Detecting Routines in Transaction Data: Applications to CRM in Ride-sharing

Ryan Dew, Eva Ascarza, Oded Netzer, Nachum Sicherman

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

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- Routine users may be better (or worse!) customers in other ways
- An additional tool for segmentation, targeting, and managing supply chains

Some Conceptual Distinctions

- Behavioral research:
  - Long history of research on habits
    (as far back as James,1890)
  - Key ideas: automaticity, often triggered by contexts
    (e.g., Wood et al., 2002; Verplanken et al., 2008; White et al., 2019)

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  - “Buying habit” = repeat purchasing
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- In economics, "habit stock" used to model overly smooth consumption
  (Dynan, 2000)

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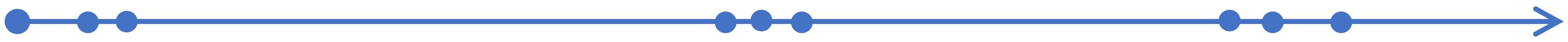

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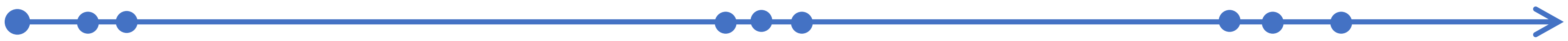

- Regularity
  (Platzer and Reutterer, 2016)

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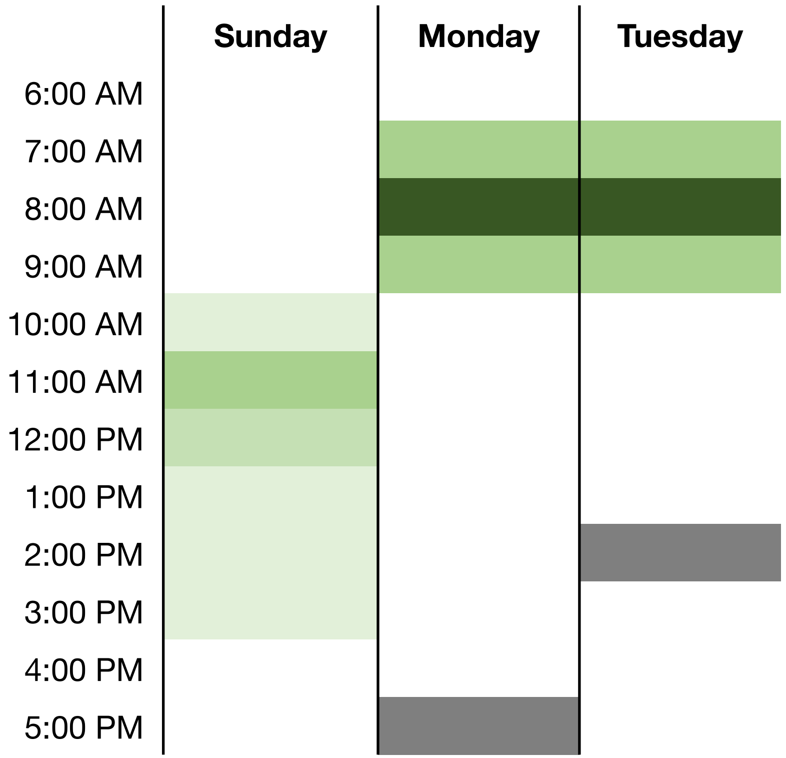
4. Explore how (temporal) routineness predicts and moderates other important customer outcomes, over and above…
    - Mere habit
    - Routines in terms of “what”
    - Regularity and clumpiness

Model

A Statistical Framework for Measuring Routineness

From transaction data, we want to capture…



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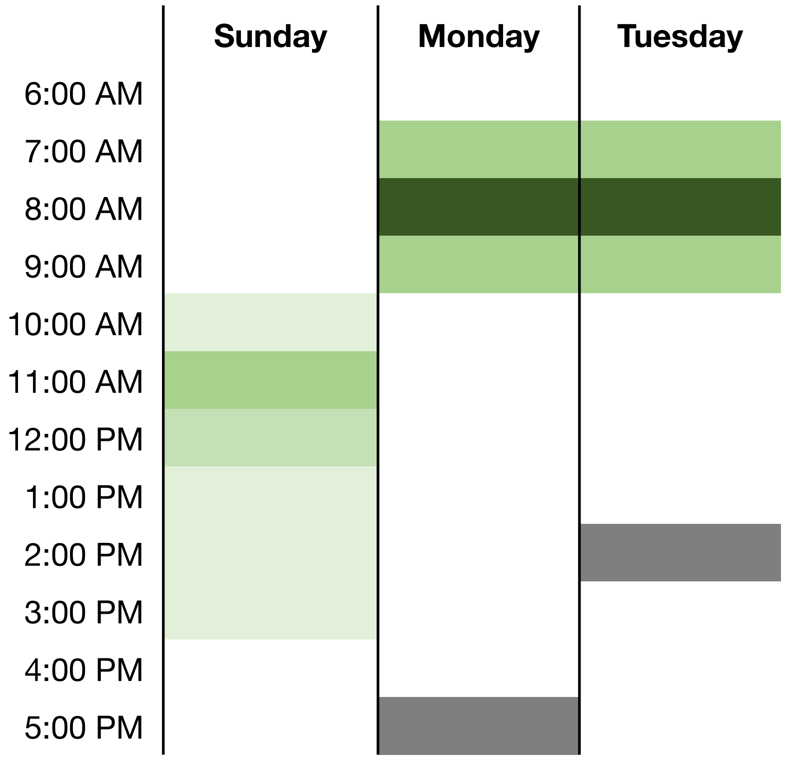

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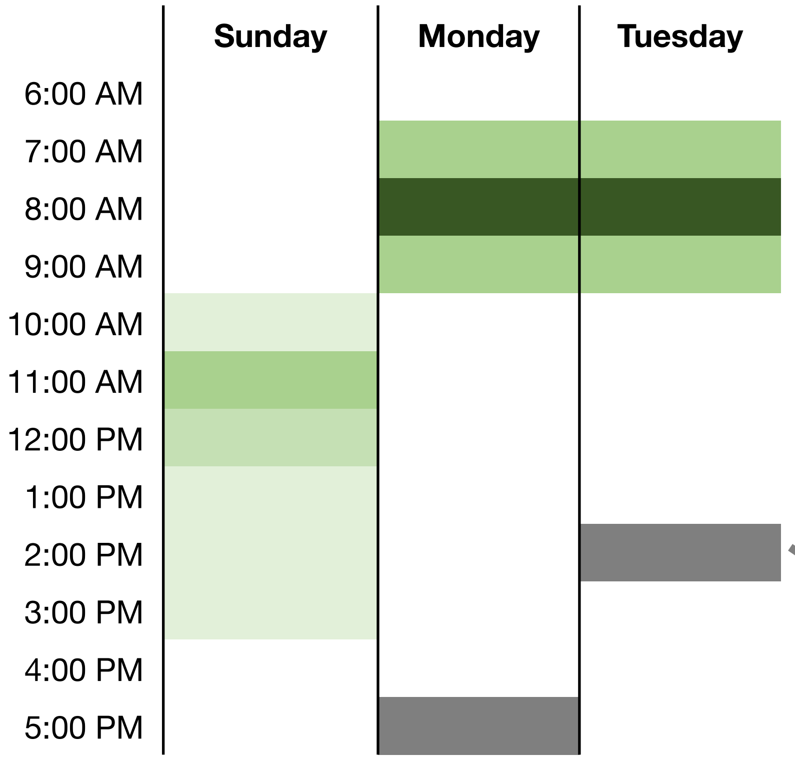

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Routine Process

Requests arrive at with an individual-specific weekly rate, and an individual-specific day-hour rate

Random Process

Requests arrive at with an individual-specific weekly rate, and a common day-hour rate

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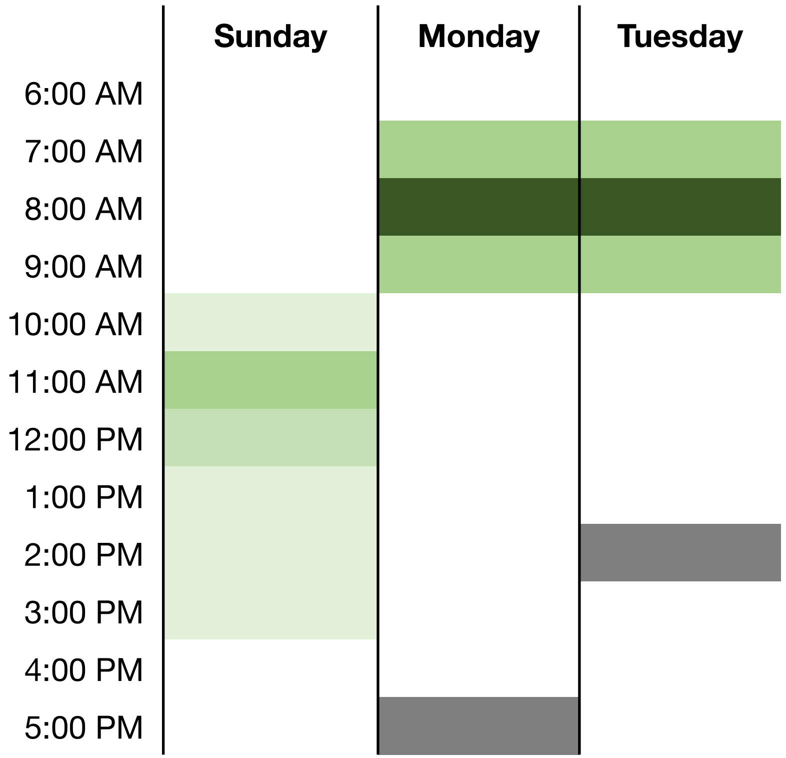

