

“CitySense”: Introduction to Probabilistic Modeling

Julia Kempe & David S. Rosenberg

CDS, NYU

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Contents

- 1 The CitySense Problem
- 2 The Case for Probability Models
- 3 The Grid Cells
- 4 Data Visualization
- 5 The Prediction Problem
- 6 Stratification Approaches

The CitySense Problem

Sense Networks

- Startup company incorporated around 2006.
- Objective: Develop and leverage expertise in **location data** analytics.
- First product was called CitySense¹ (2008).
 - A real-time, data-driven guide to nightlife in San Francisco.

¹See “CitySense: Multiscale space time clustering of GPS points and trajectories” by Markus Loecher and Tony Jebara (2009). <http://www.cs.columbia.edu/~jebara/papers/CitySense.JSM2009.pdf>

CitySense (2008)

Citysense™
Live San Francisco Nightlife Activity

Where is everybody?

- How busy is the city? Know when to go out
- See the top nightlife hotspots in real-time
- Find out what's there in one click
- Find out where everyone's going next

[More info](#)

 For real-time nightlife
on your iPhone®, visit
the [App Store](#)

 Also available for the
BlackBerry®
[Go to www.citysense.com](#)
on your BlackBerry® to
download.



(Sadly, no longer in the App Store.)

CitySense: Use Cases

Two use cases:

- ① I'm new to the city – where does everybody hang out at night?
- ② I know the city, but is there anything **special** going on tonight?

CitySense: Data Source

- Taxi GPS data for sale in San Francisco

The screenshot shows the homepage of the Yellow Cab Cooperative website. At the top, there is a navigation bar with links for HOME, SERVICE, FAQS, ACCOUNTS, ABOUT, CONTACT, and SAN FRANCISCO. Below the navigation bar, there is a date indicator (TUESDAY, MAY 01, 2012) and a text size adjustment button. On the left side, there is a sidebar with a yellow cab image and a "GET A CAB NOW" button with the phone number 415.333.3333. Below this, there is a "BOOK A CAB ONLINE" button. The main content area features a large yellow cab in front of a modern building with the text "YELLOW MAKES IT EASY." and a descriptive paragraph about auto-dispatch. At the bottom, there are two sections: "Our History" and "Our Community".

- Main Idea: Taxi destinations are a proxy for where people are going.
- Can use taxi data to bootstrap
 - Once we had users, we could use the locations from their phones.
- Taxi feed is **real-time**, so can use it to find those big secret parties.

Data Science Strategy

- ① Model “typical” behavior of each area of the city.
- ② Rank areas with activity levels that are “most unusual”.

We'll discuss modeling strategies shortly.

Plan for this lecture

- Examine the CitySense “anomaly detection” problem.
- But use the NYC taxi pickup data – more local and more recent.
- Our dataset is from 2009.
- Currently (2017/11/09) you can download 2013 data from
<https://github.com/andresmh/nyctaxitrips>
- You can also request data directly from the NYC Taxi and Limousine Commission via the Freedom of Information Law.
<http://www.nyc.gov/html/tlc/html/passenger/records.shtml>

The Case for Probability Models

Predicting Probability Distributions

So far we've discuss two problem classes:

- **Classification**
 - Outcome space $\mathcal{Y} = \{-1, 1\}$
 - Action space $\mathcal{A} = \mathbf{R}$ (threshold to get hard classifications)
- **Regression**
 - Outcome space $\mathcal{Y} = \mathbf{R}$
 - Action space $\mathcal{A} = \mathbf{R}$.
- Today we consider a third type of **action space**:
$$\mathcal{A} = \{\text{Probability distributions on outcome space } \mathcal{Y}\}$$
- Why?

The Joy of Probability Distributions

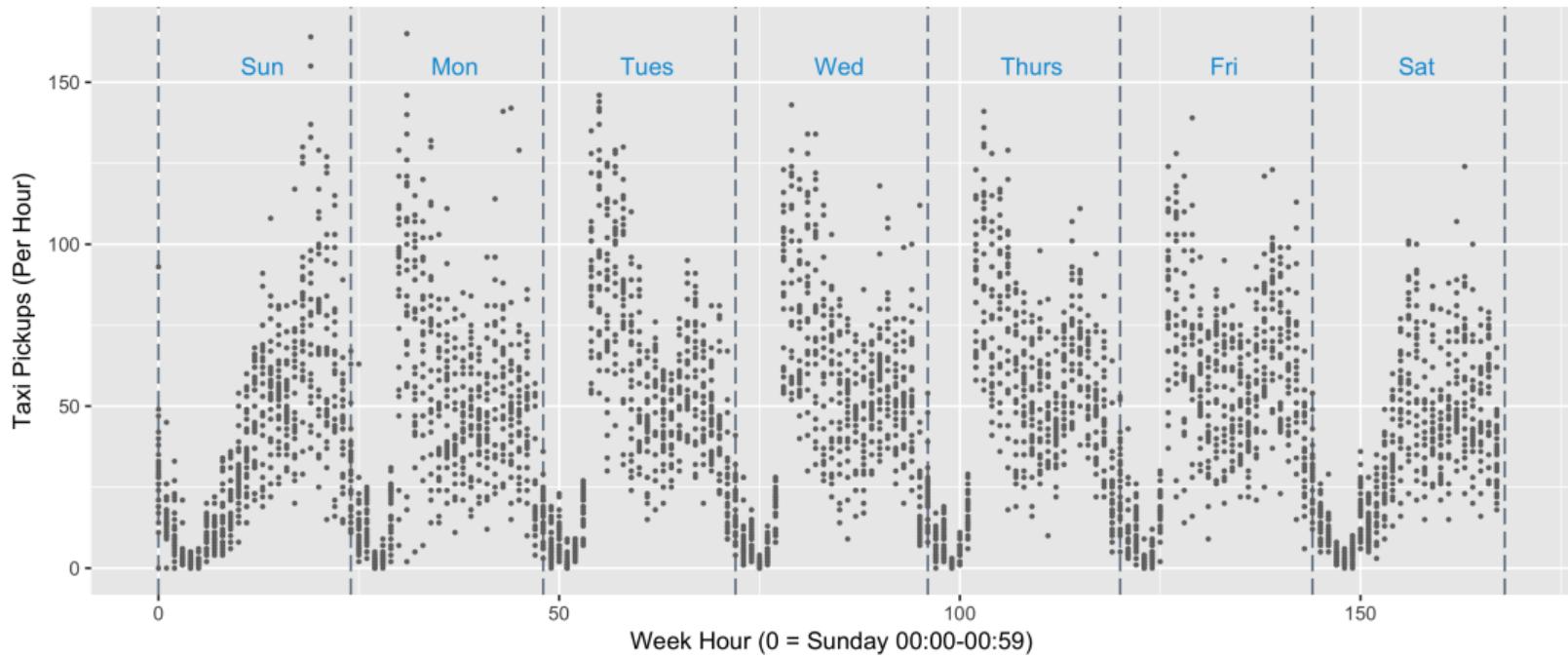
- Outcome space $\mathcal{Y} = \mathbf{R}$ (some regression problem)
- For input x , suppose we produce a **probability density** on \mathcal{Y} :

