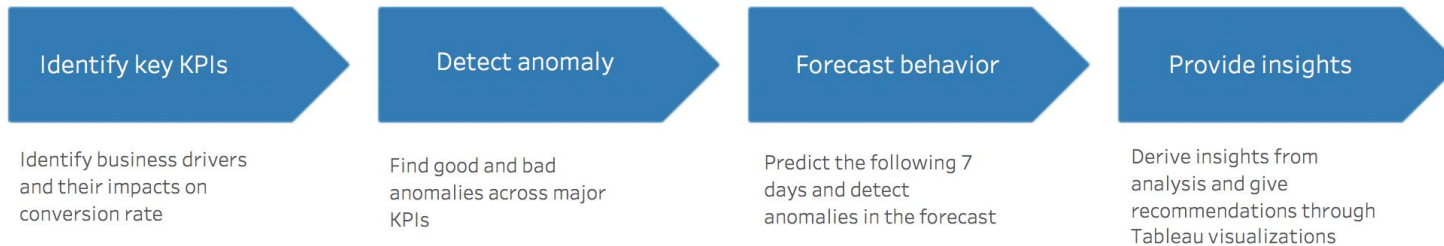


## Summary

### Business Problem

- A telecommunication major wanted to understand whether there is a problem on its website
- Current process was manual and the expected state is to derive anomalous behavior across major KPIs in an automated manner

### Methodology



### Some Insights

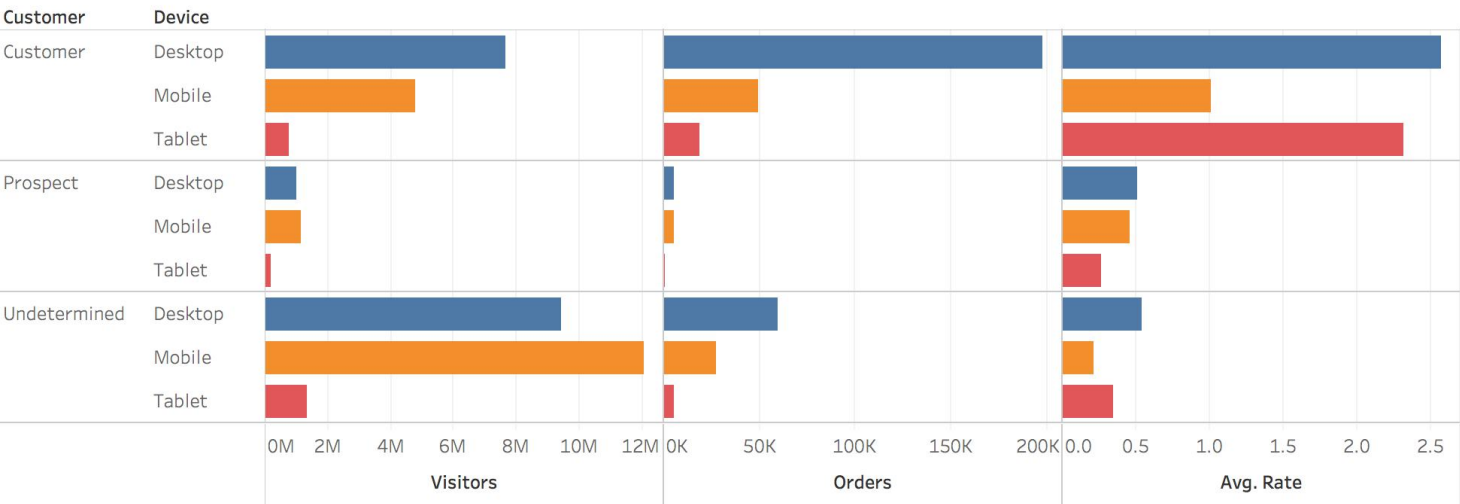
- There's a potential customer tagging problem - whenever undetermined increases, customer and prospect decrease, and vice versa.
- Many visitors browse from phones but do not place orders through mobile that often compared to desktop.
- More customer browse on desktop while more undetermined browse on mobile.
- Traffic of undetermined > customer > prospect. Avg conversion rate of customer > prospect > undetermined.
- Traffic of desktop > mobile > tablet. Avg conversion rate of desktop > tablet > mobile.
- Changes of traffic and orders stay consistent across device types but vary from customer types.
- On 2/3, three metrics all go down:  
Visitors and orders from Prospect and Customer decrease  
Visitors and orders from Undetermined experience a little bump up but not enough to affect the downward trend
- On 2/22, visitors, digital orders and conversion rate all spike up:  
Large volumes from Undetermined visit the website and place orders  
Fewer visitors and orders from Prospect and Customer  
Conversion rate of Prospect on this day increases while that of Customer decreases