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Routine Process
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Joint Process
Superposition of the routine and random processes

Random Process
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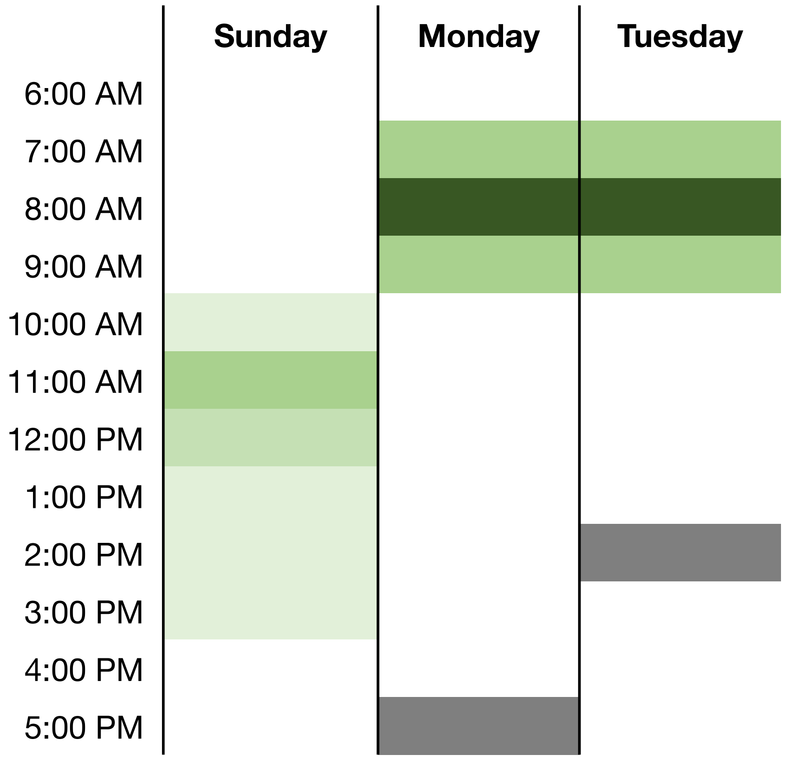

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Dependent variable: Usage (y)

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:

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

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

$$\alpha_i(w) \sim \mathcal{GP}(m_{\alpha_i}, k_e(w, w'; \phi_\alpha))$$

$$\gamma_i(w) \sim \mathcal{GP}(m_{\gamma_i}, k_e(w, w'; \phi_\gamma))$$

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Bayesian nonparametric priors over function spaces

$$f(x) \sim \mathcal{GP}(m(x), k(x, x'))$$

$$\Updownarrow$$

$$f(x_1, \ldots, x_N) \sim \mathcal{N}(m(x_1, \ldots, x_N), K), \ \text{s.t.} \ K_{ij} = k(x_i, x_j)$$

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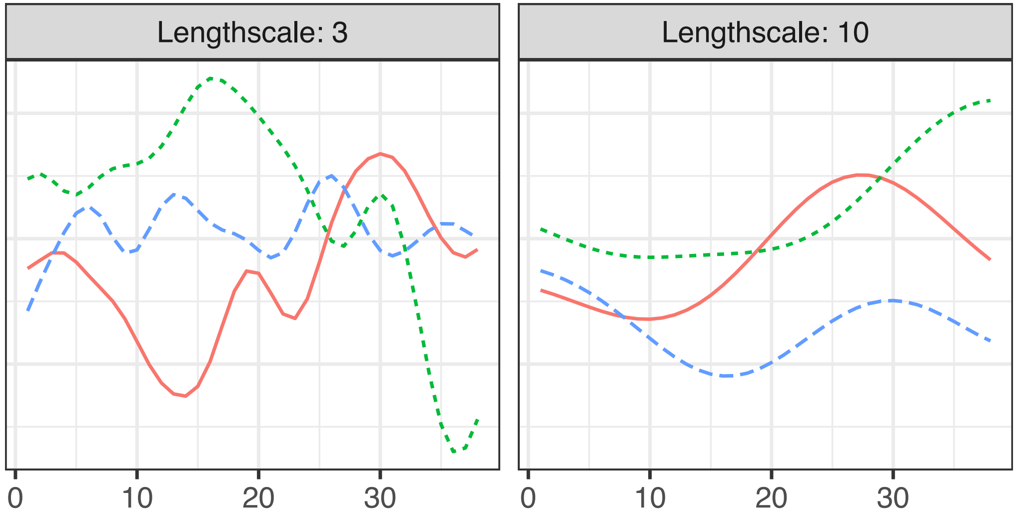
$$\boxed{k_e(w, w') = \sigma^2 \exp\left(-\frac{|w - w'|}{\ell}\right)}$$



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

$$\mu(d, h) \sim \mathcal{GP}\left(0, k_{\mathrm{DH}}(d, h; \phi_\mu)\right)$$
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$$\boxed{k_{\mathrm{DH}}(\mathbf{d}, \mathbf{h}; \boldsymbol{\phi}) = \Omega_{d,d'} \times \exp\left[-\frac{2}{\rho^2}\sin^2\left(\frac{\pi|h-h'|}{24}\right)\right]}$$

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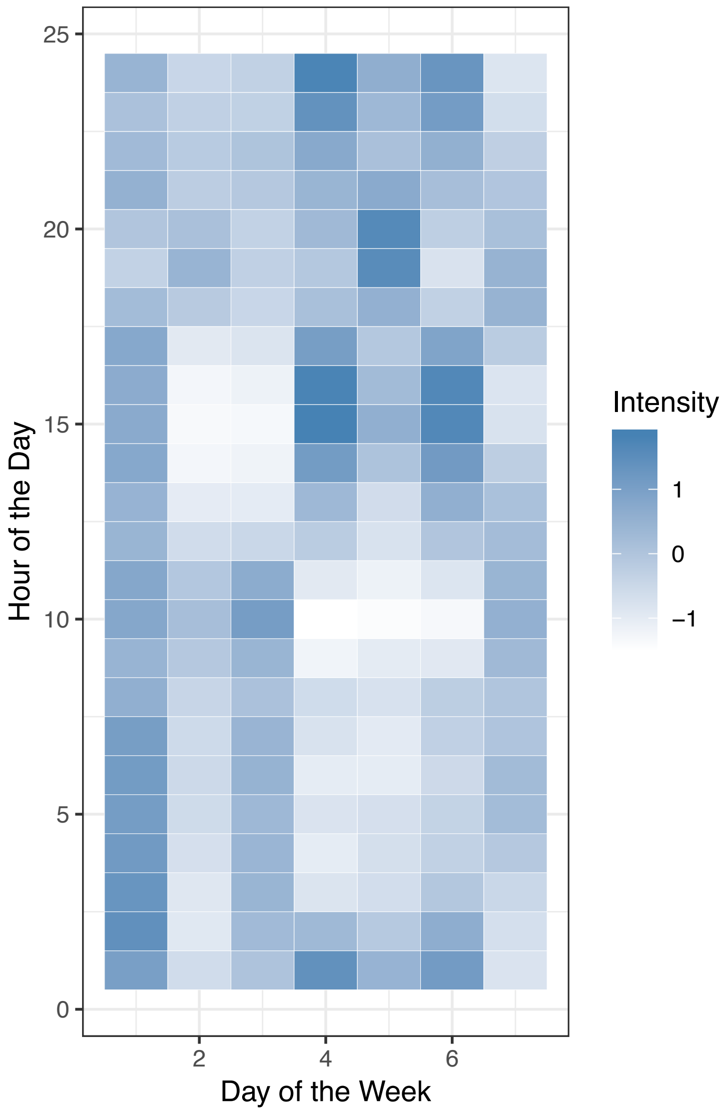