$$x \mapsto p(y)$$

- We can interpret this setting as modeling the **conditional probability density** $p(y | x)$.
- If we know $p(y | x)$, we can find a \hat{y} that minimizes any loss function for a given x :
 - For square loss, give the mean of $p(y | x)$. [From homework]
 - For ℓ_1 loss, give the median of $p(y | x)$. [From homework]
 - Can produce a **prediction interval** that $p(y | x)$ assigns a 95% probability
-

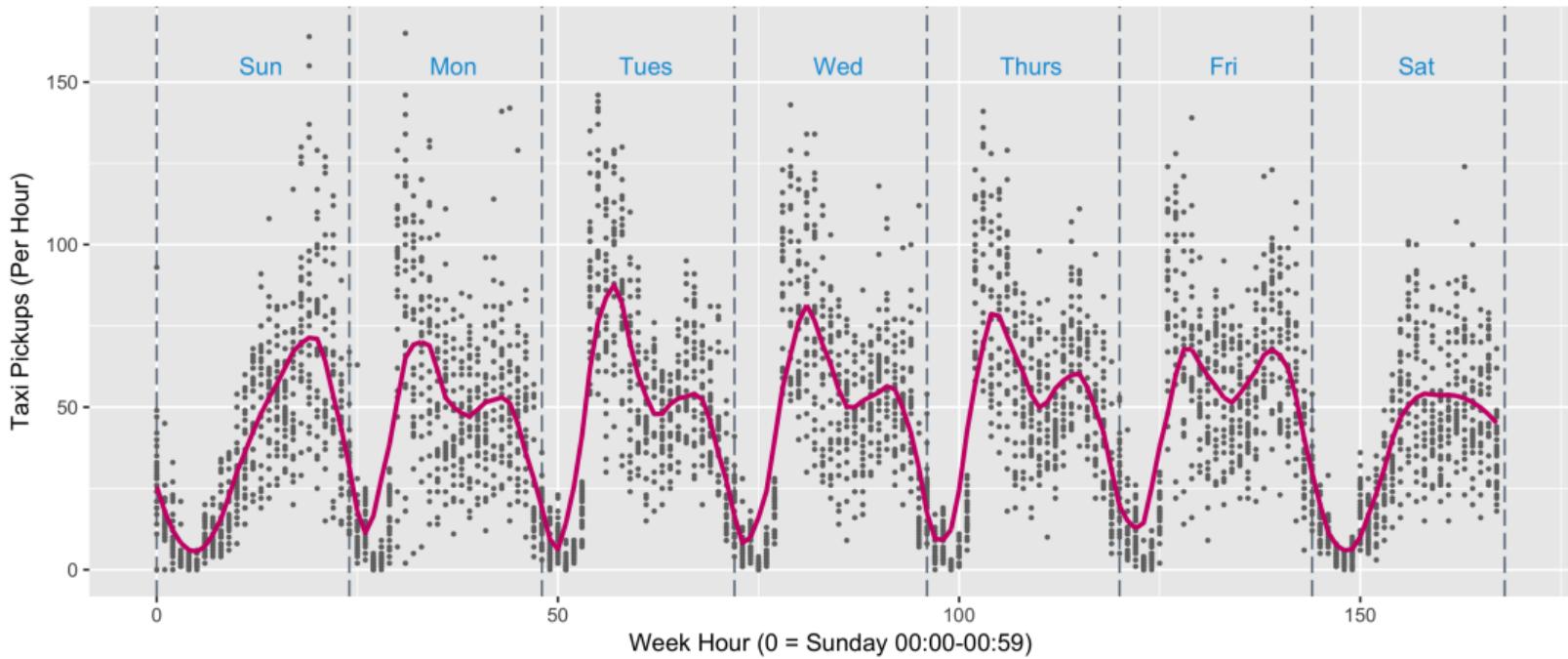
Penn Station Taxi Pickup Counts - 27 Weeks

Penn Station Taxi Pickups, by Hour-of-Week (27 Weeks)



Penn Station Taxi Pickup Counts - Regression

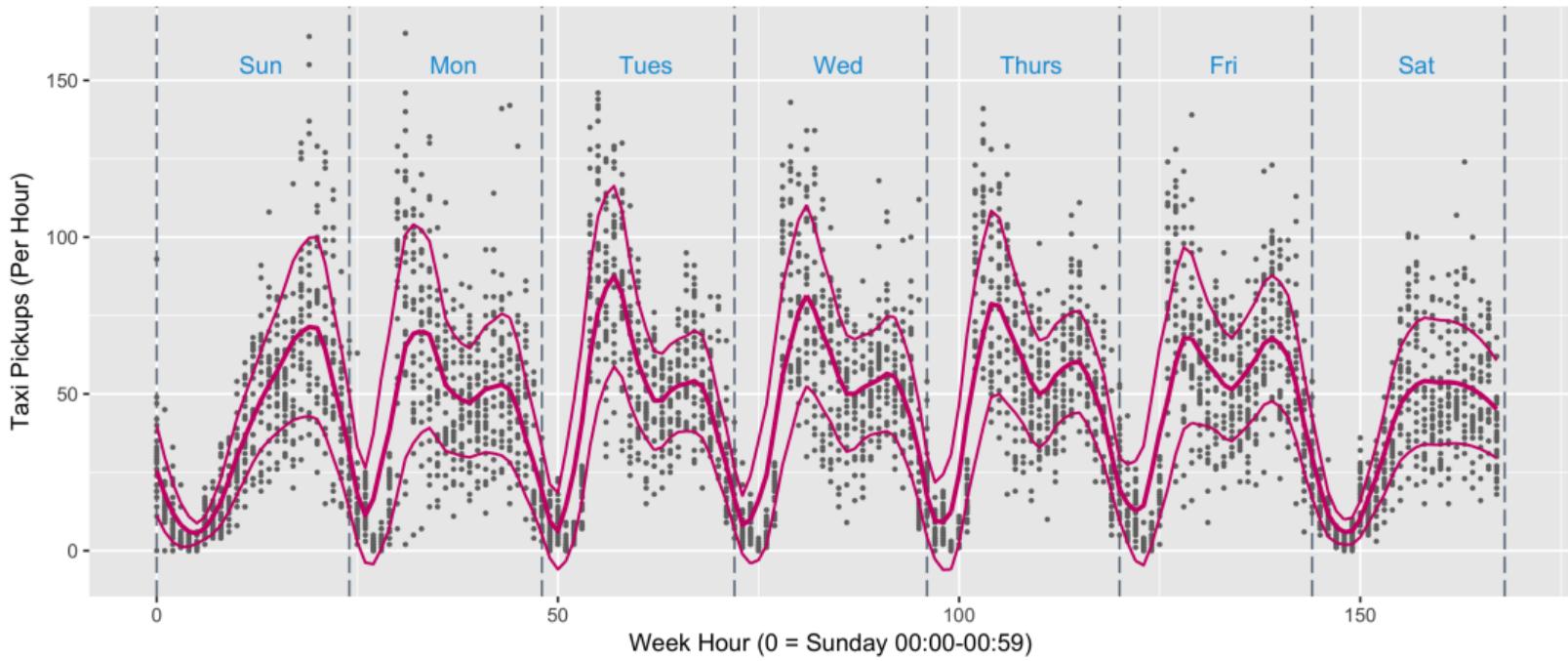
Penn Station Taxi Pickups, by Hour-of-Week (27 Weeks)