## Executive Overview

Count of Date	Visitors	Orders	Avg. Conversion Rate	Avg. Ind Conversion Rate
59	38,321,205	368,753	0.96%	2.43%

Visitors				Orders				Rate			
Customer	Device			Customer	Device			Customer	Device		
	Desktop	Mobile	Tablet		Desktop	Mobile	Tablet		Desktop	Mobile	Tablet
Customer	7.64M	4.79M	0.79M	Customer	197.98K	49.10K	18.77K	Customer	2.57%	1.01%	2.32%
Prospect	1.00M	1.16M	0.18M	Prospect	5.14K	5.29K	0.47K	Prospect	0.51%	0.46%	0.27%
Undetermined	9.41M	12.07M	1.34M	Undetermined	59.36K	27.40K	5.20K	Undetermined	0.55%	0.21%	0.35%

## Visitors, Orders and Rate by Customer and Device Type



\* Visitors and orders from Gaming Console and E-Reader are low so they are excluded from analysis

\* Reference: <https://www.growcode.com/blog/ecommerce-conversion-rate/>

Tagging concern: whenever Undetermined increase, Customer and Prospect decrease, and vice versa.

Visitors

Orders

Rate

Day of Date [2019]

Tagging concern: whenever  
Undetermined increase,  
Customer and Prospect  
decrease , and vice versa.

- ☒ Customer, Desktop
- ☐ Prospect, Desktop
- ☐ Undetermined, Desktop

**Device**

- ☐ (All)
- ☒ Desktop
- ☐ Mobile
- ☐ Tablet

**Customer**

- ☒ (All)
- ☐ Customer
- ☐ Prospect
- ☐ Undetermined

## Model Selection

### Pros

### Cons

#### ARIMA

- Well-studied
  - Parameters( $p, d, q$ )  
-> more accurate
- Model assumption – stationary
  - Parameter tuning

#### Twitter+IQR

- Catch seasonality
  - No loops – easily scaled
- No long term trend
  - IQR is easily skewed by outliers