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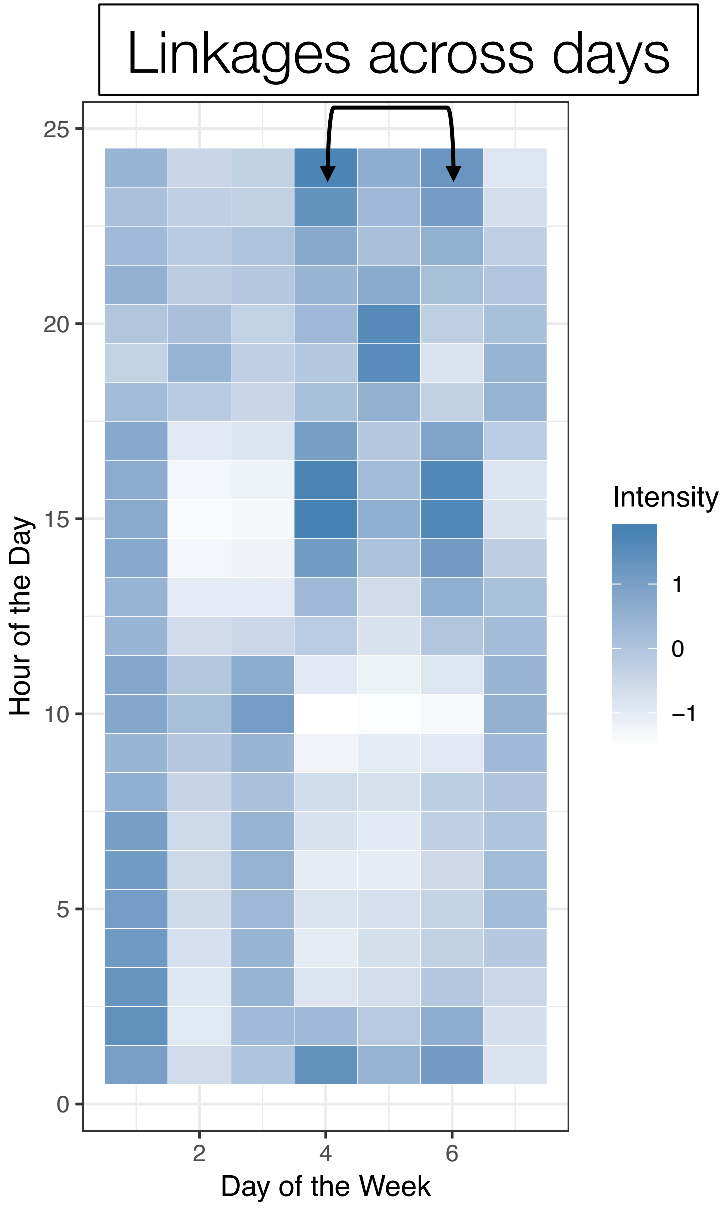

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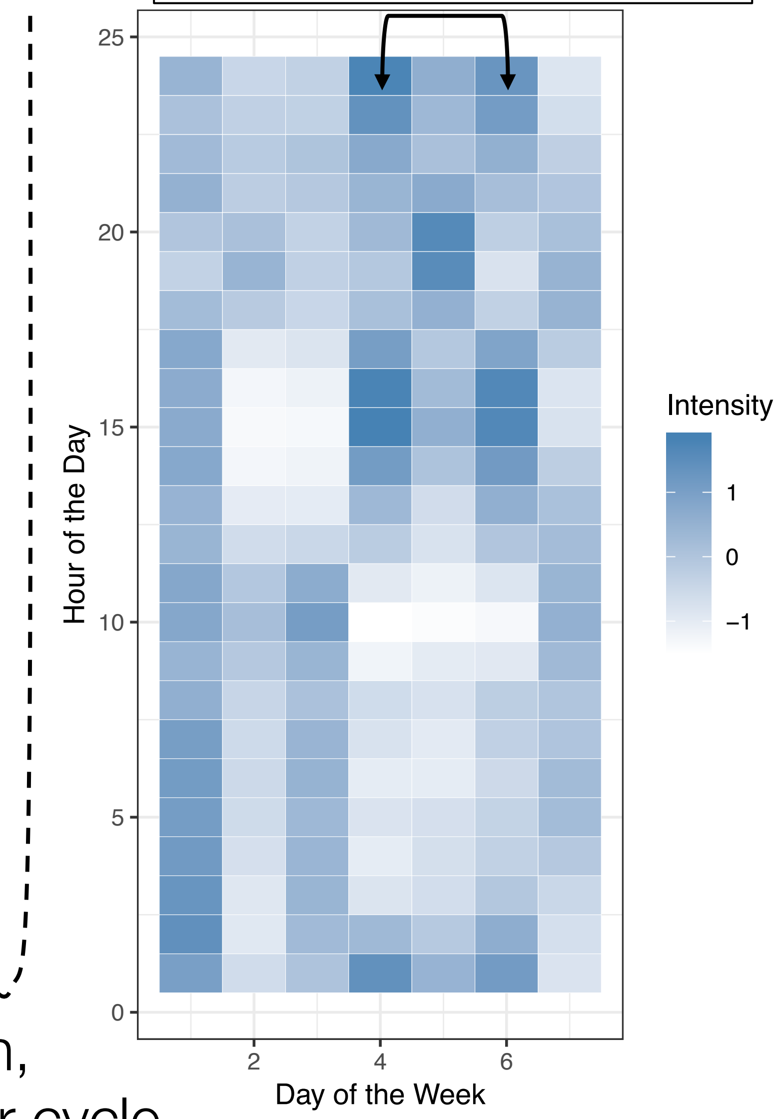
Linkages across days



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})

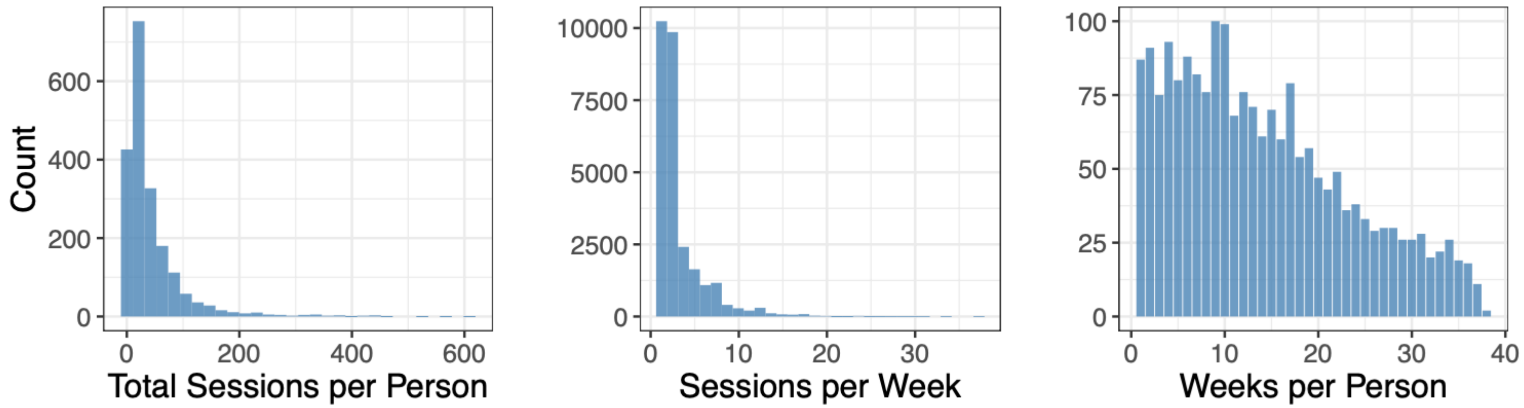
Results

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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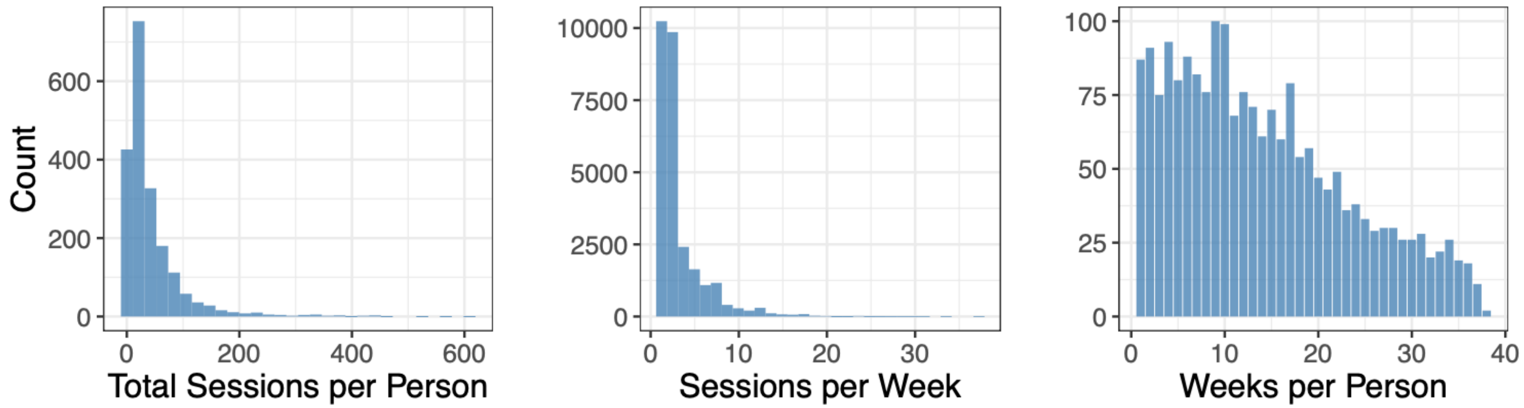

