Forecasting Street and Sidewalk Cleaning Services in San Francisco

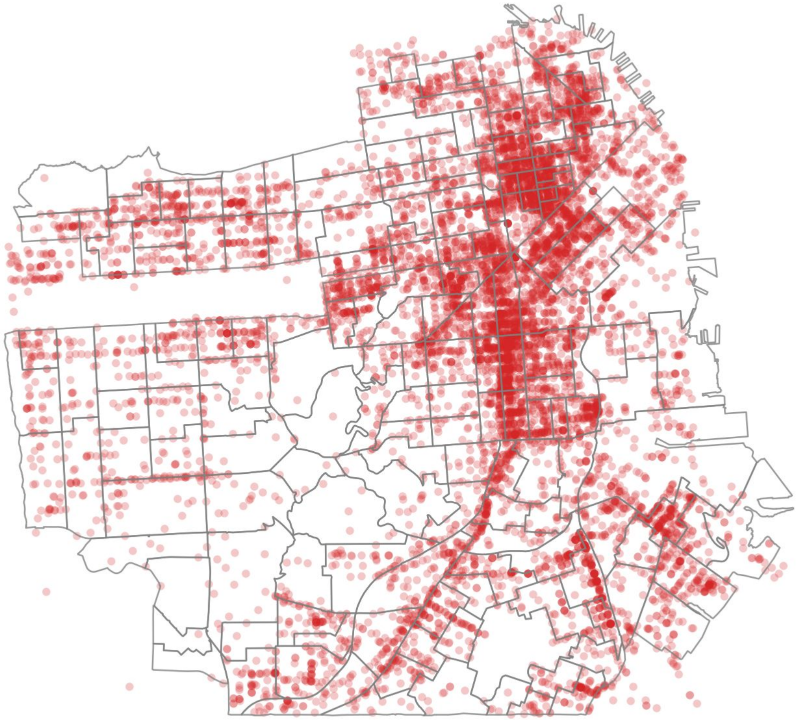
Jared Schober and Peter Amerkhanian

San Francisco 311

“Street and sidewalk cleaning requests are generated internally and **through calls received by the City's 311 customer service center.** [...] Public Works' Radio Room **triages the request to the appropriate crew**.” (source)

We examine call counts **at the hour level** between 1/1/2009 and 12/31/2022:

```
----- Descriptive Statistics -----
count    122712.000000
mean         17.626622
std          22.591759
min           0.000000
25%           2.000000
50%           8.000000
75%          25.000000
max         553.000000
Name: calls, dtype: float64
Sum: 2162998
```



Goals and Applications

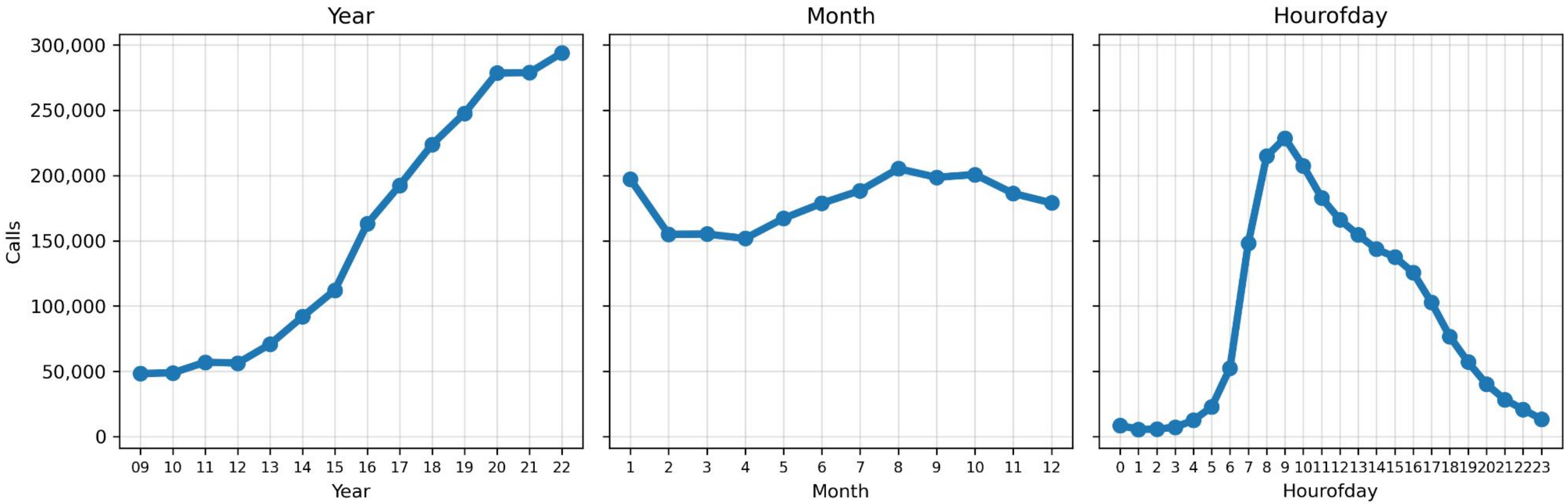
Our goal: Use machine learning to predict the number of requests that the city will receive in any given hour.

