Daily Call Volume Prediction

Using Historical Call Volume, Time, and Weather Data as parameters

Linear & Degree 2 Polynomial Regression Models

Glance at the dataset

*Only includes first 20 columns and 5 rows here. There are 149 columns and 894 rows in total.

ind ex	Date	Day of the Week	Total Inbound Calls	AW ND	PR CP	SN O W	SN WD	TA VG	TM AX	TM IN	AWN D_La g1	AWN D_La g2	AWN D_La g3	AWN D_La g4	AWN D_La g5	AWN D_La g6	AWN D_La g7	AWN D_La g8	AWN D_La g9	AWND _Lag1 0
0	2022-01-0 1 00:00:00	Saturda y	0.0	10. 07	0.6	0.0	0.0	44	48. 0	27. 0	NaN									
1	2022-01-0 2 00:00:00	Sunday	0.0	13. 42	0.0	0.1	0.0	24	27. 0	16. 0	10.07	NaN								
2	2022-01-0 3 00:00:00	Monday	78.0	5.5 9	0.0	0.0	0.0	21	34. 0	13. 0	13.42	10.07	NaN							
	2022-01-0 4 00:00:00	Tuesday	73.0	13. 42	0.0	0.0	0.0	32	43. 0	26. 0	5.59	13.42	10.07	NaN						
	2022-01-0 5 00:00:00	Wednes day	70.0	15. 88	0.0	0.0	0.0	34	42. 0	20. 0	13.42	5.59	13.42	10.07	NaN	NaN	NaN	NaN	NaN	NaN

NaN cells only exist in several top rows, because there is no Lag data for those days. I eliminated those rows in later analysis.

Parameters

2022-1 to 2024-6, excluding non-Sunday 0 call days

5 Historical Call Volume Parameters:

1-5 Lag Days

2 Time Parameters & 1 market index:

Year, Month (together as 1 column), S&P 500 index

• 140 (8 *20) Weather parameters:

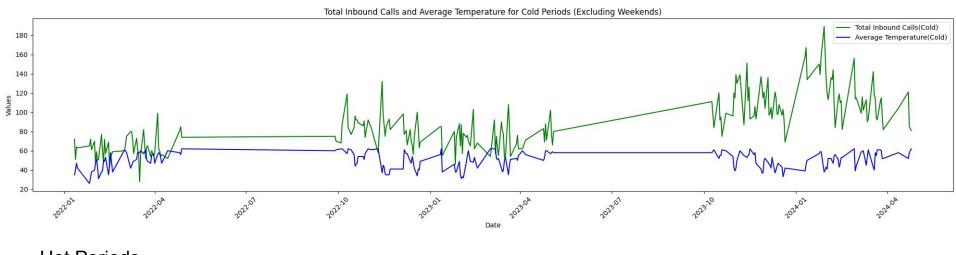
0-19 Lag Days

AWND - Average wind speed **SNOW** - Snowfall **HAIL** - Hail

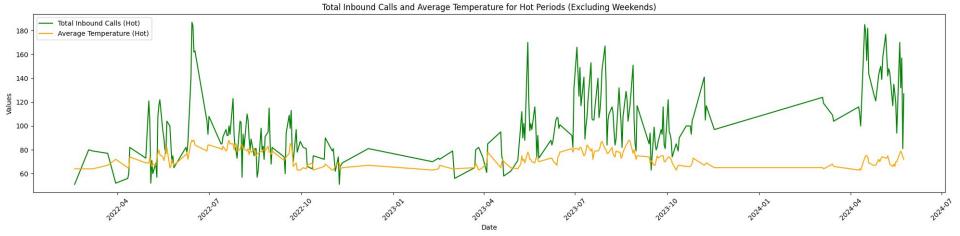
TMAX - Maximum temperature **TAVG** - Average Temperature