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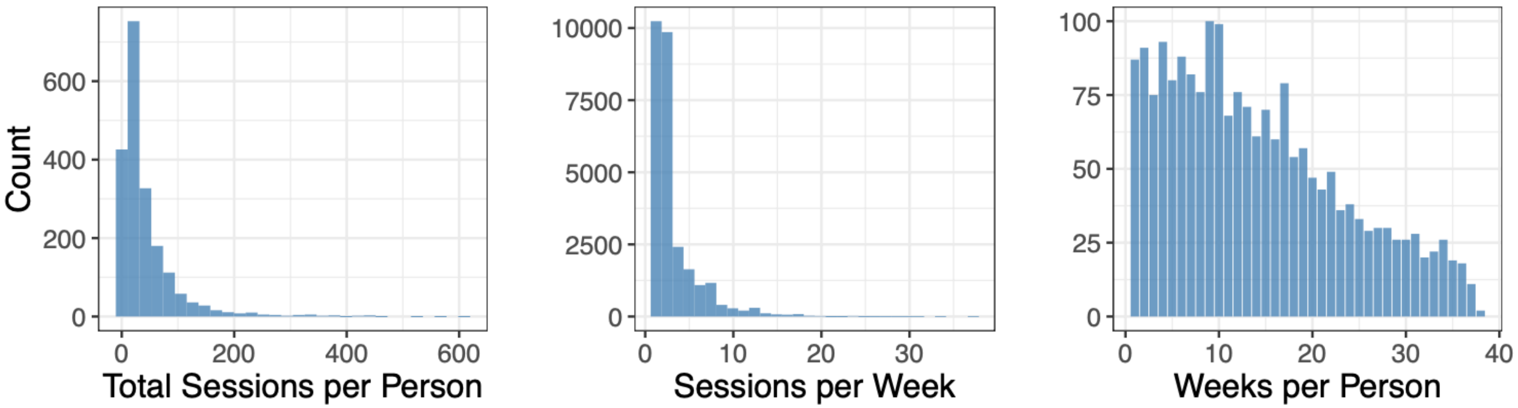
Basic unit of analysis:
a "session"



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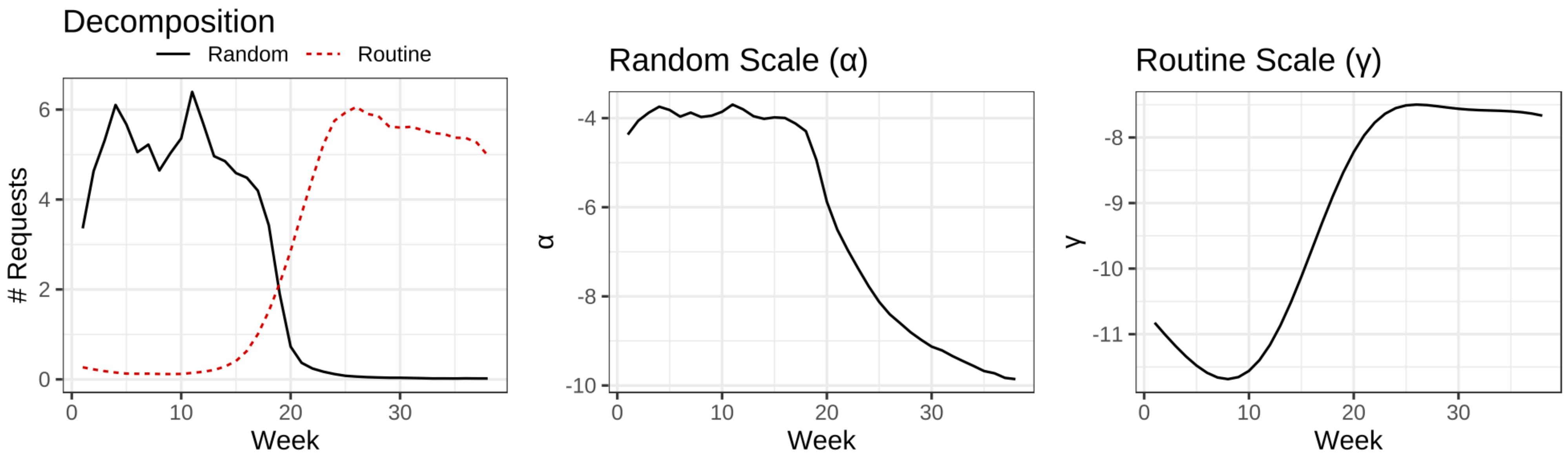

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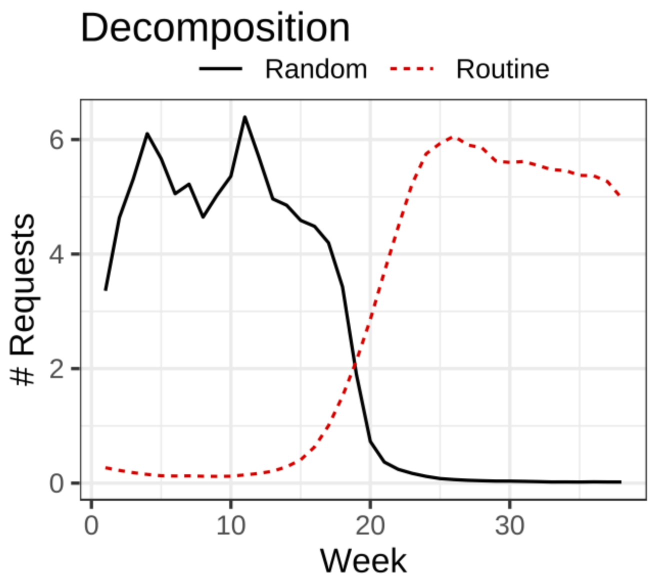

