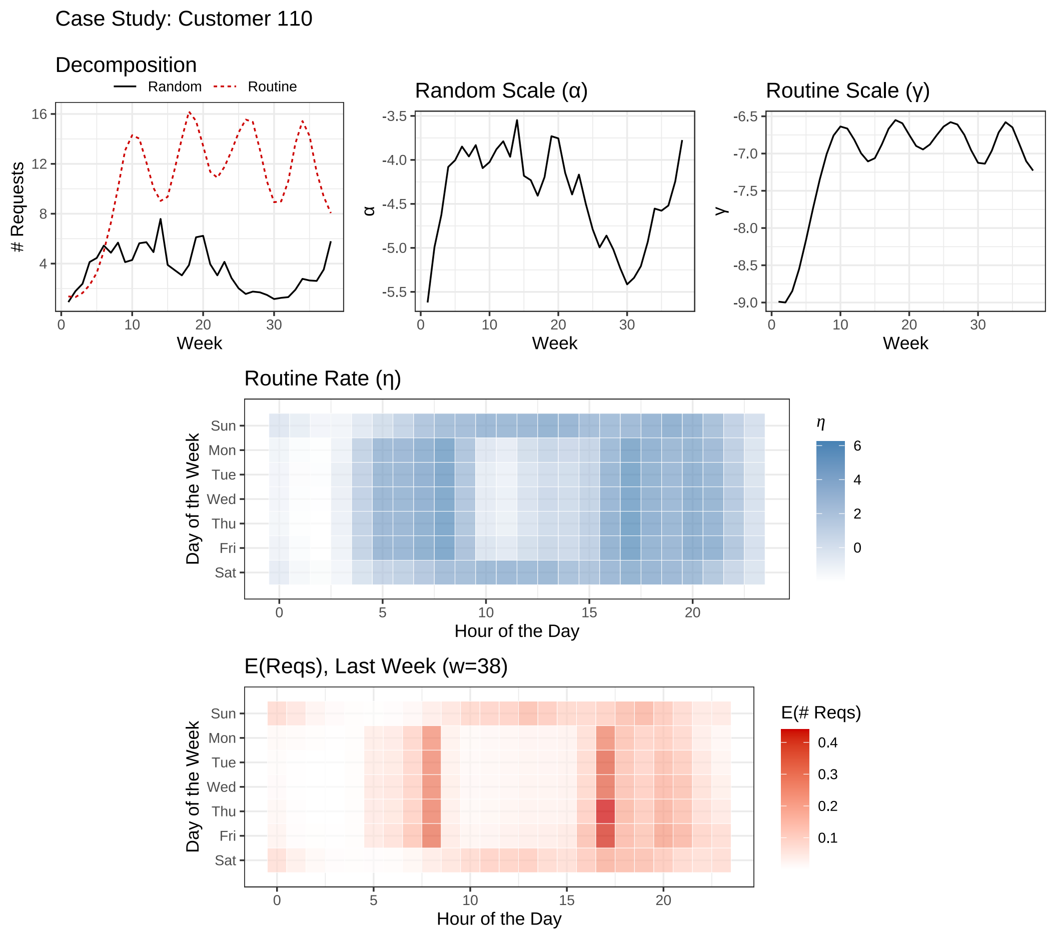






Real Case Studies