Policy applications: Understand how much staffing will be needed for the 311 call center and public works street cleaning teams at a given time, anticipate sidewalk and street cleaning costs.

SF Public Works Clean Corridors

Approach and Challenges

- **311 grew** considerably during this time period.
- We were concerned it would be difficult to forecast within year trends with such a strong secular trend across years.
- We focused on capturing hour-level patterns in our modeling



Data and Cross Validation Approach

Lagged Dataset (48 hours picked via exploration)

	calls	lag_1	lag_2	lag_3	lag_4	lag_5	lag_6	lag_7	lag_8	lag_9	...	lag_39	lag_40	lag_41	lag_42	lag_43	lag_44	lag_45	lag_46	lag_47	lag_48
datetime																					
2009-01-03 00:00:00	0	6.0	0.0	1.0	1.0	3.0	5.0	19.0	20.0	19.0	...	6.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2009-01-03 01:00:00	0	0.0	6.0	0.0	1.0	1.0	3.0	5.0	19.0	20.0	...	4.0	6.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2009-01-03 02:00:00	1	0.0	0.0	6.0	0.0	1.0	1.0	3.0	5.0	19.0	...	10.0	4.0	6.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0
2009-01-03 03:00:00	3	1.0	0.0	0.0	6.0	0.0	1.0	1.0	3.0	5.0	...	8.0	10.0	4.0	6.0	1.0	0.0	0.0	0.0	0.0	0.0
2009-01-03 04:00:00	0	3.0	1.0	0.0	0.0	6.0	0.0	1.0	1.0	3.0	...	5.0	8.0	10.0	4.0	6.0	1.0	0.0	0.0	0.0	0.0

Cross Validation: Train, Test, **standardize, clip at ±3std, compute metrics**

	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Fold Size	8712	8760	8760	8784	8760	8760	8760	8784	8760	8760	8760	8784	8760	8760

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etc…

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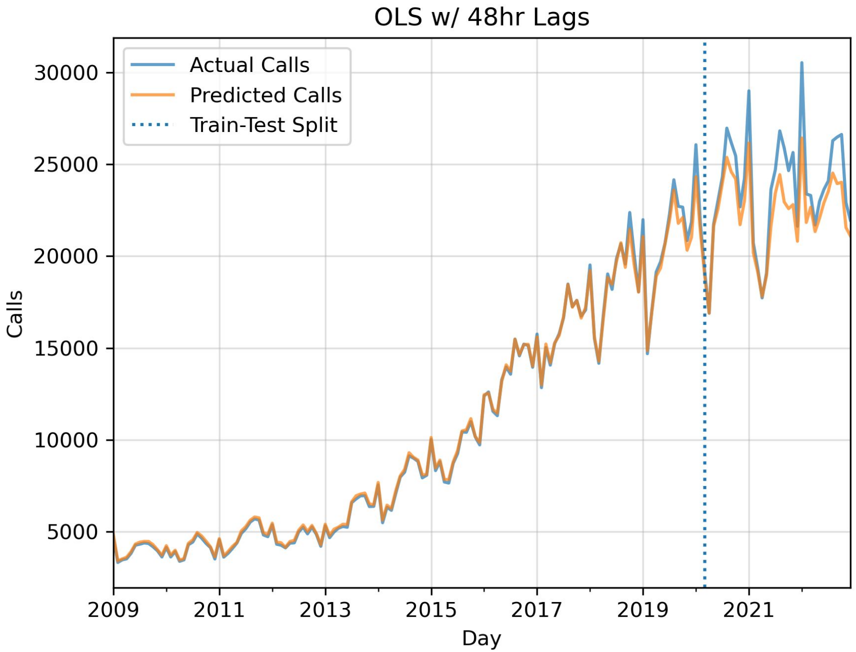
Summary