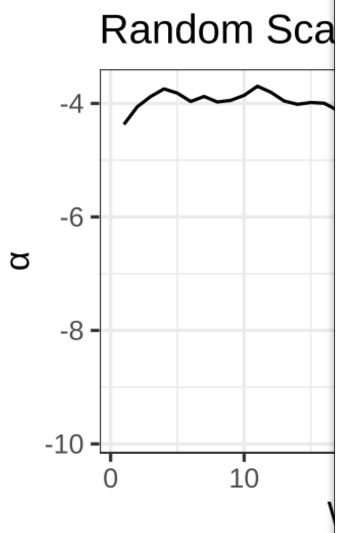

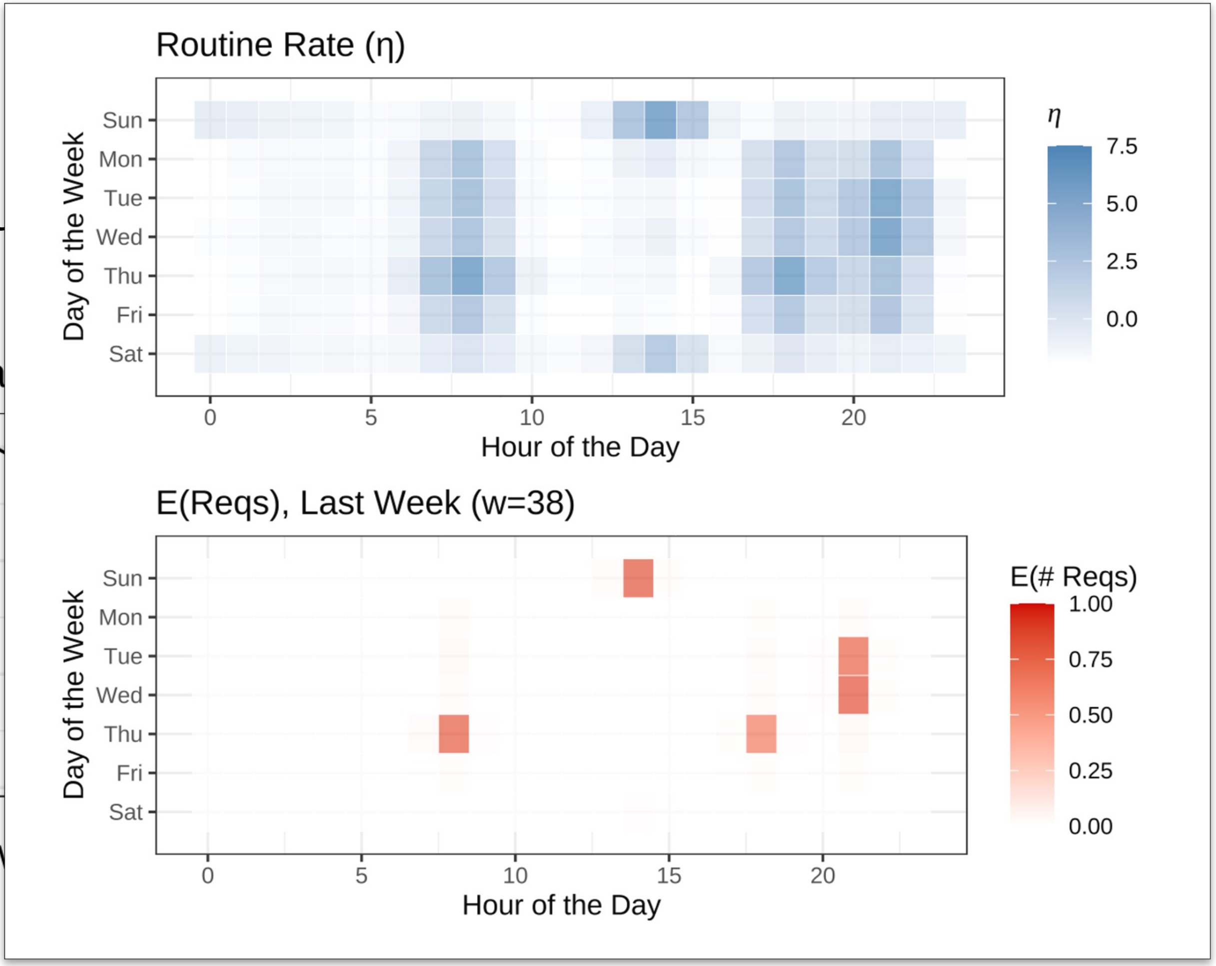

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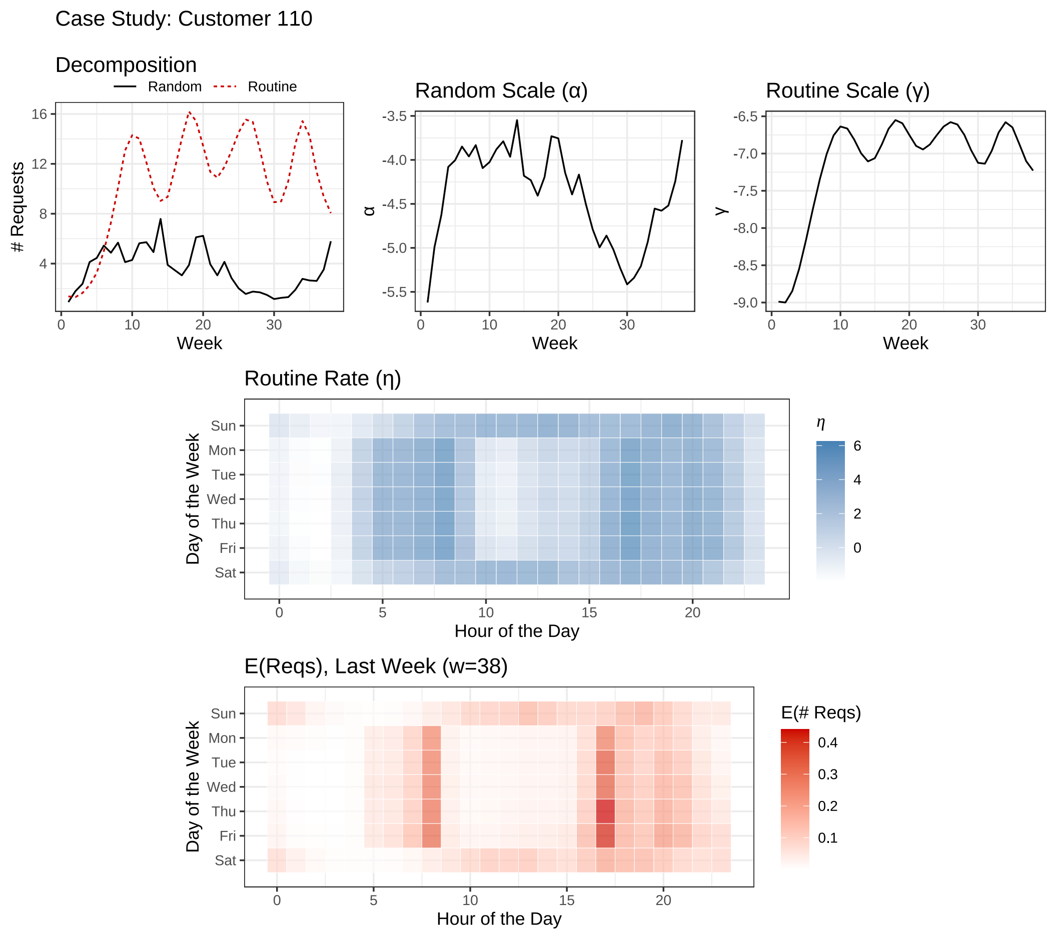