Regression line predicts **mean** pickups. But what's the typical range?

Penn Station Taxi Pickup Counts - Prediction Intervals

Penn Station Taxi Pickups, by Hour-of-Week (27 Weeks)



Here plotting estimated ± 1 standard deviation.

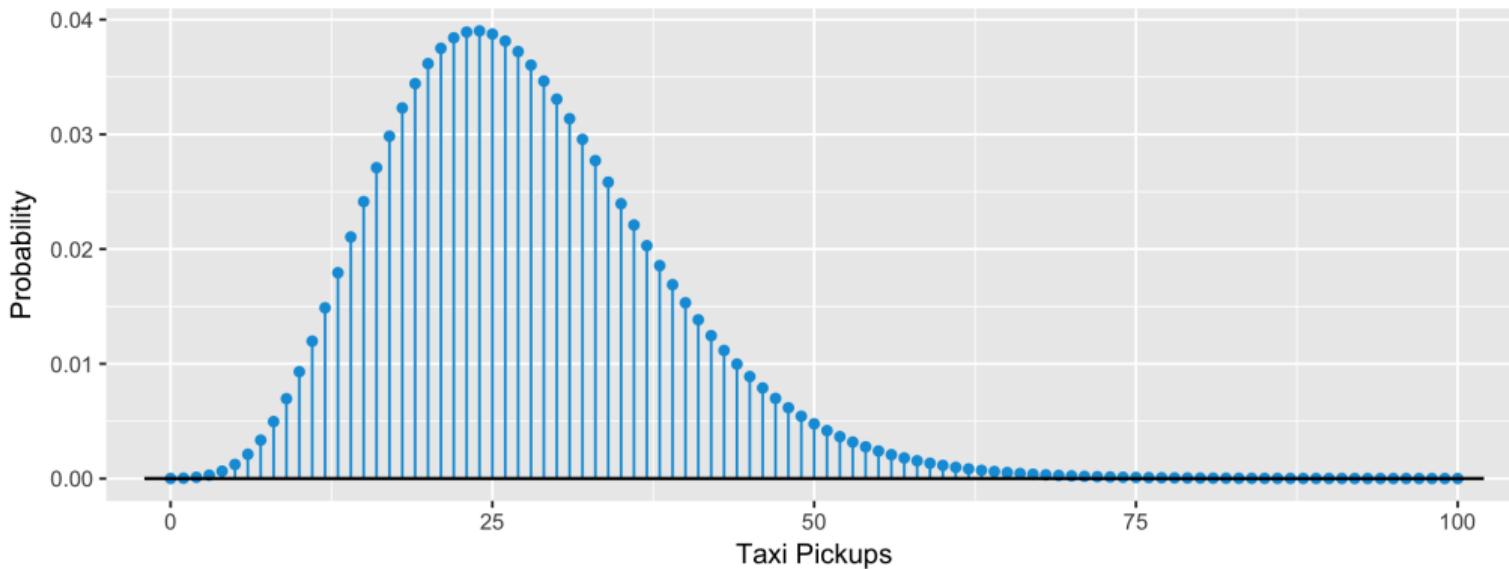
Penn Station Taxi Pickup Counts - Predictive Distribution

- Consider predictions for a particular weekhour $x \in \{0, \dots, 167\}$, say $x = 10$.
- **Regression** gives a single number: $\mathbb{E}[y | x = 10] \approx 30.1$ taxi pickups
- A **prediction interval** gives two numbers: $\mathbb{P}(y \in [17.8, 42.3] | x = 10) \approx 68\%$.
- We can also produce an estimate of the full **conditional probability distribution** for $p(y | x = 10) \dots$

Penn Station Taxi Pickup Counts - Predictive Distribution

- For weekhour 10 (i.e. $x = 10$), we predict the following distribution for $p(y | x = 10)$:

Predicted Distribution for Pickup Count (Penn Station, Week Hour = 10)



- According to this predictive distribution, how likely are we to get 90 taxi pickups?

Predictive Distributions for Anomaly Characterization

- At week-hour 10,
 - the expected number of taxi pickups 30.1.
 - the 68% prediction interval was [17.8, 42.3].
- Suppose we observe 90 taxi pickups.
- How can we characterize how unusual this event is?
- We can directly calculate the probability of 90 or more taxi pickups:

$$\mathbb{P}(y \geq 90 | x = 10) = \sum_{c=90}^{\infty} p(y = c | x = 10)$$

measures how unusual this event is.

Prediction Intervals from Probability Distributions

- Given a conditional probability distribution $p(y | x)$,
 - it's usually straightforward to compute a **prediction interval**.
- A 95% prediction interval is an interval $[a, b]$ such that

$$\mathbb{P}(y \in [a, b] | x) \approx .95$$

- We can get $[a, b]$ by finding the 2.5% and 97.5% quantiles of the distribution $p(y | x)$.
- [Alternatively, can do this with **quantile regression**.]