TMIN - Minimum temperature **PRCP -** Precipitation **SNWD** - Snow depth

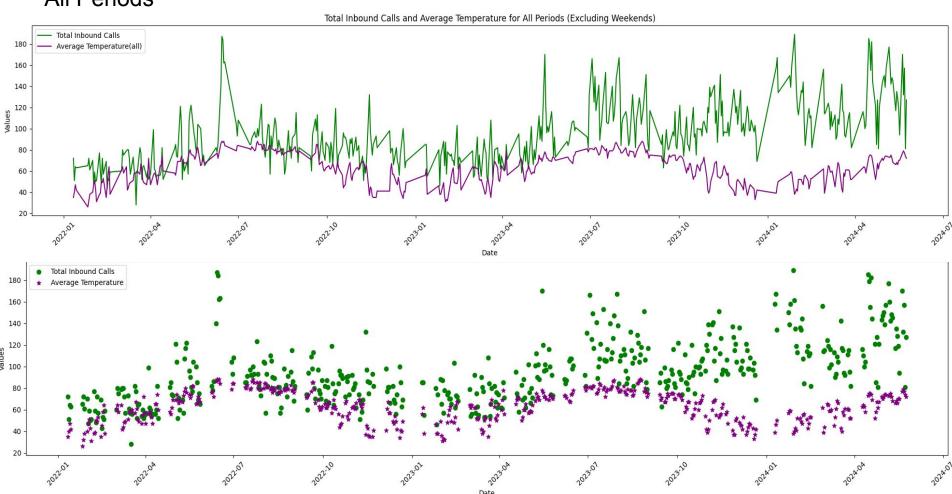
Cold Periods







All Periods



Linear Regression for Cold Periods

OLS Regression Results

```
0.913
Dep. Variable:
                   Total Inbound Calls
                                           R-squared:
Model:
                                     OLS
                                           Adj. R-squared:
Method:
                          Least Squares
                                           F-statistic:
                       Mon, 24 Jun 2024
                                           Prob (F-statistic):
                                                                          1.58e-80
Date:
Time:
                                16:53:14
                                           Log-Likelihood:
                                                                           -1197.0
No. Observations:
                                     305
                                           AIC:
                                                                             2568.
                                                                             2892.
Df Residuals:
                                     218
                                           BIC:
                                      86
Df Model:
Covariance Type:
                               nonrobust
```

Set **Friday** as the benchmark:

Monday: 54.51 more calls on average

Tuesday: 4.17 more calls on average*

Wednesday: 11.33 more calls on average*

Thursday: 5.75 more calls on average*

Saturday: 43.24 less calls on average

Sunday: 58.66 less calls on average

Set **Sunday** as the benchmark:

Monday: 103 calls on average

Tuesday: 62 calls on average

Wednesday: 70 calls on average

Thursday: 63 calls on average

Friday: 58.66 calls on average

Saturday: 15.42 calls on average

Important parameters interpretation

spending 0.0005 0.000

For every 1000 dollars spent on Google Ads, the inbounded call volume increases by 5 per day on average.

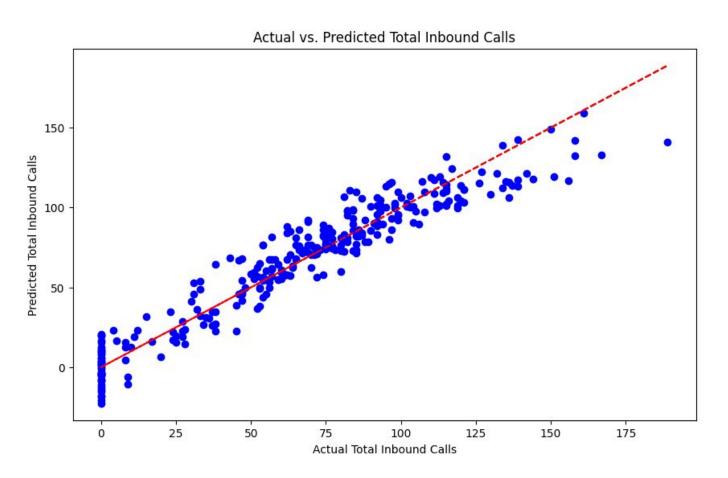
PRCP 5.0746 0.271 *

if precipitation increases by 1 inch, the inbounded call volume will increase by 5 per day on average.