Model	Avg RMSE	Avg R^2	Avg max residual
Baseline	12.58	0.379	171
Linear regression	8.29	0.595	157.33
Ridge Regression (CV) (*α=0.0001*)	8.29	0.595	157.34
ARIMA	11.37	0.56	161.376
Random Forest (*max_depth=None, estimators=200, etc.*)	7.943	0.607	154.093
RNN	62.13	0.18	398.465

Average metrics are computed across year-folds. All models have optimized hyperparameters for each fold's predictions

Linear regression

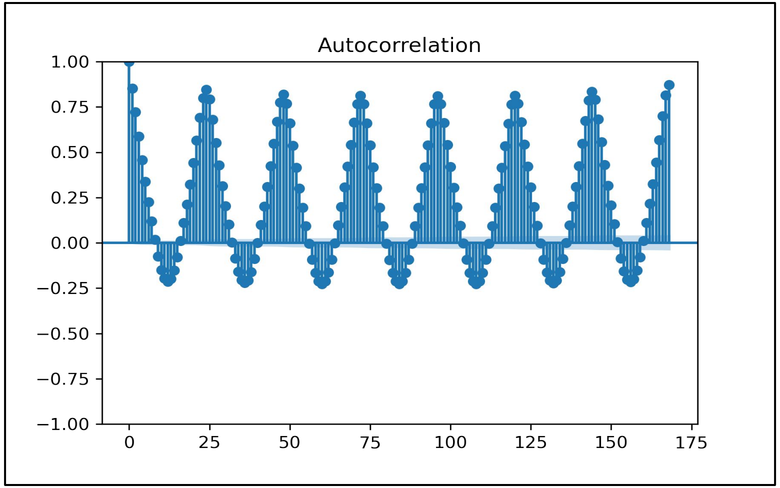
- Consistent underestimates in the test period – **heteroskedastic**
- Fairly accurate overall
- Perhaps lots of linear relationships in the data? Parametric model more suited to small (~8k) training data?

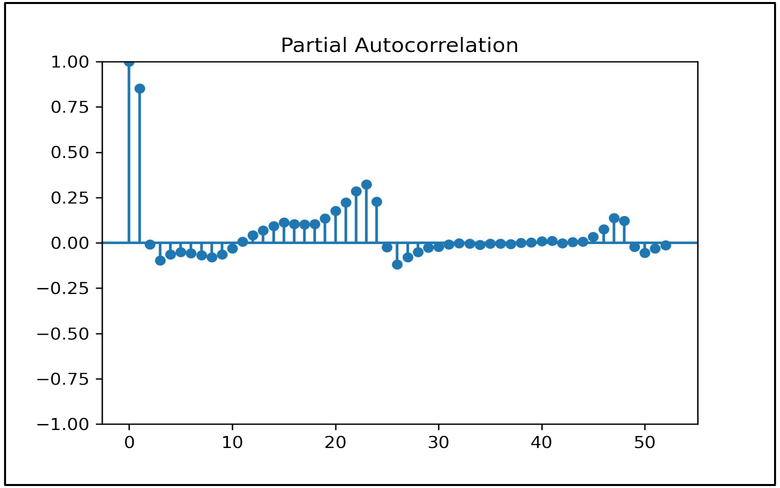


(80-20 train test split pictured for clarity)