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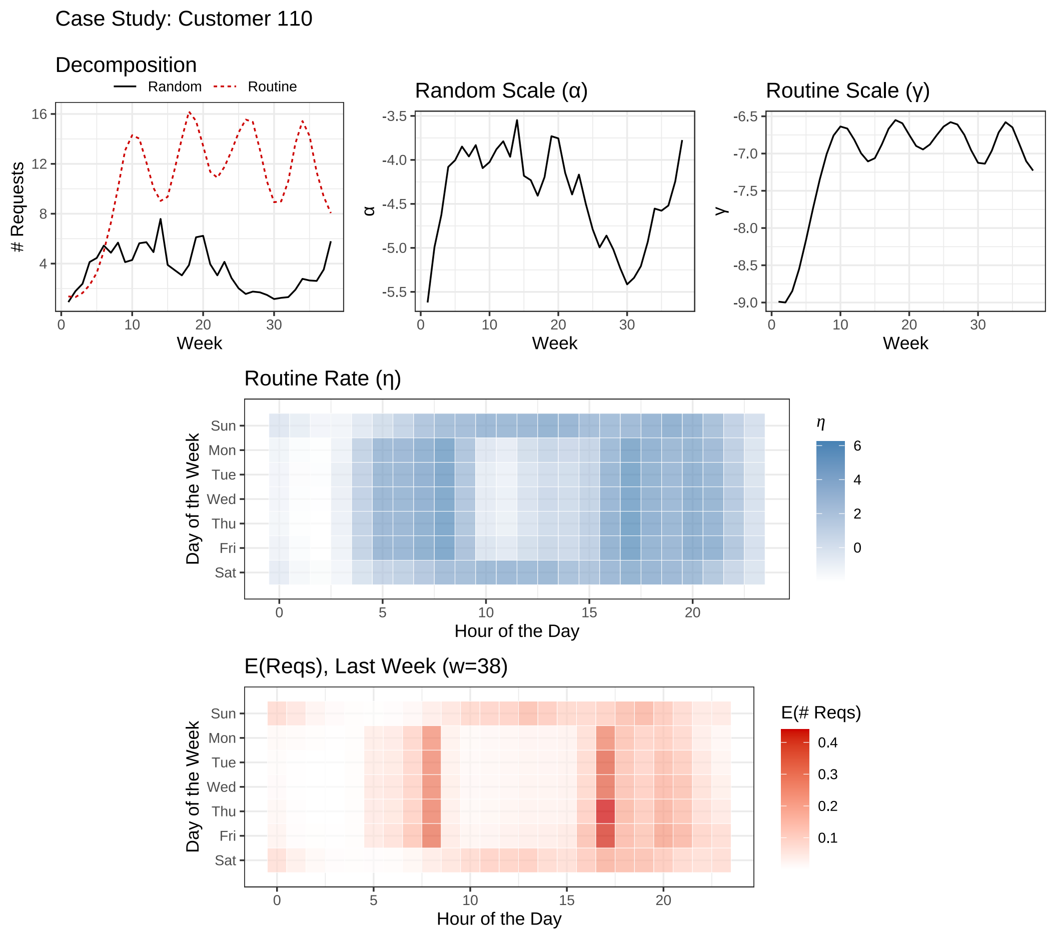