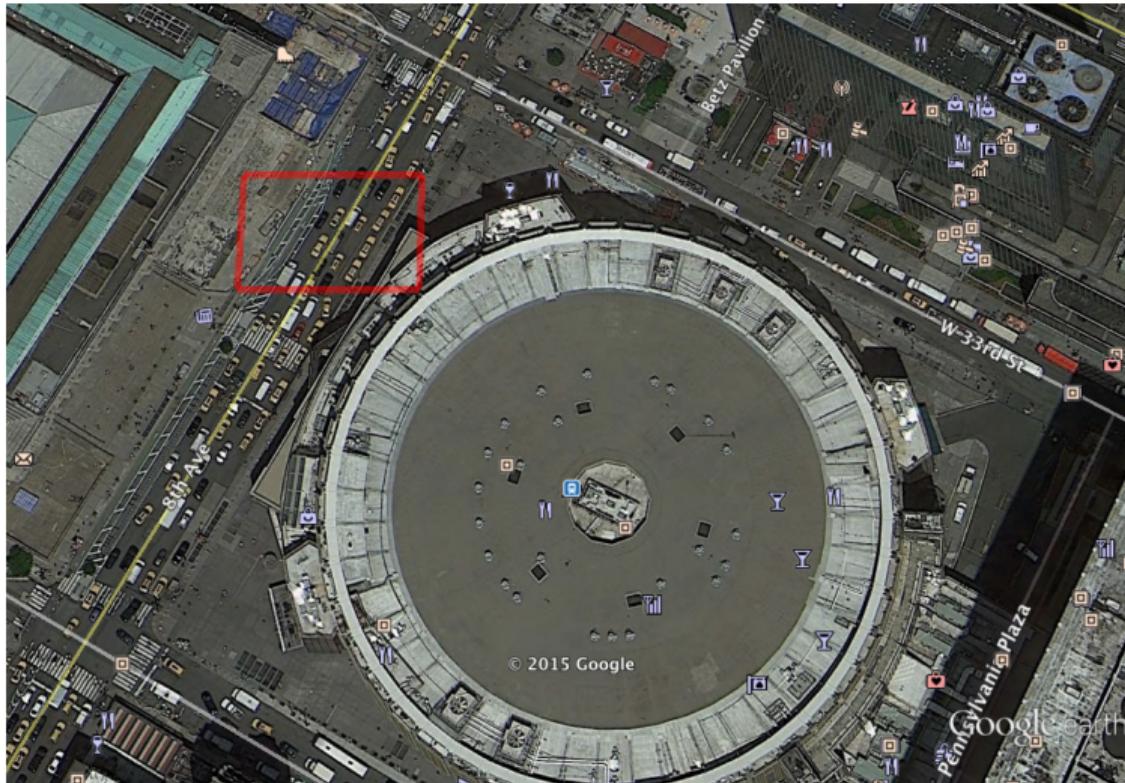
The Grid Cells

The Basic Approach

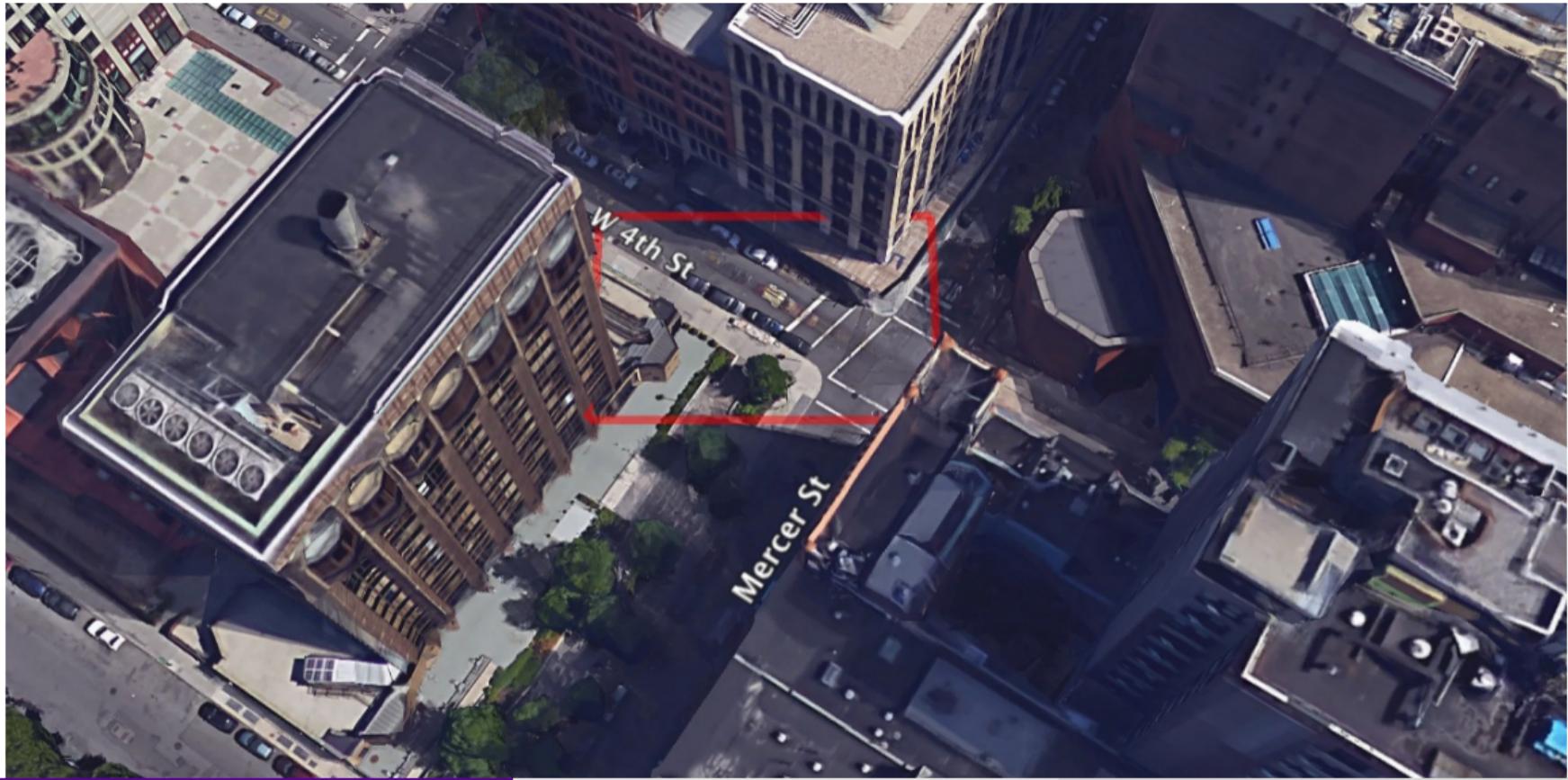
- Raw input is [roughly] continuous in
 - space (lat/lon) and
 - time (seconds since 1970-01-01).
- To make it easier to handle, we partition space and time into buckets.
- Spatial partitioning
 - Divide earth into regularly spaced grid cells.
 - About 400,000 grid cells to cover NYC
- Time partitioning
 - Only consider times at the hour level.
- Aggregate taxi pickup counts at the Grid Cell / Hour level.