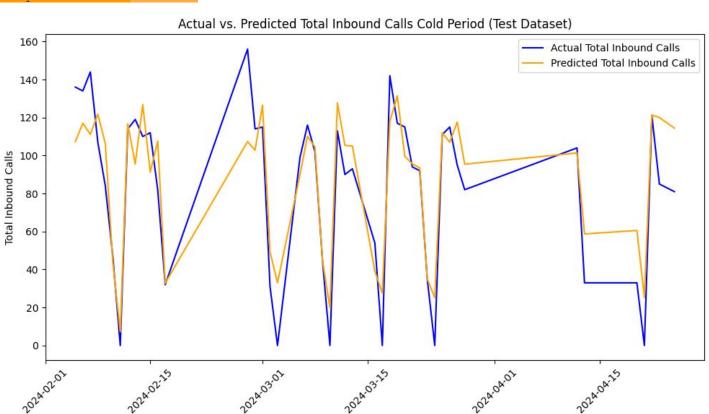
Month_index_continous 1.1995 0.000

Every month later, the call volume will increase by 1 per day on average.

Linear Regression for Cold Periods



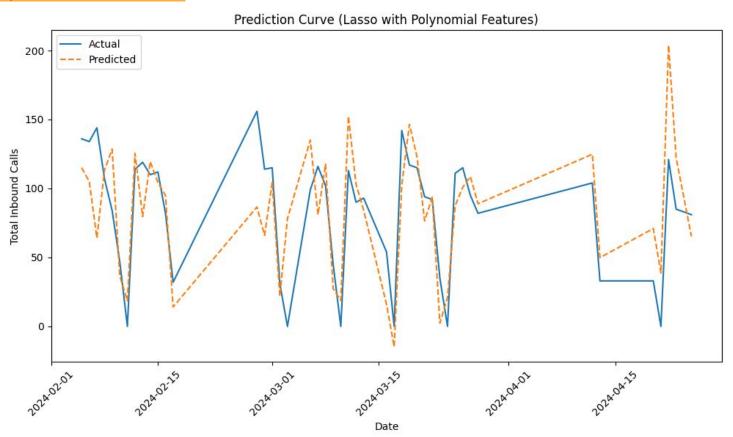
Mean Squared Error: 388.799



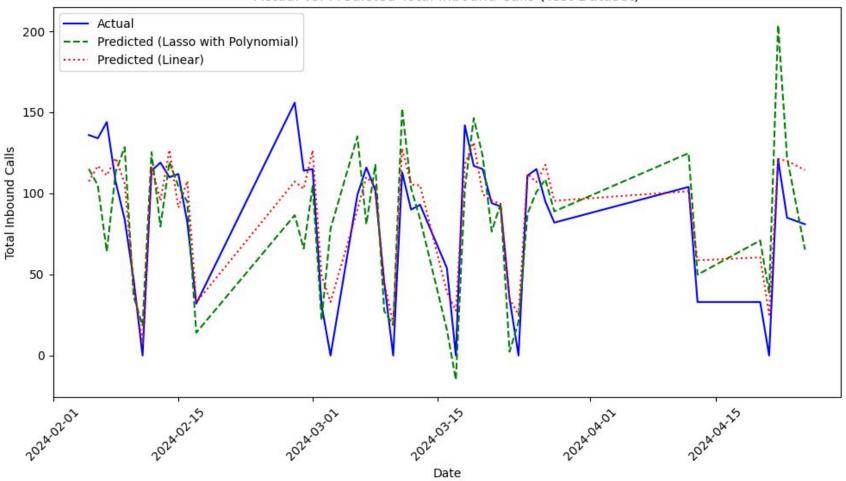
Date

Polynomial Regression for Cold Periods

Mean Squared Error: 1092.20



Actual vs. Predicted Total Inbound Calls (Test Dataset)