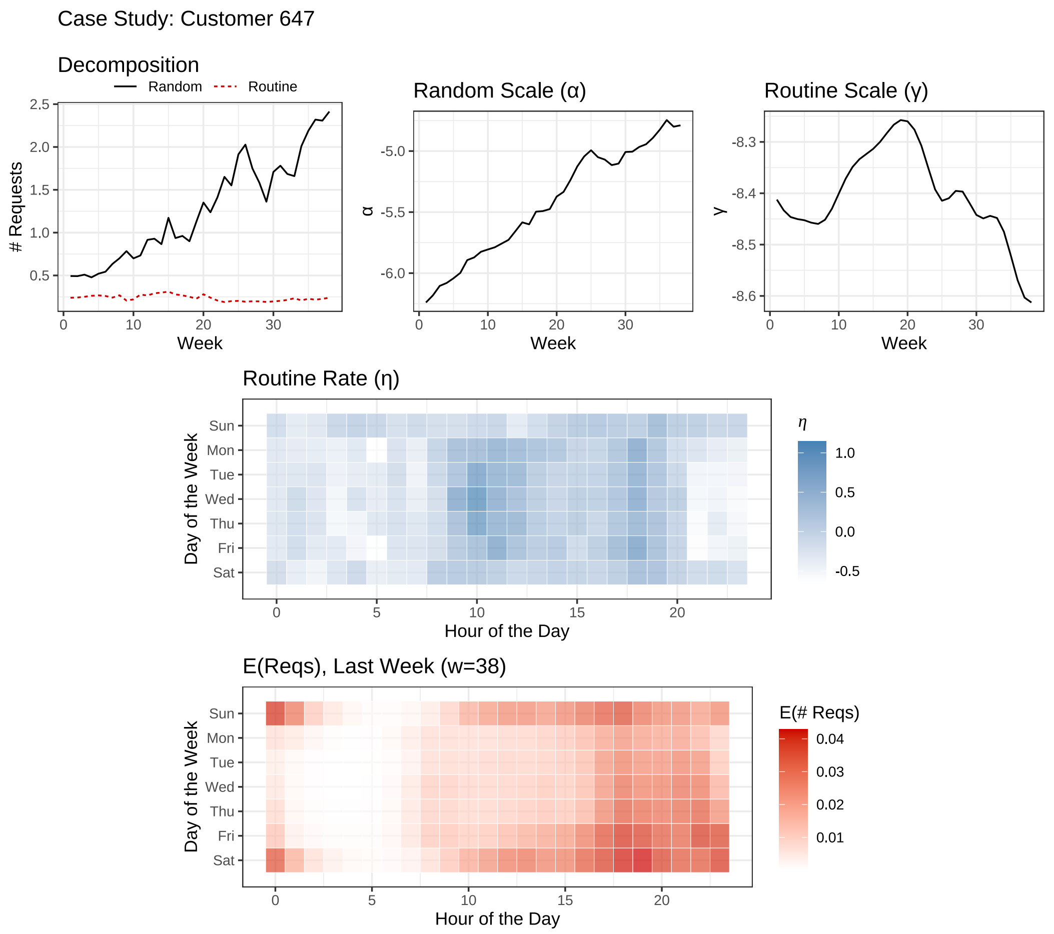
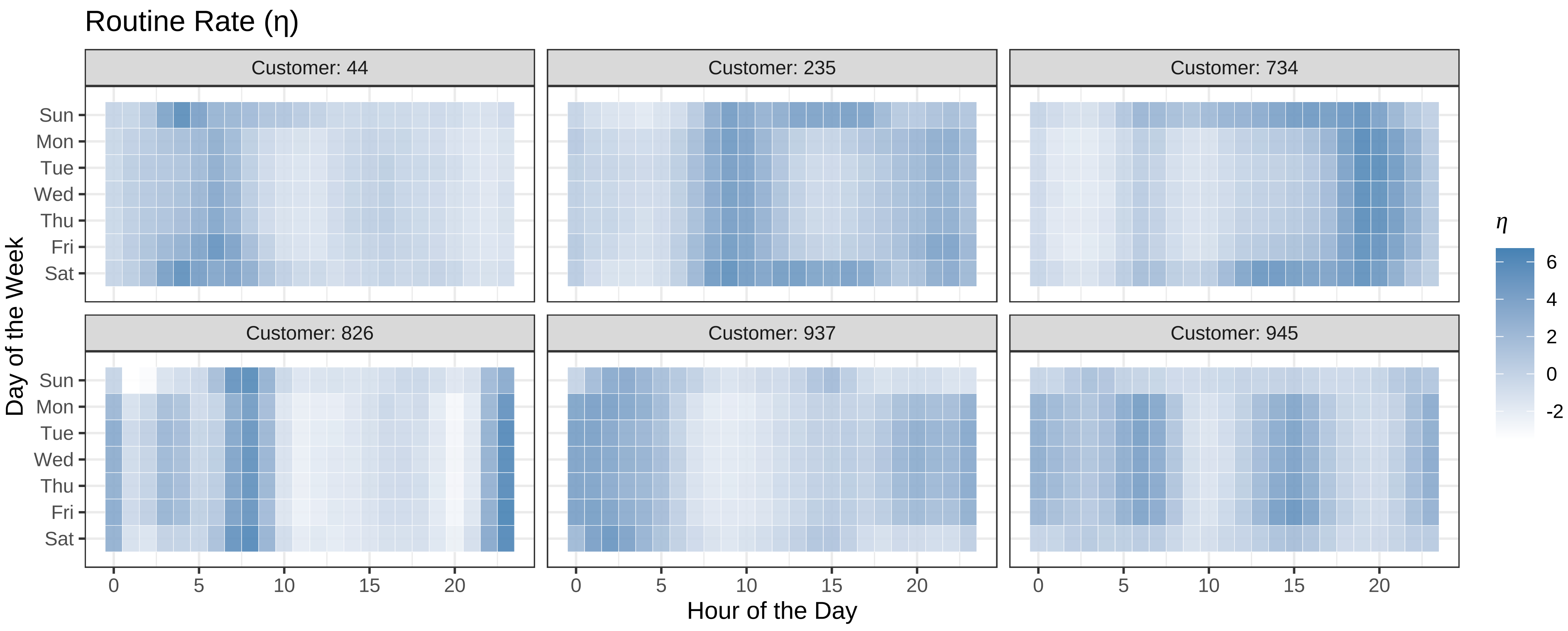