Initial data analysis, including aggregation by grid cell and hour, was done by Blake Shaw.

Most Active Grid Cell: Penn Station (Grid ID 7750)

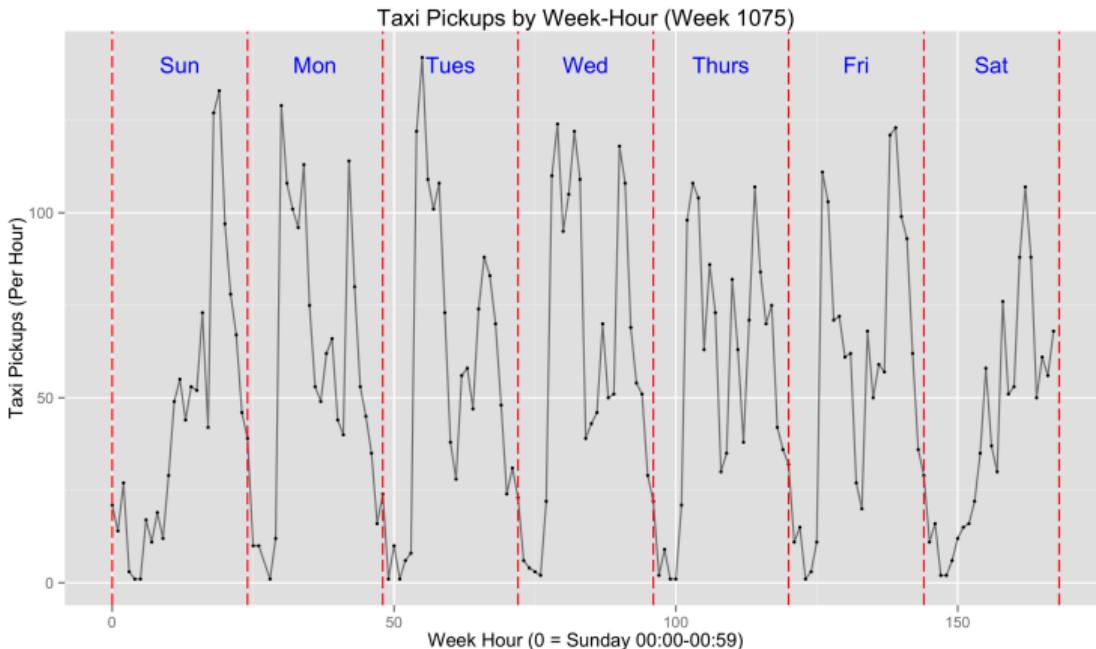


Courant Institute (Grid ID 21272)