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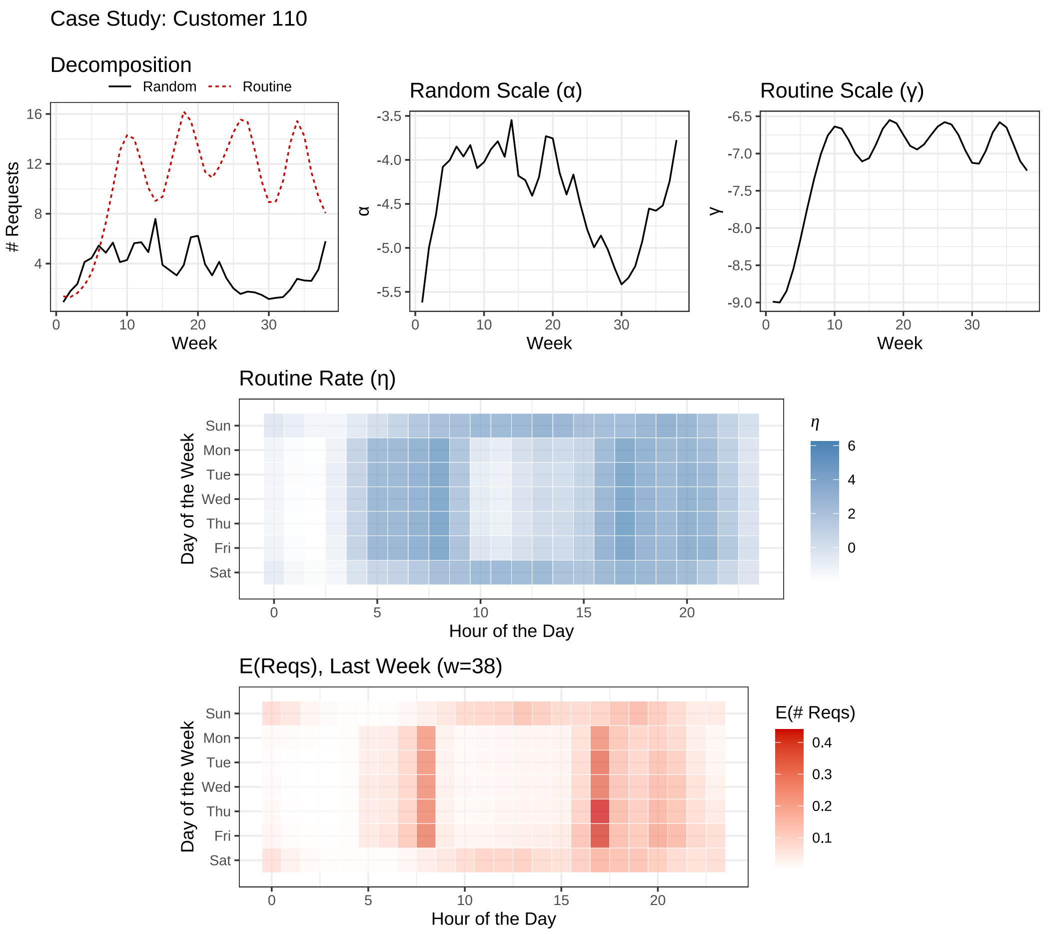
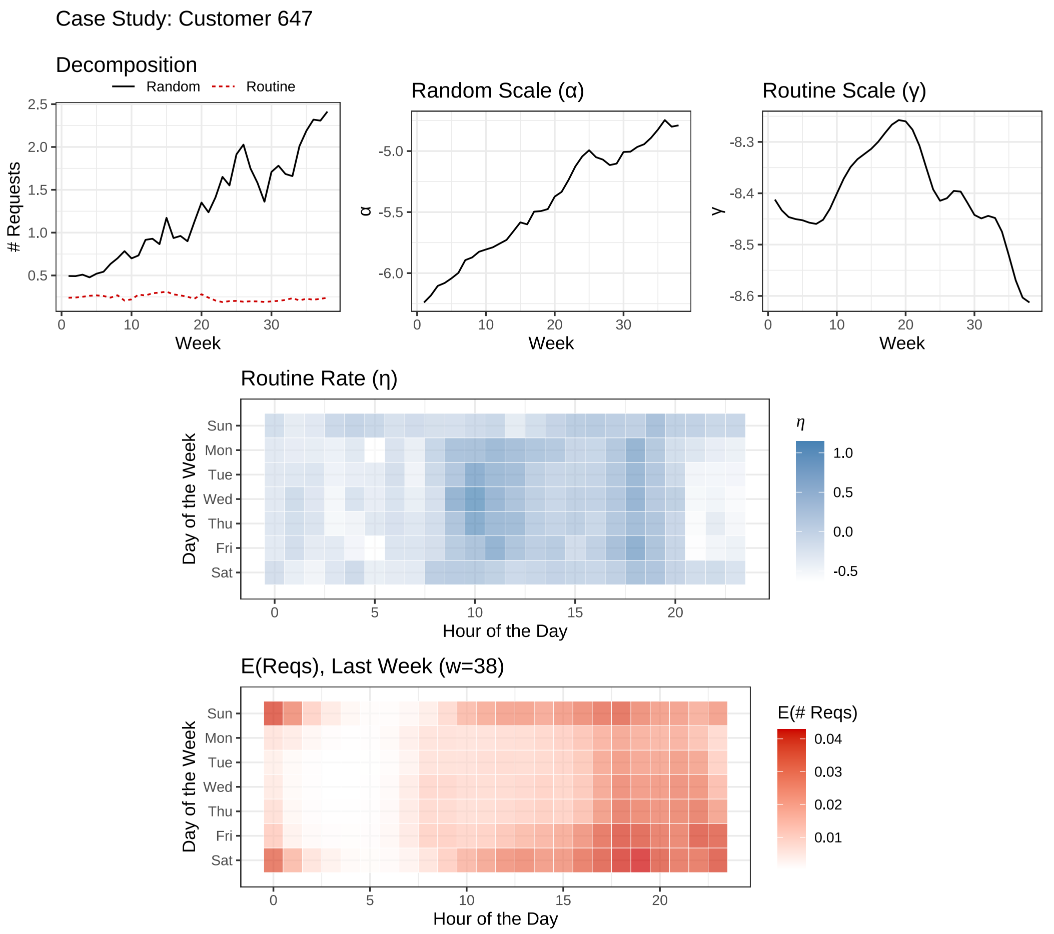
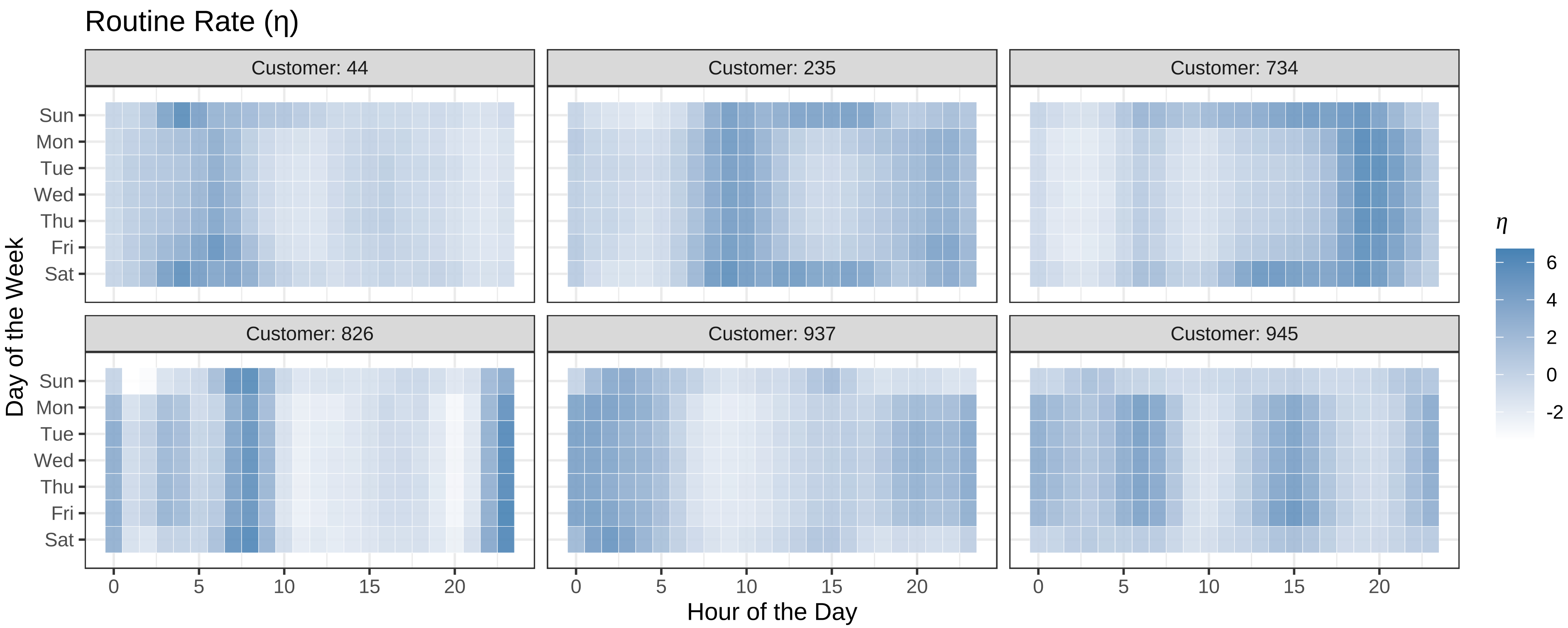




Many types of routines



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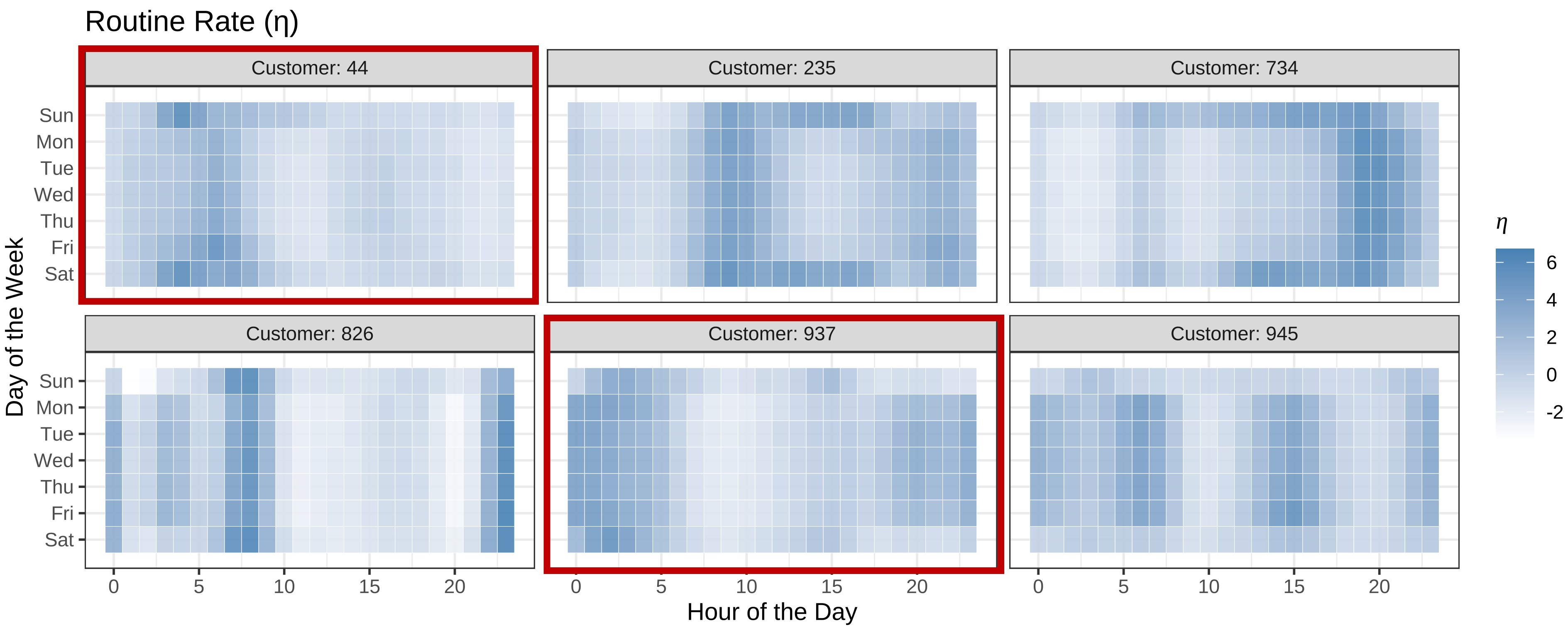


"Night owls"