Many types of routines



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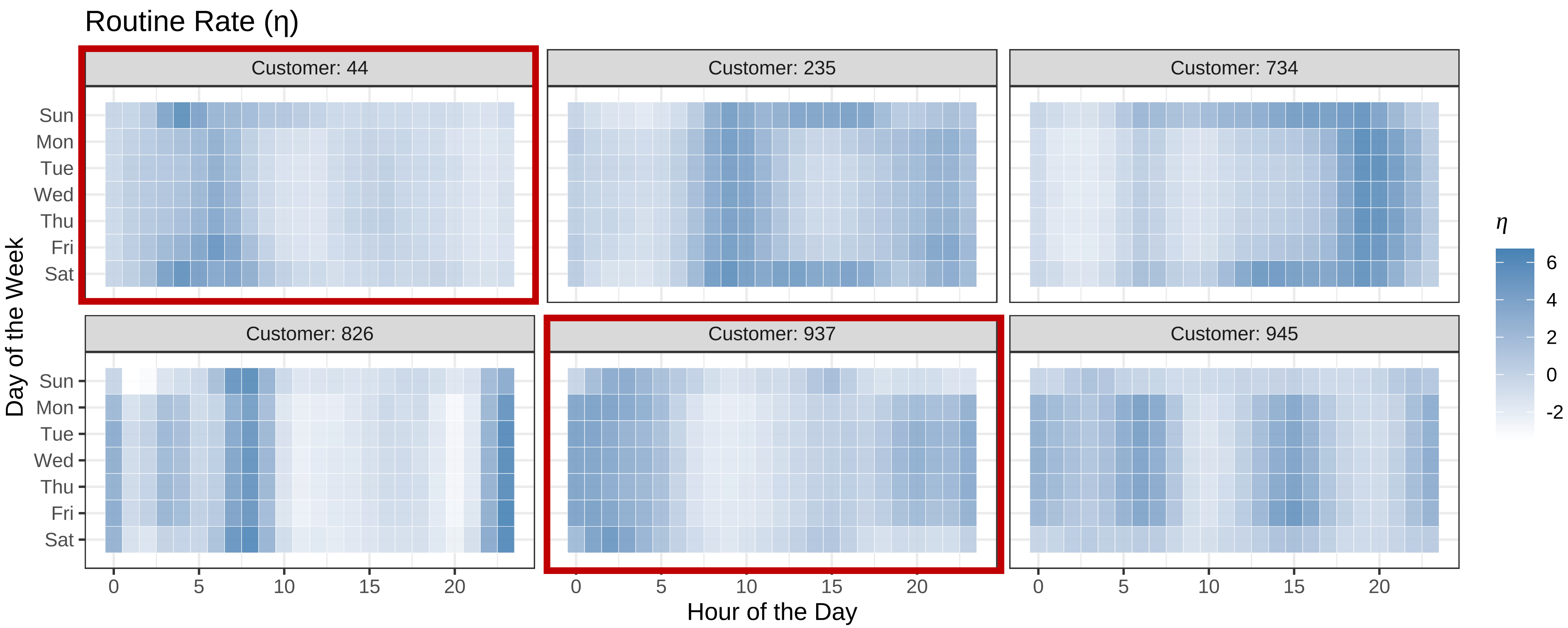

“Night owls”

Many types of routines

“Morning and night”

Validation

Can we trust these results?