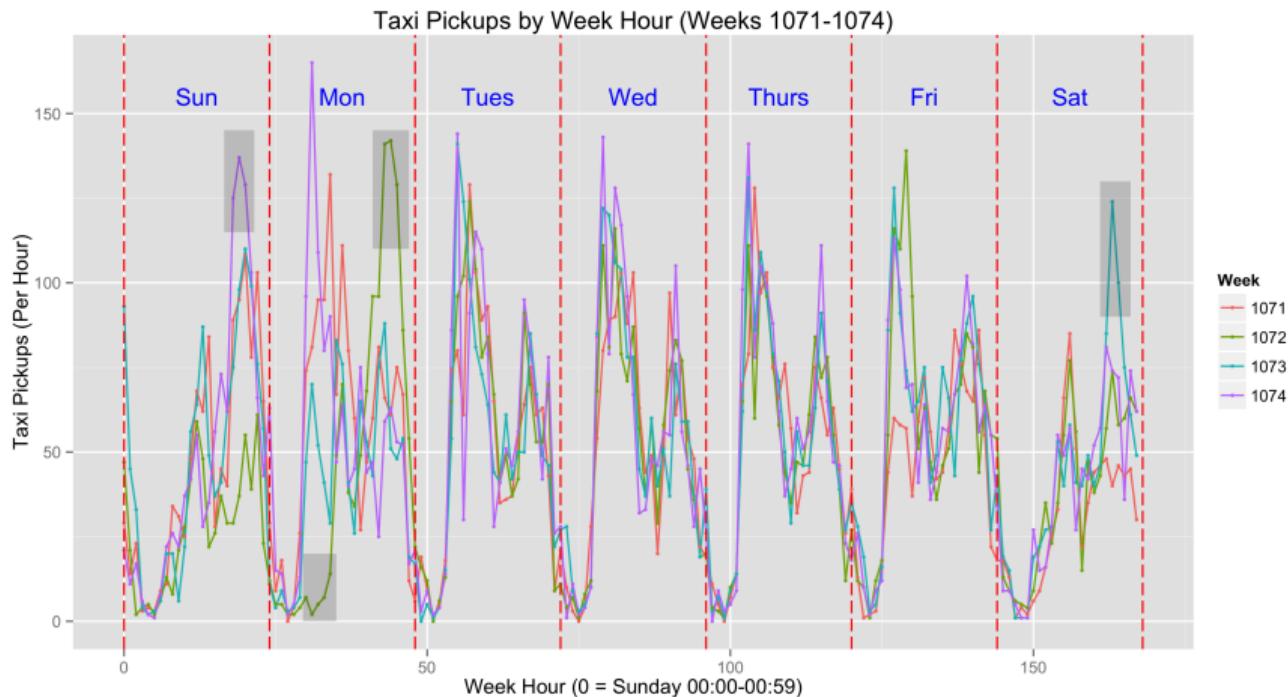
Data Visualization

Penn Station (Cell 7750): 1300 Taxi Pickups Per Day

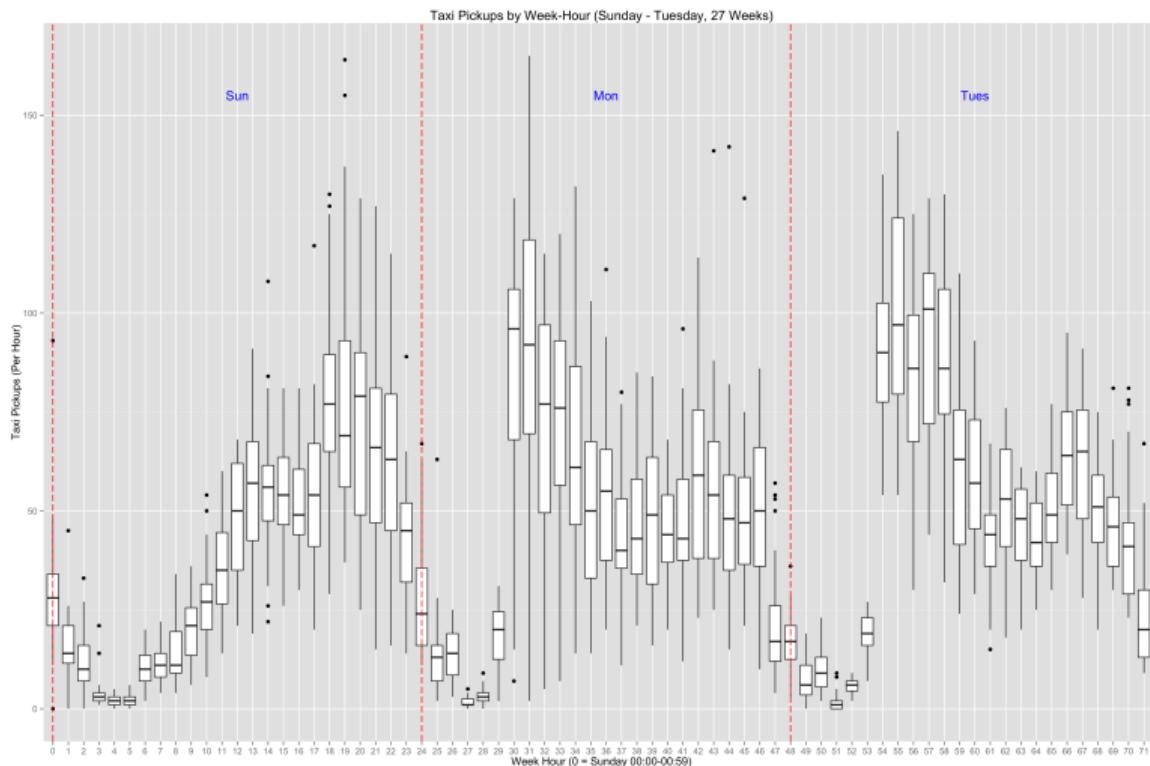


Note difference between weekend and weekday patterns.

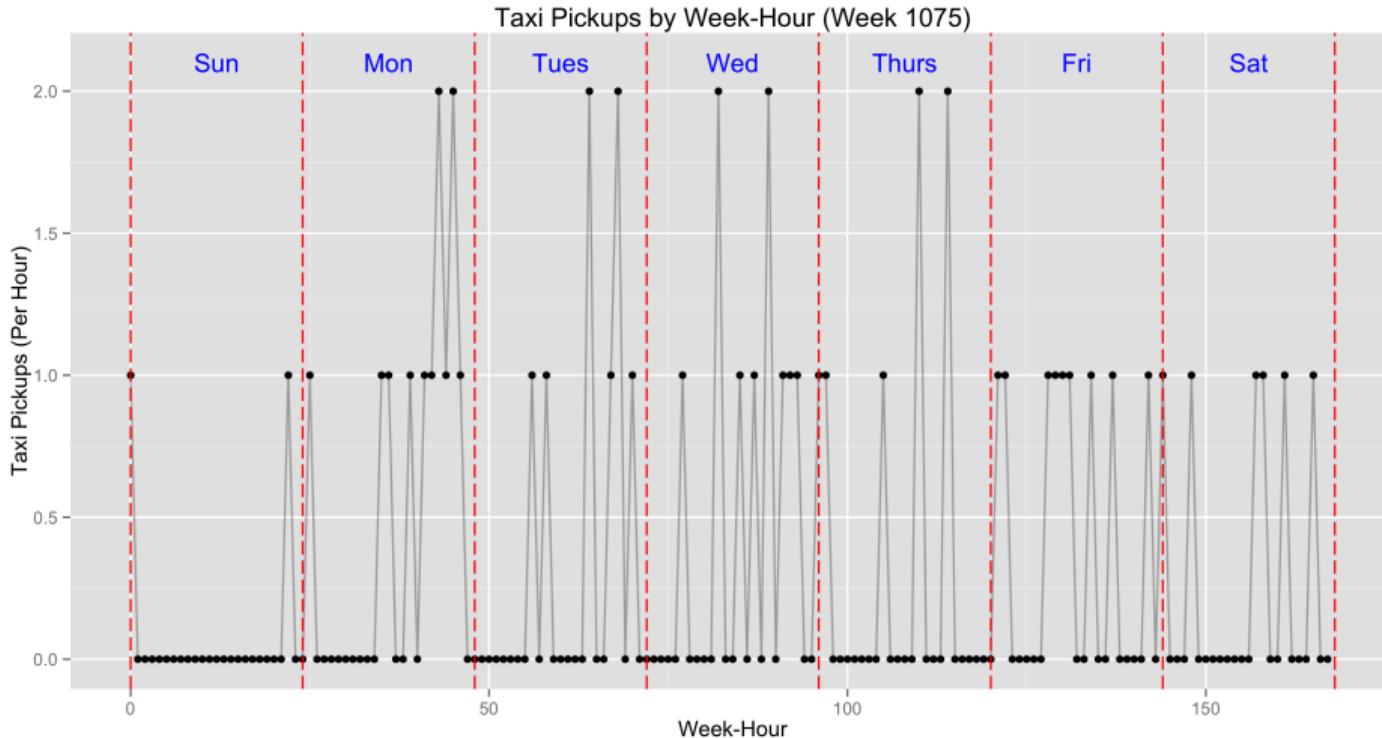
Penn Station (Cell 7750): Four Weeks, Some Outliers