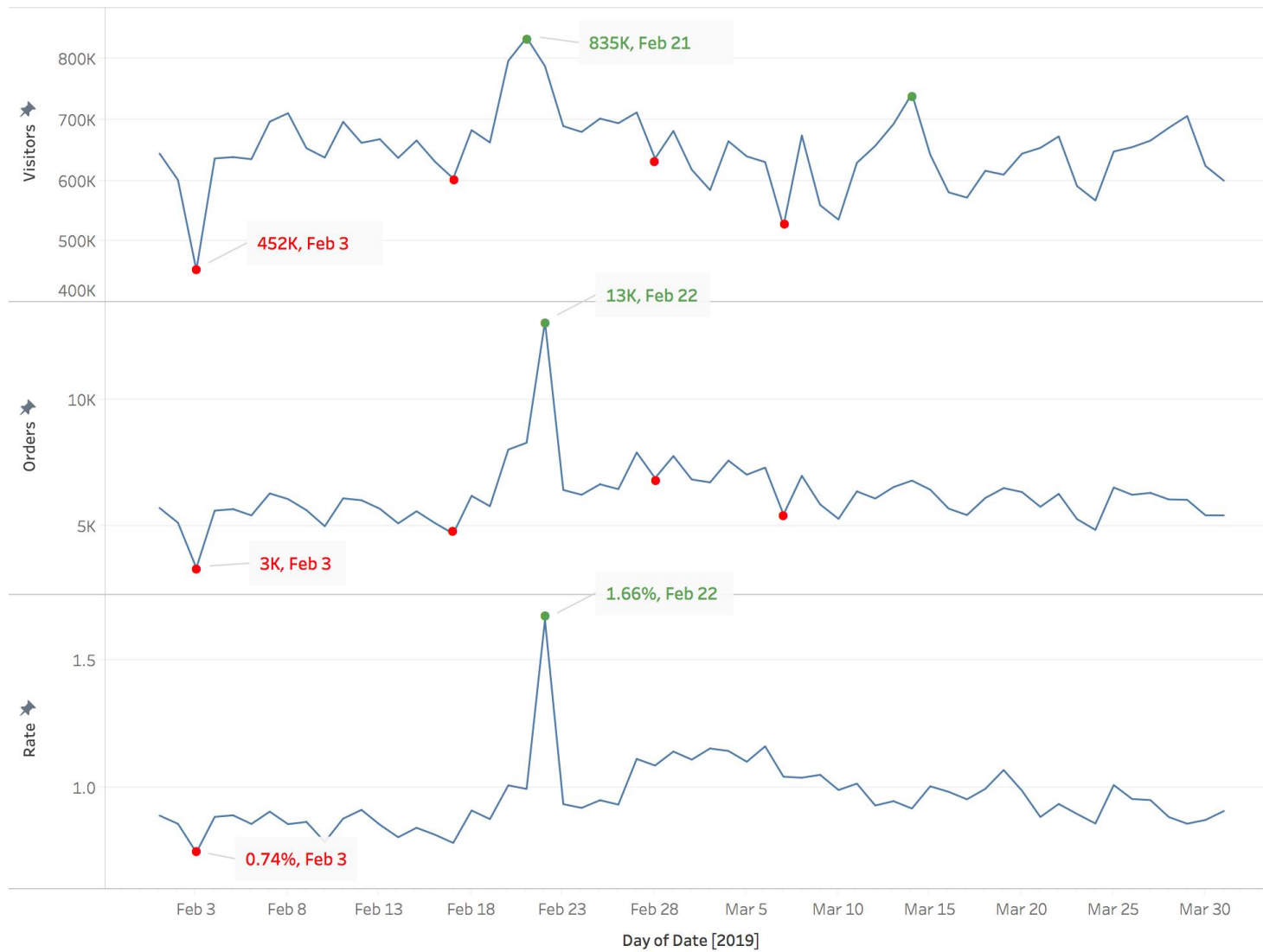
#### ★ STL+GESD

- More sensitive to capture anomalies
  - Less resistant to outliers
- Iterative – more expensive