Linear Regression for Hot Periods

OLS Regression Results

Dep. Variable:	Total Inbound Calls	R-squared:	0.877
Model:	OLS	Adj. R-squared:	0.845
Method:	Least Squares	F-statistic:	27.14
Date:	Mon, 24 Jun 2024	Prob (F-statistic):	8.72e-91
Time:	15:27:25	Log-Likelihood:	-1451.5
No. Observations:	347	AIC:	3049.
Df Residuals:	274	BIC:	3330.
Df Model:	72		
Covariance Type:	nonrobust		
=============			

Set **Friday** as the benchmark:

Monday*: 42 more calls on average

Tuesday: 11 (-9.353, 28.943) 95%

Wednesday: 3 (-17.699, 24.227) 95%

Thursday: 0 (-18.485, 15.570) 95%

Saturday*: 69 less calls on average

Sunday*: 87 less calls on average

Set **Sunday** as the benchmark:

Monday: 129 calls on average

Tuesday: 98 calls on average

Wednesday: 90 calls on average

Thursday: 87 calls on average

Friday: 87 calls on average

Saturday: 18 calls on average

Important parameters interpretation

HAIL 22.2346 14.289 1.556 **0.121** -5.897 50.366

Every inch increase in hail will result 22 more calls

spending 0.0003 0.000 2.340 **0.020** 4.33e-05 0.001

For every 1000 dollars spent on Google Ads, the inbounded call volume increases by 3 per day on average.

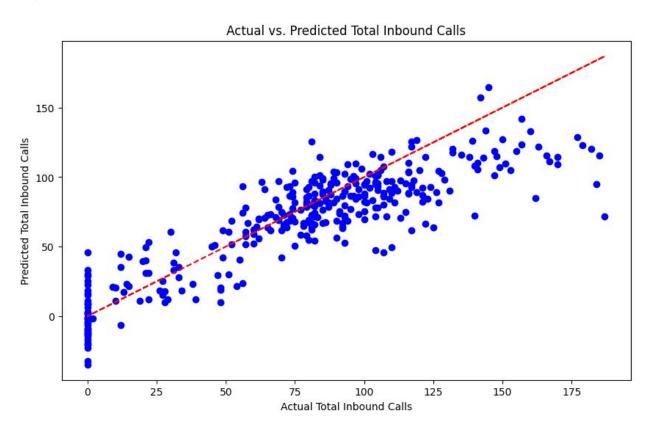
PRCP_Lag8 6.5472 3.703 1.768 **0.078** -0.742 13.837

if there is a precipitation 8 days ago, every 1 inch precipitation will increases the inbounded call volume by 6.5 per day on average.

Month_index_continous 0.8187 0.279 2.929 **0.004 0.269** 1.369

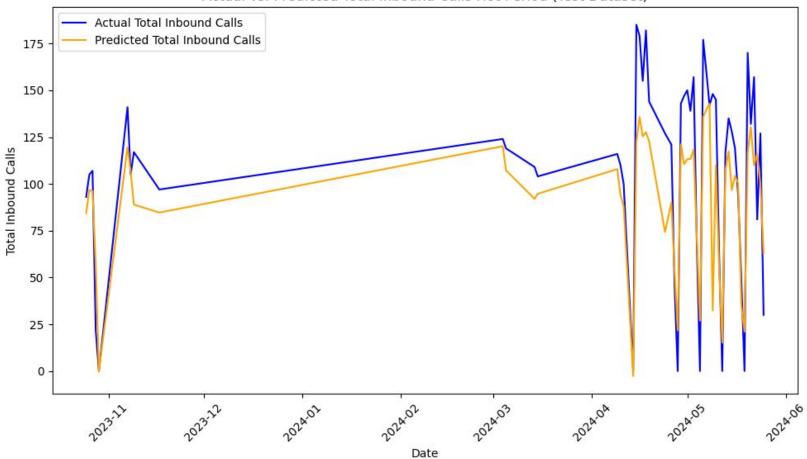
Every month later, the call volume will increase by 0.8 per day on average.