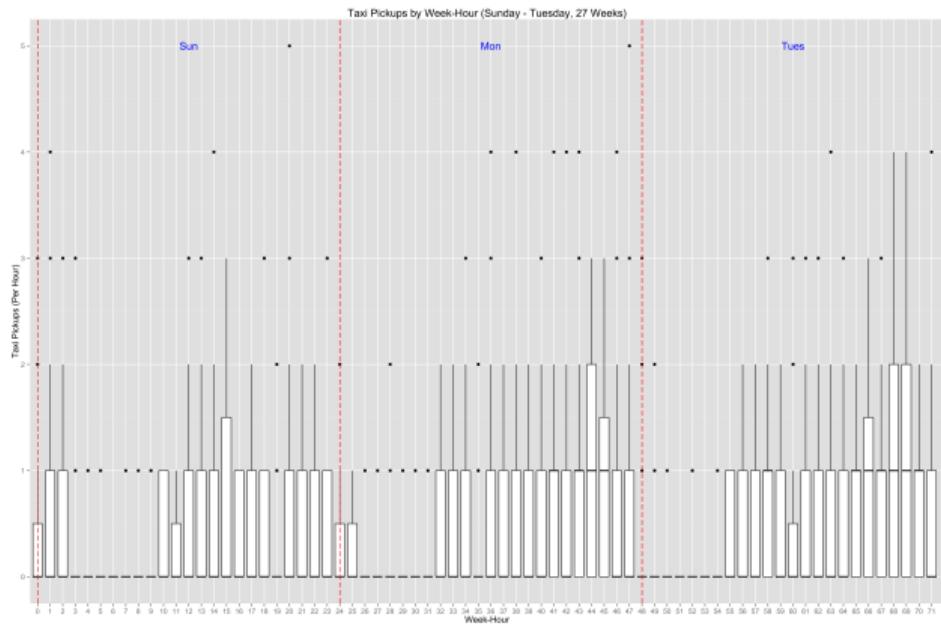
Penn Station: Sunday-Tuesday, 27 Weeks



Courant (Week 1075): 12 Taxi Pickups Per Day



Courant Institute: Sunday-Tuesday, 27 Weeks



Note: At least 25%, sometimes 75%+ of counts are zero.
Box plot clearly shows extreme values (ranging up to 5).

The Prediction Problem

The Prediction Problem

Somebody queries a **grid cell** and a **week-hour**, we tell them what to expect.

- Input space: $\mathcal{X} = \{(g, h) \mid g \in \{1, \dots, 398245\} \text{ and } h \in \{0, \dots, 167\}\}$, where
 - g is the grid Cell ID and
 - h is the week-hour
 - Possible future inputs: Holiday? Raining? Special event?
- Action space: $\mathcal{A} = \{\text{Probability distributions on number of pickups}\}$
- Outcome space: $\mathcal{Y} = \{0, 1, 2, 3, \dots\}$
 - Actual number of taxi pickups.
- Evaluation? Loss function? We'll come back to these questions...

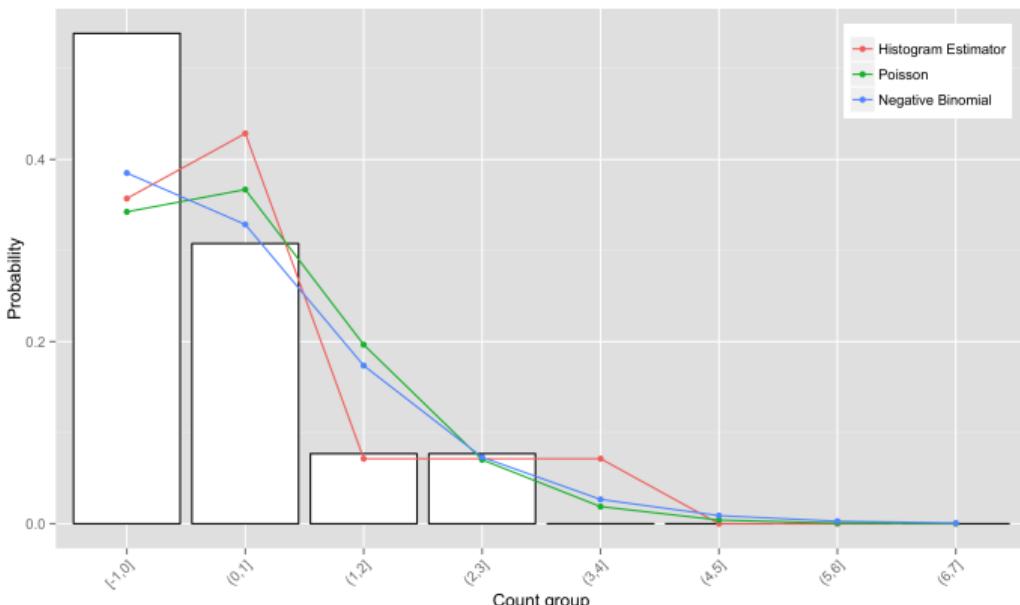
Setting up the Learning Problem

- Labeled data look like:
 - (Grid Cell = 10321, Week Hour = 120) \mapsto Count = 3
 - (Grid Cell = 192001, Week Hour = 6) \mapsto Count = 12
 - (Grid Cell = 1271, Week Hour = 154) \mapsto Count = 0
- How to split the data into a training set and a test set?
- Our approach:
 - First 14 weeks are **training set**.
 - Last 13 weeks are **test set**.

Stratification Approaches

Approach 1: Full Stratification (Courant, Tuesdays 7-8pm)

- Estimate distribution for each grid cell / week hour pair.
- Colored lines are from training. White bars are from test.



Terminology: Stratification and Bucketing

Definition

We say we are **stratifying** if we partition our input space into groups, and treat each group separately. For example, in modeling we would build a separate model for each group, without information sharing across groups.

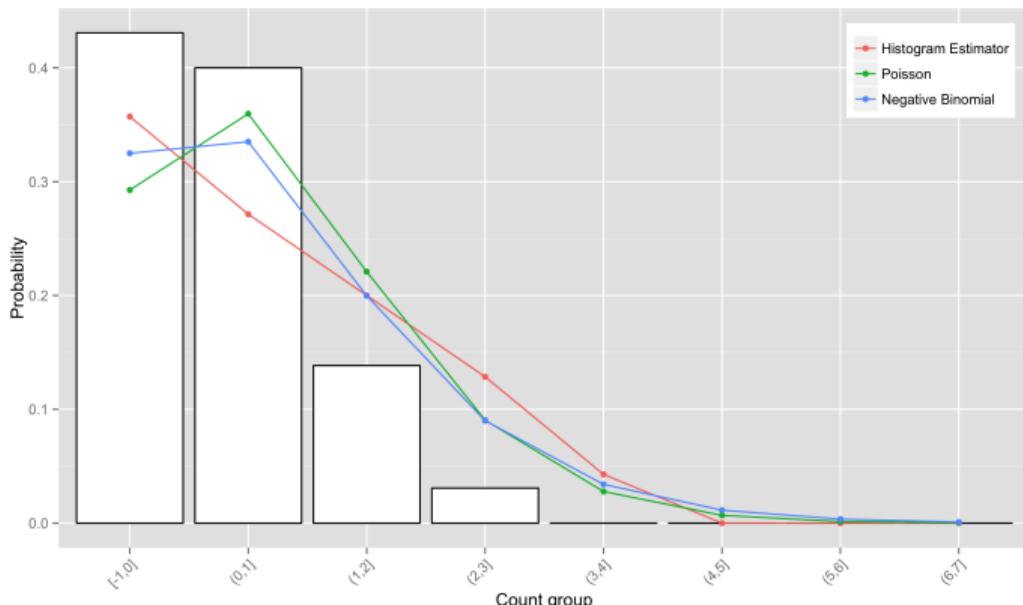
On the other hand,

Definition

We say we are **bucketing** (or **binning**) if we are combining natural groups in the data into a single group, rather than building a separate model for each group. For example, combining all weekdays together would be “bucketing”.