ARIMA setup

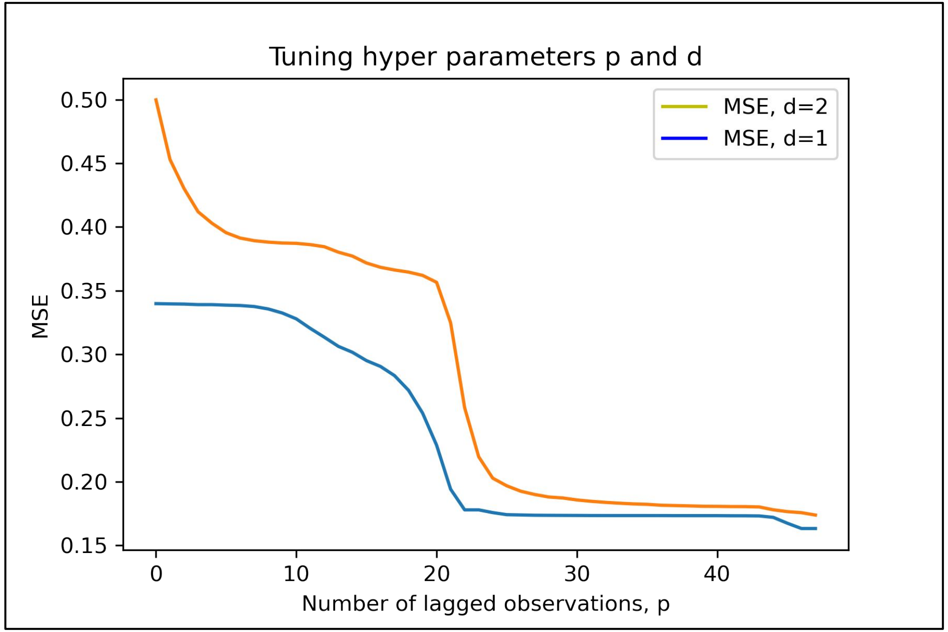
- Autocorrelation - significant hourly at the **week level** (and beyond)
- Partial autocorrelation - significant hourly up to about **2 days**
- Challenge: **intense computational requirements** as time lag increases
- Because of this, we **restricted our ARIMA model to 2 days**
- We **normalized the data** by each year and **clipped outliers** to be within 3 standard deviations





ARIMA hyperparameter tuning

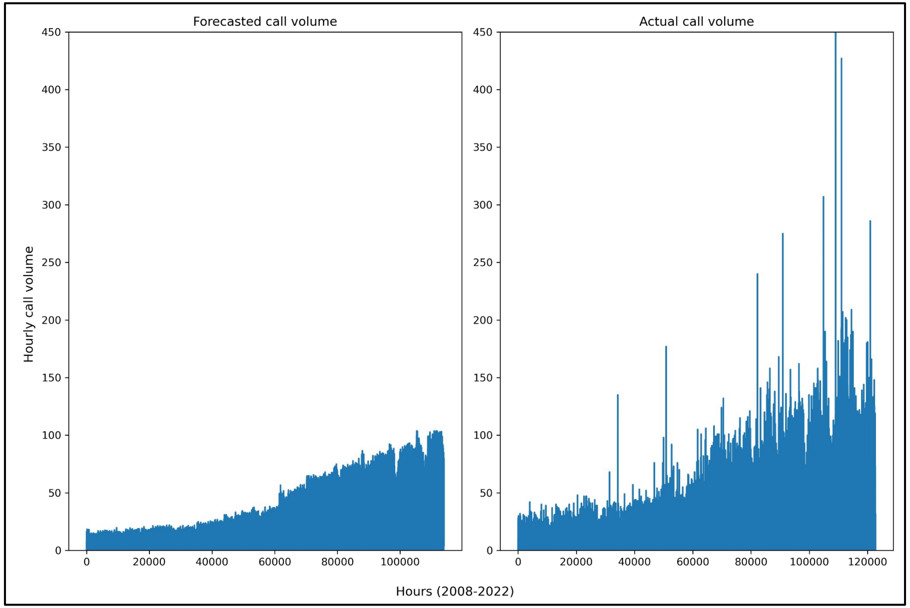
- Our model uses the **Auto Regressive (AR)** and **Integrative (I)** parts of the ARIMA model
- Because of this, we tuned the number of lagged observations (p) and the degree of differencing (d)
- We evaluated ARIMA models for **p=1** → **48** and **d=1** → **2**, evaluating RMSE and AIC