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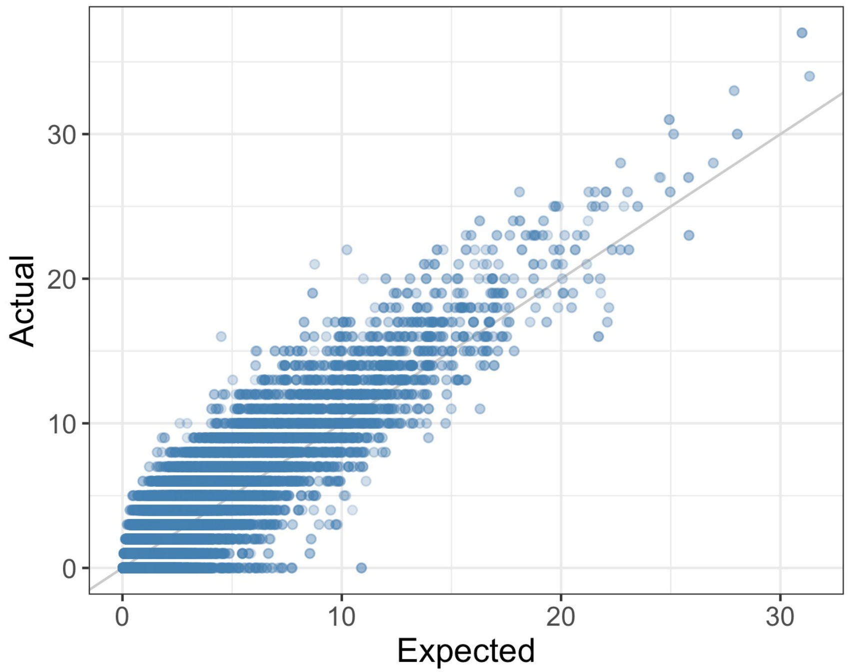

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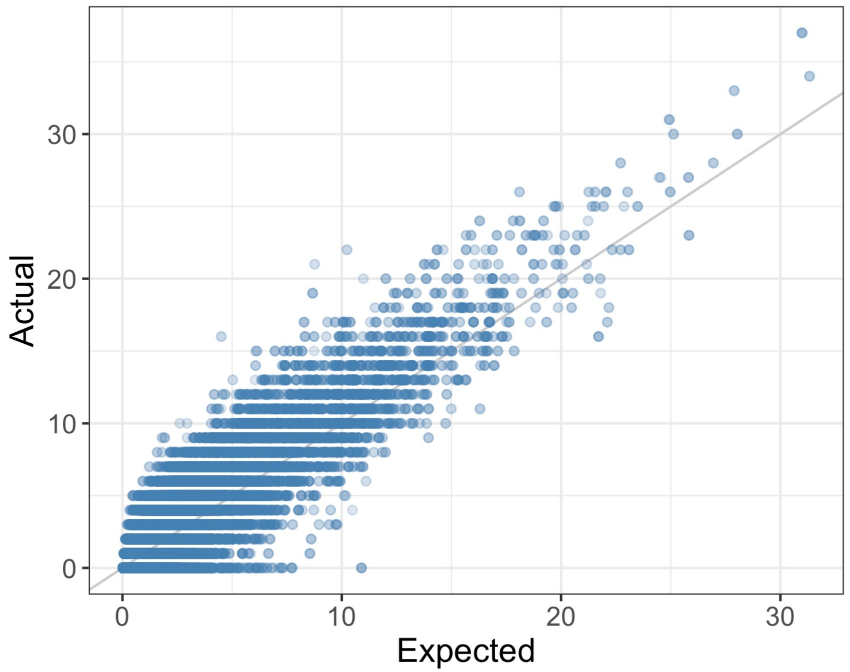

Prediction of transaction times:

- Predict timing of <u>routine</u> rides
- 100+% improvement over "universal" routine
- Also outperforms sophisticated LSTM-based benchmarks

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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In short: **yes!**

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

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In short: **yes!**

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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