Many types of routines

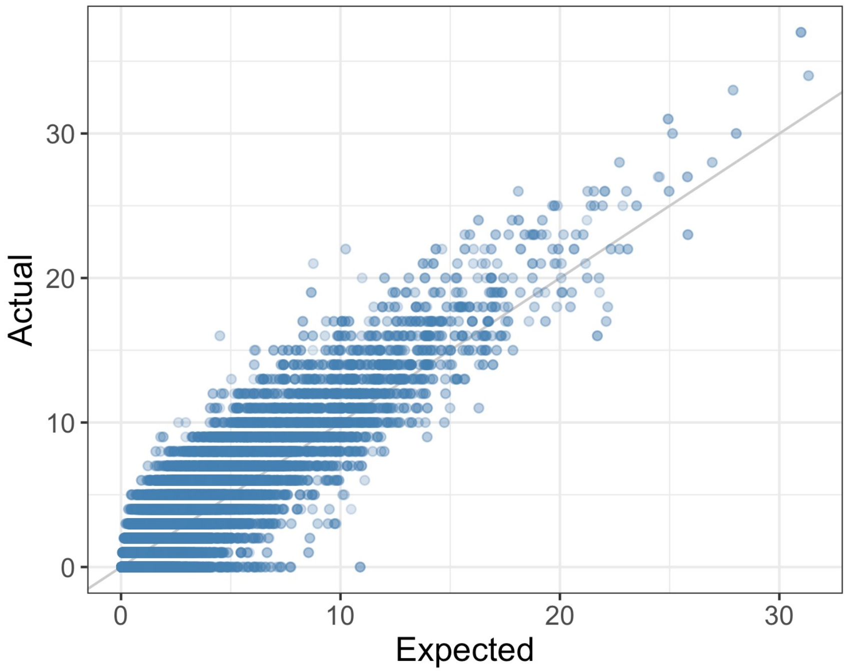
Morning and night

Validation

Fit and Forecasting Relative to Benchmarks

[Skip]

Predictive Performance



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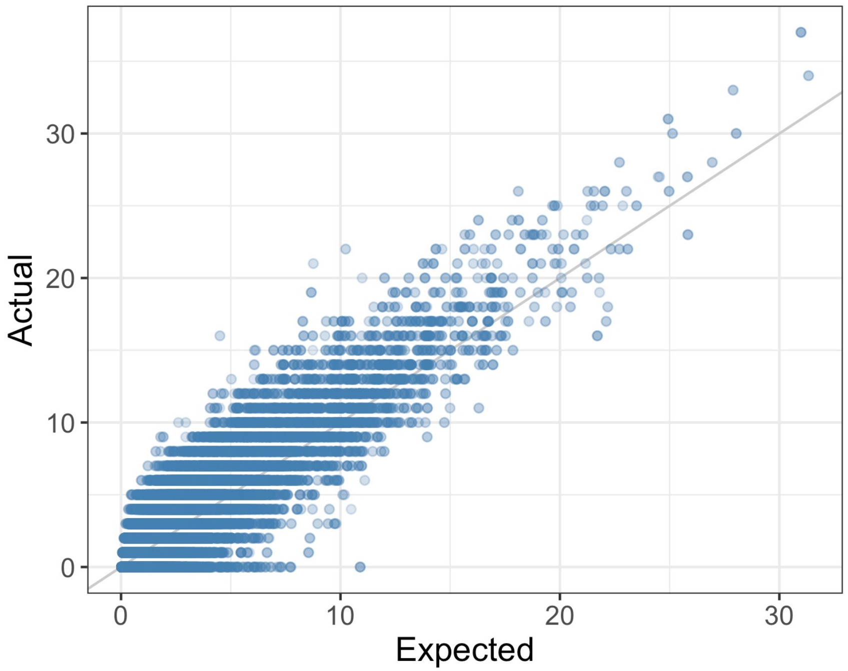

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  - Current model with no routines
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  - Customer-specific LSTM trained to predict ride times

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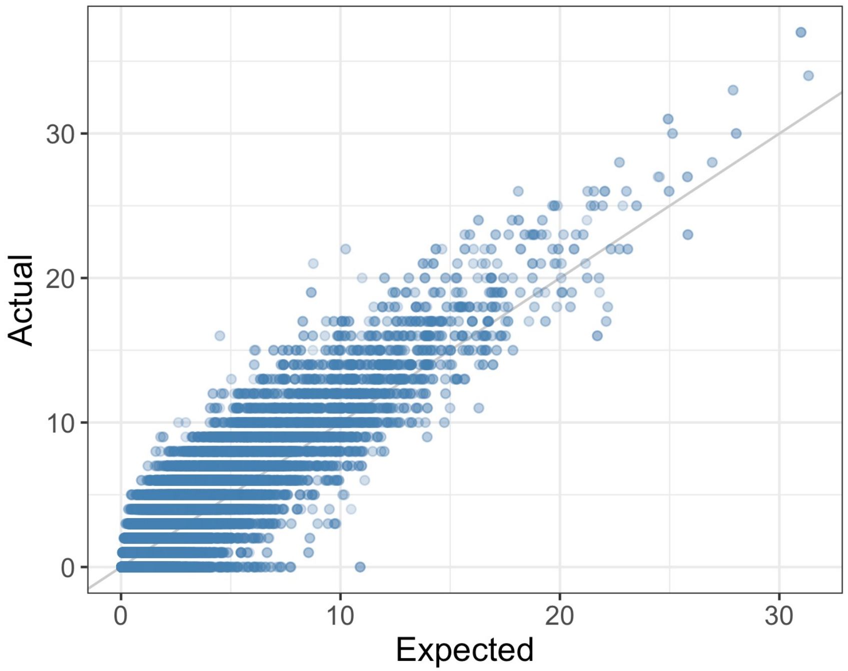

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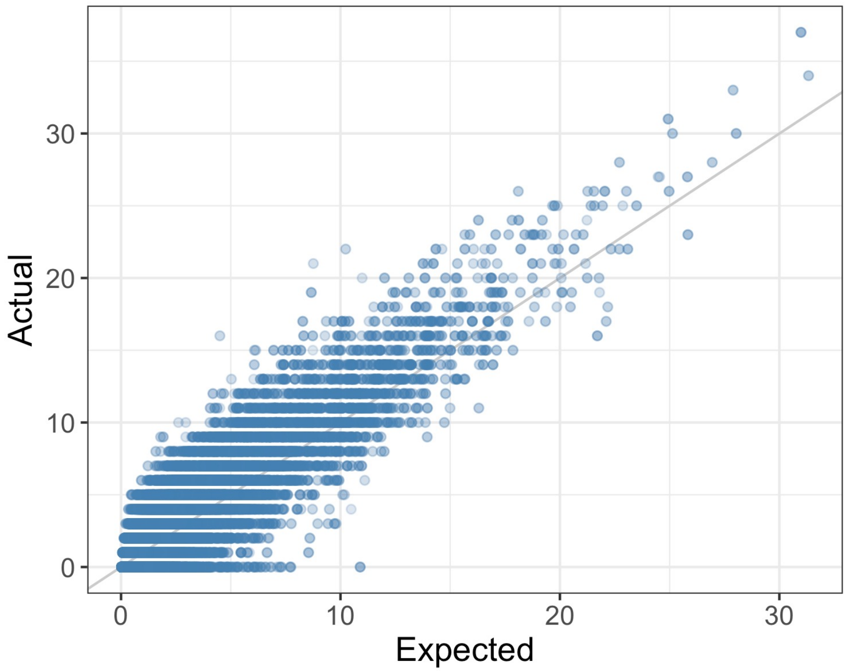

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- Forecasting # sessions (MAE):
  - Equivalent performance to Pareto-GGG
  - Significantly outperforms LSTM
- More interesting: predicting ride times
  - Measured by ranking expected request times
  - Significantly outperforms all benchmarks

[More Info]

Implications

Why should we care about routines?

Are routine customers more valuable?

	Dependent variable:			
	Full Holdout	Last 5 Weeks	Full Holdout	Last 5 Weeks
	OLS	*OLS*	*logistic*	*logistic*
	(1)	(2)	(3)	(4)
Requests ($w = 38$)	1.768***	0.467***	0.398***	0.178***
	(0.235)	(0.150)	(0.104)	(0.055)
Recency	−0.222***	−0.122***	−0.141***	−0.125***
	(0.042)	(0.026)	(0.010)	(0.010)
Frequency	0.090***	0.048***	−0.001	0.004**
	(0.007)	(0.004)	(0.002)	(0.002)
Routine ($w = 38$)	5.435***	2.802***	1.057***	0.288**
	(0.377)	(0.240)	(0.328)	(0.123)
Observations	2,000	2,000	2,000	2,000
R^2	0.574	0.424		
Note:				*p<0.1; **p<0.05; ***p<0.01 Intercept omitted for clarity.

Are routine customers more valuable?

Total Requests
(Week 38)

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Note:			*p<0.1; **p<0.05; ***p<0.01	
			Intercept omitted for clarity.	

Are routine customers more valuable?