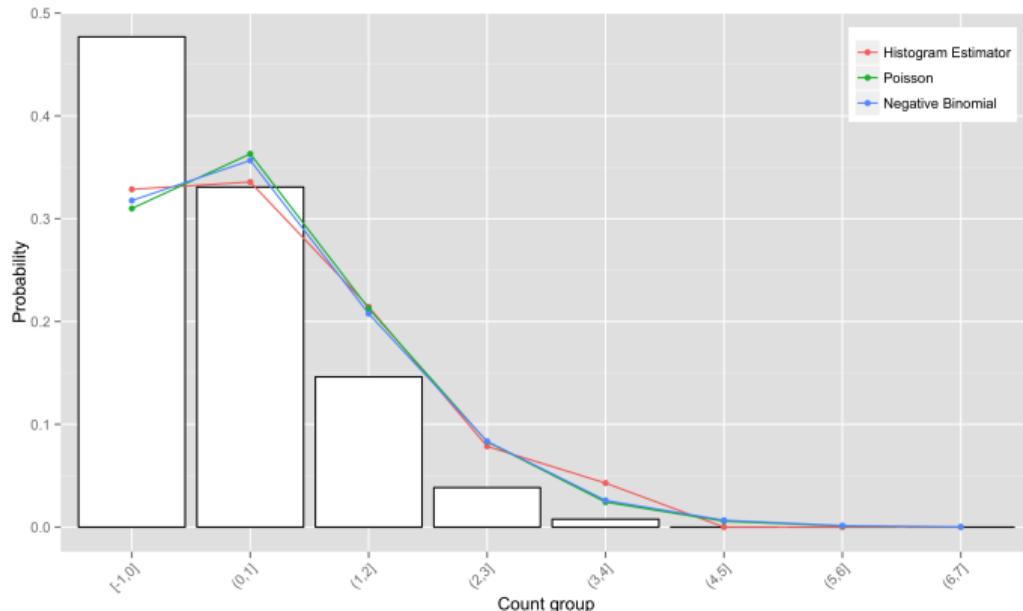
Approach 2: Weekday Bucketing (Courant, M-F 7-8pm)

- Data inspection suggests that day patterns are similar Mon-Fri.



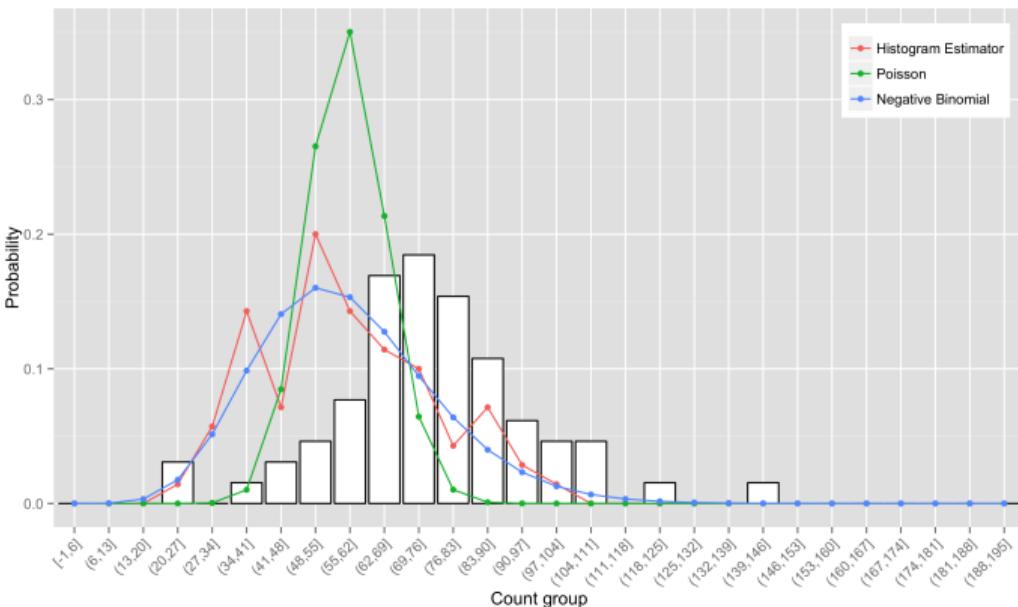
Approach 3: (Courant, M-F 6-8pm)

- Also, 6-7pm looks similar to 7-8pm, so join together



Penn Station, M-F 7-8pm

- Negative binomial fits empirical much better than Poisson. (overdispersion)
- Massive shift between train and test!



The Estimation/Approximation Tradeoff of Stratification

- With a separate probability distribution for every grid cell / week-hour pair, model is highly specific!
- Could capture idiosyncrasy of Friday @5pm that we would miss if combining all weekdays.
 - That is, we're decreasing approximation error.
- With relatively little data in a particular stratum, estimates may have high estimation error.
- By “bucketing”, or combining strata:
 - We can reduce estimation error.
 - It may cost us in approximation error.
 - By bucketing in a smart way, you can minimize increase in approximation error.
- Note: This is often referred to as a **bias / variance tradeoff**:
 - $\text{bias} \approx \text{approximation error}$; $\text{variance} \approx \text{estimation error}$

Is there a more convenient way?

- We can tradeoff between estimation and approximation error by varying the stratification and the bucketing.
- It's a great way to start your data analysis.
 - You get a feel for the data and gain some intuition.
- Our classification and regression techniques also trade off between approximation and estimation:
 - We had to choose our features.
 - We had to tune our regularization parameter.
- Can we do something similar for predicting distributions?
- Yes – to be discussed in our module on conditional probability modeling.