Linear Regression for Hot Periods

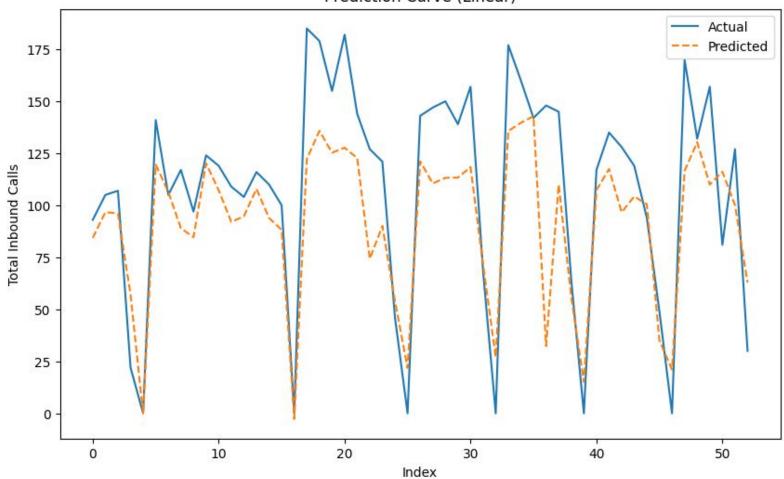


MSE: 1521

Actual vs. Predicted Total Inbound Calls Hot Period (Test Dataset)

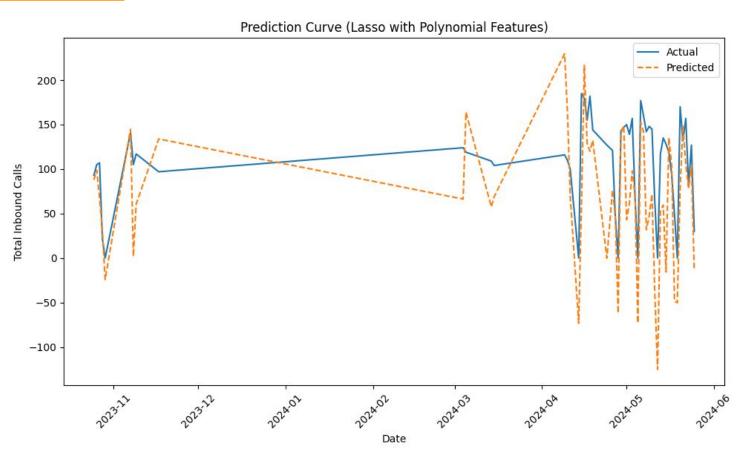


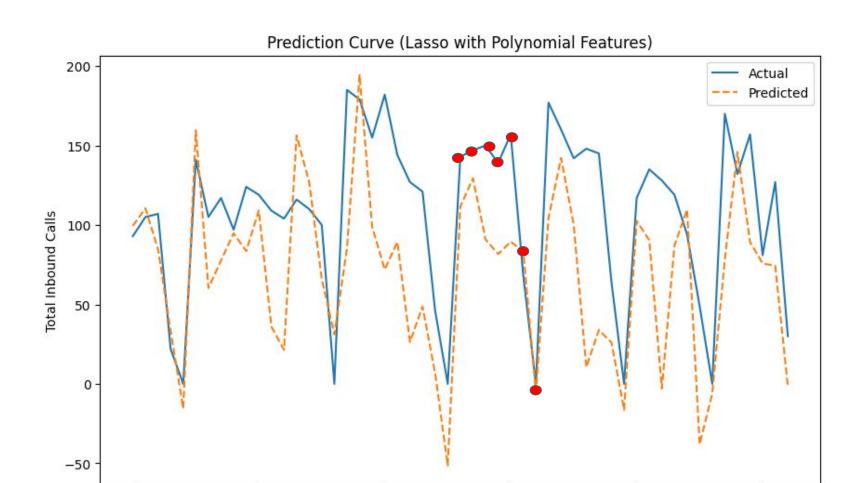




Polynomial Regression for Hot Periods

Mean Squared Error: 3189





Index

Prediction Curve (Lasso with Polynomial Features)