Total Requests
(Week 38)

RF(M) Controls
(Week 38)

	Dependent variable:			
	Full Holdout	Last 5 Weeks	Full Holdout	Last 5 Weeks
	OLS	*OLS*	*logistic*	*logistic*
	(1)	(2)	(3)	(4)
Requests ($w = 38$)	1.768***	0.467***	0.398***	0.178***
	(0.235)	(0.150)	(0.104)	(0.055)
Recency	−0.222***	−0.122***	−0.141***	−0.125***
	(0.042)	(0.026)	(0.010)	(0.010)
Frequency	0.090***	0.048***	−0.001	0.004**
	(0.007)	(0.004)	(0.002)	(0.002)
Routine ($w = 38$)	5.435***	2.802***	1.057***	0.288**
	(0.377)	(0.240)	(0.328)	(0.123)
Observations	2,000	2,000	2,000	2,000
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Routineness vs. Regularity vs. Clumpiness

	Dependent variable:			
	# Requests		Activity (binary)	
	OLS		*logistic*	
	(1)	(2)	(3)	(4)
Requests ($w = 38$)	3.838***	1.614***	0.611***	0.461***
	(0.184)	(0.241)	(0.103)	(0.106)
Recency	−0.238***	−0.284***	−0.140***	−0.134***
	(0.045)	(0.043)	(0.010)	(0.010)
Frequency	0.130***	0.097***	0.0003	−0.002
	(0.008)	(0.008)	(0.002)	(0.002)
Regularity (k)	10.533***	4.511**	0.313	0.005
	(1.986)	(1.952)	(0.463)	(0.484)
Clumpiness (H)	9.269***	8.443***	−1.491***	−1.520***
	(1.918)	(1.836)	(0.380)	(0.381)
Routine ($w = 38$)		5.216***		1.035***
		(0.385)		(0.328)
Observations	2,000	2,000	2,000	2,000
R^2	0.540	0.579		

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Regularity's effect significantly dampened

Routineness remains positive

More to the story

- Routine trips are different: customers appear less sensitive to price during their routines, but much more sensitive to trip speed

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- Location (i.e., *what*) doesn't matter as much as timing (i.e., *when*)
- **Heterogeneity:** Many of these effects vary by the routine type
- **Spillovers:** Small but significant average correlation (0.095) between prior week's routineness and next week's randomness

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

Supplement

Forecast Metrics

- Benchmarks:
  - Pareto-GGG (as implemented in the BTYDPlus package)
  - Individual-specific LSTM, trained to predict ride times

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- Predict number of future requests: mean absolute error across customers

Model	MAE	CI
Ours	7.73	[7.171, 8.284]
P-GGG	7.513	[6.973, 8.051]
LSTM	26.13	[19.454, 32.796]

Forecast Metrics

- Benchmarks:
  - Pareto-GGG (as implemented in the BTYDPlus package)
  - Individual-specific LSTM, trained to predict ride times
- Predict number of future requests: mean absolute error across customers
- Predict *when* rides will take place: rank all possible times, compute precision metrics

Conditional Precision:

Model	Mean	CI
Ours	0.072	[0.066, 0.079]
P-GGG	0.016	[0.013, 0.018]
LSTM	0.089	[0.076, 0.102]

Average Precision:

Model	Mean	CI
Ours	0.131	[0.124, 0.139]
P-GGG	0.043	[0.041, 0.045]
LSTM	0.110	[0.076, 0.102]

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Routine Trips are Different

- DVs, measured throughout data:
  - Accept proposal, given characteristics
  - Request again within 7 days, given proposal and trip characteristics
- IVs / Controls:
  - Key moderator: the routineness of the day-hour
  - Customer fixed effects
  - Ride characteristics (car type, time of day, etc.)
- Key findings:
  - Less price sensitive during routine
  - More sensitive to speed

	Dependent variable:	
	Accept Proposal	Request Again
	(1)	(2)
Routineness	−0.007	−0.010
Price	−0.0001***	−0.00004***
Driver ETA	−0.023***	0.0003
Speed	0.007**	0.001
Pickup Walking Dist.	−0.0003***	0.00002
# Passengers	0.019***	0.018***
Pickup Delay		−0.0002
Dropoff Delay		−0.0002***
Dropoff Walking Dist.		−0.00003*
# On-board (Pickup)		−0.004**
# On-board (Dropoff)		0.001
Max On-board		−0.002
Routine x Price	0.0001***	0.0001***
Routine x Driver ETA	0.005	−0.0002
Routine x Speed	1.425***	−0.218
Routine x Pickup Walking Dist.	0.0002	−0.0001
Routine x # Passengers	−0.037	0.048*
Routine x Pickup Delay		0.001
Routine x Dropoff Delay		0.001
Routine x Dropoff Walking Dist.		0.0001
Routine x # On-board (Pickup)		0.012
Routine x # On-board (Dropoff)		0.0002
Routine x Max On-board		−0.004
Customer Fixed Effects	Yes	Yes
Observations	113,042	73,630
R^2	0.070	0.015

Note: *p<0.1; **p<0.05; ***p<0.01

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Routine Customers are Different

- Same DVs as before, but during *just the holdout*
- IVs / Controls:
  - Key IV/moderator: # routine requests at week 38 (end of training)
  - Customer random effects
  - Ride characteristics (car type, time of day, etc.)
- Key findings:
  - Routine customers are less sensitive to trip characteristics (price, driver ETA)
  - More sensitive to convenience factors (walking distance, pickup delay)

	Dependent variable:	
	Accept Proposal	Request Again
	(1)	(2)
# Requests (Week 38)	−0.004	0.021***
Routineness	0.015***	0.011**
Price	−0.00003***	−0.00003***
Driver ETA	−0.015***	−0.0003
ETA Destination	−0.001**	−0.0002
Speed	−0.030***	0.007
Pickup Walking Dist.	−0.0004***	−0.00002
# Passengers	−0.005	0.008
Pickup Delay		−0.004***
Dropoff Delay		−0.0003
Dropoff Walking Dist.		−0.0001
# On-board (Pickup)		−0.006
# On-board (Dropoff)		0.001
Max On-board		0.003
Routine x Price	−0.00000	0.00000***
Routine x Driver ETA	0.001***	0.0001
Routine x ETA Destination	−0.00000	−0.0001
Routine x Speed	0.063***	−0.009
Routine x Pickup Walking Dist.	−0.00003***	0.00000
Routine x # Passengers	−0.0003	0.002
Routine x Pickup Delay		0.001**
Routine x Dropoff Delay		0.00003
Routine x Dropoff Walking Dist.		0.00000
Routine x # On-board (Pickup)		0.001
Routine x # On-board (Dropoff)		−0.0001
Routine x Max On-board		−0.0005
Observations	38,166	14,704
R^2	0.051	0.093
Note:		*p<0.1; **p<0.05; ***p<0.01

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Routines of “what” vs. “when”

Consumers can have routines in both *when* and *what* they buy.

- In ride-sharing: are people routine in *where* people are going, in addition to *when* they’re going?
- Data: full set of locations for each customer, measured by “block”
- Two metrics of **location dispersion**:
  - Shannon entropy
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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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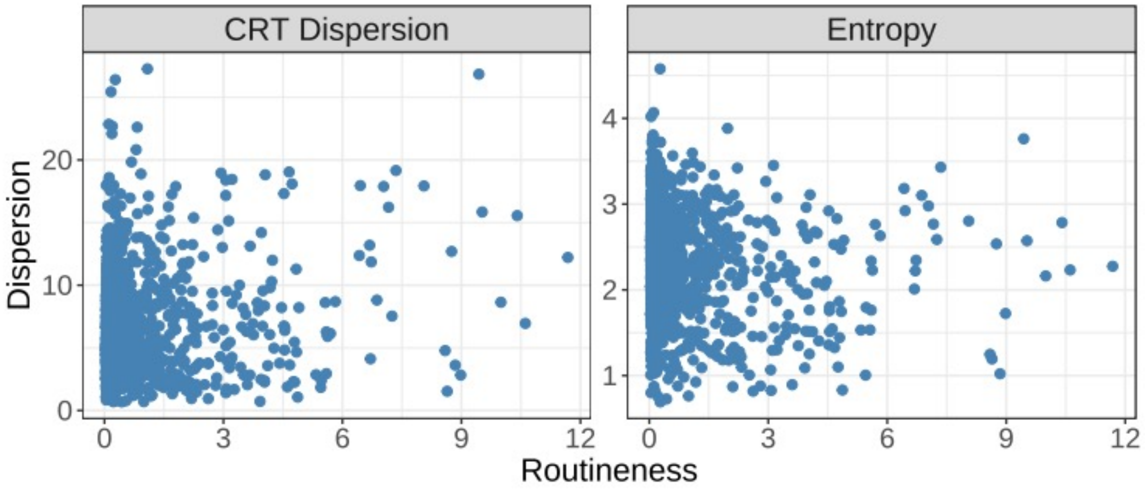

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	# Requests	Activity
	OLS	*logistic*
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Requests ($w = 38$)	2.263***	0.381***
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Recency	−0.193***	−0.140***
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Routine ($w = 38$)	5.593***	1.132***
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Entropy	−1.753	0.080
	(1.092)	(0.240)
CRT Disp.	0.159	−0.011
	(0.199)	(0.046)
Observations	2,000	2,000
R^2	0.568	
Note:	*p<0.1; **p<0.05; ***p<0.01	
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