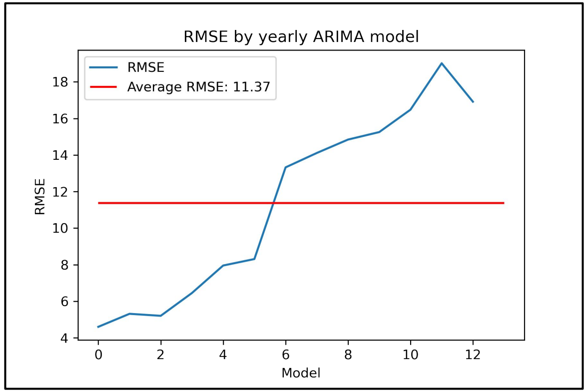


Note: RMSE graph reflects normalized data

ARIMA results

- Average RMSE across yearly models: **11.62**
- Positive trend in call volume data reflected in **heteroskedasticity of the error term**
- Normalization and outlier clipping improved RMSE but may exacerbate ARIMA issues with predicting volume spikes





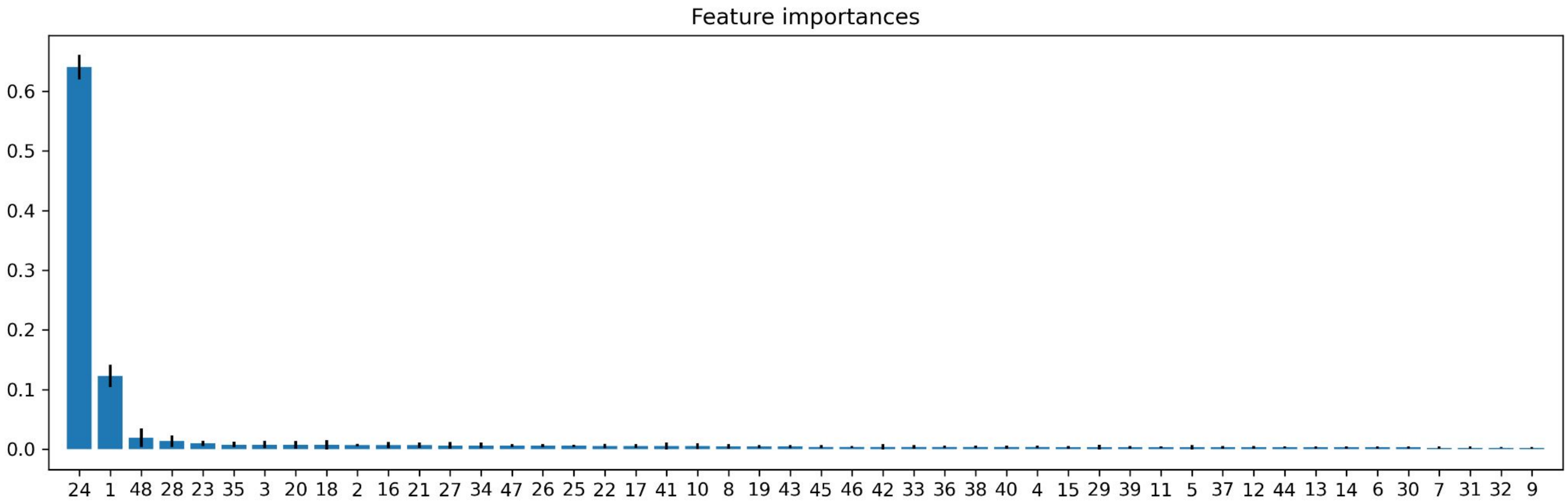
Recurrent Neural Network

- Tried LSTM, but hypothesized that data is too small, stuck to RNN
- Through hyperparameter exploration, we found that **deeper architectures were more effective**, but computationally costly – final RNN took 55 minutes to cross validate for **performance that was much weaker than simple linear regression**.

```
model = Sequential()
model.add(SimpleRNN(200,
activation='relu', return_sequences=True,
input_shape=(n_steps, 1)),)

model.add(Dropout(0.5))
model.add(SimpleRNN(units=150,
activation='relu', return_sequences=True))

model.add(Dropout(0.5))
model.add(SimpleRNN(units=100, activation='relu',
return_sequences=True))

model.add(Dropout(0.5))
model.add(SimpleRNN(units=50, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(1))
model.compile(optimizer='adam', loss='mse')
```

Random Forest Regression

- Our best model
- Easy to parallelize
- Focuses on similar features to the ARIMA



Next Steps

- Train optimal model at the census tract level (even smaller data) to let forecasting pick up geographic variation ⟹
- Further exploration of why RNN underperforms