### Detect Good & Bad Anomalies



## Using selected model - STL+GESD

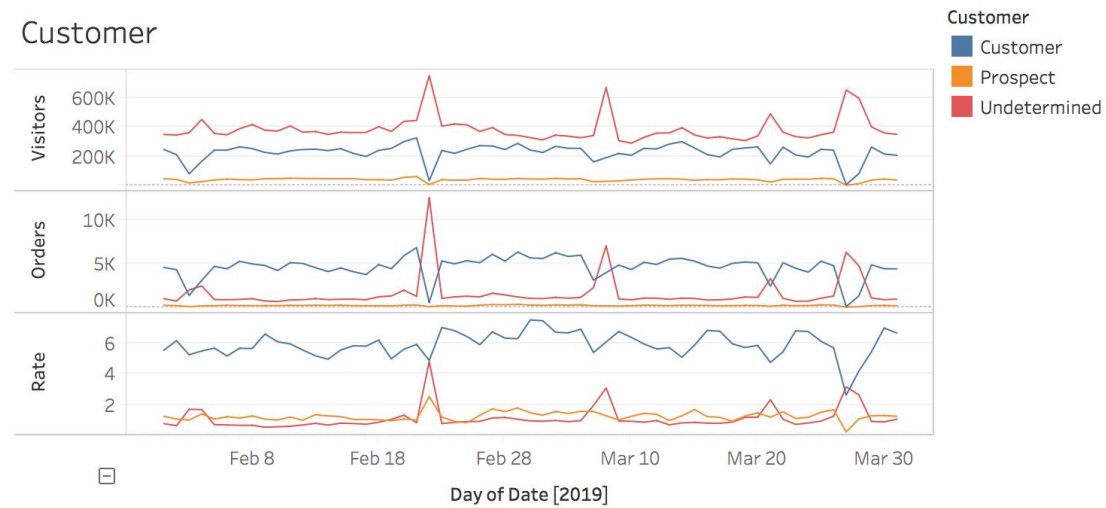


# Breakdown

## Key Points

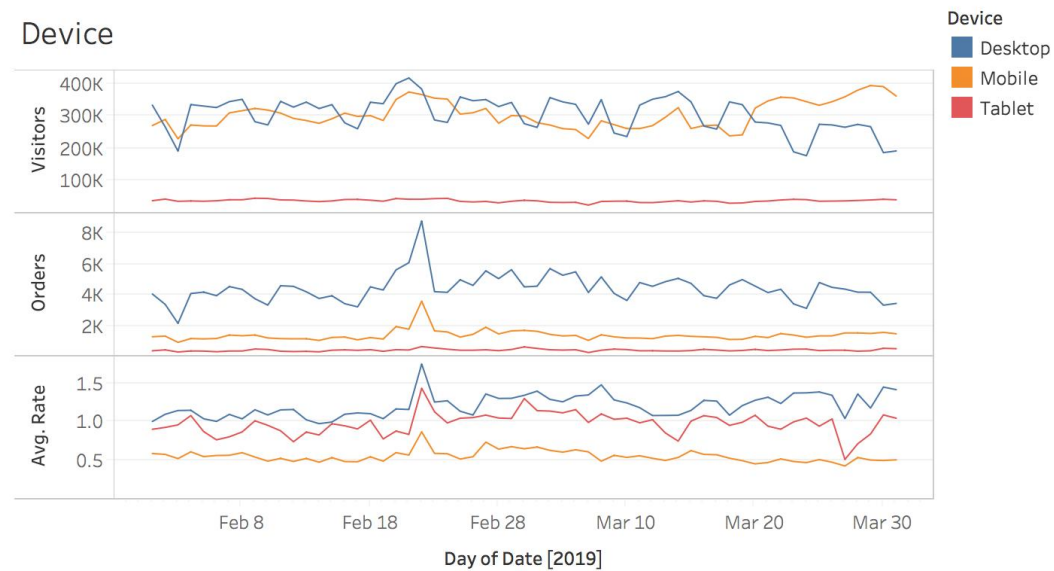
- On Feb 3, fewer **Customer** and **Prospect** visit the website and place the orders. Those from **Undetermined** experienced a little bump up but not enough to affect the downward trend.
- On Feb 22, large volumes of traffic and orders come from **Undetermined**, and conversion rate also increases on this day.
- On Feb 17, Feb 28 and Mar 7, anomalies are found in both visitors and orders but the rates get smoothed out.

## Customer



## Device

- In general, the trends from three devices stay consistent.
- On Feb 3, the decrease in visitors and orders is mainly caused by **Desktop**. The conversion rates do not experience noticeable changes.
- On Feb 22, visitors, orders and rate increase from all of the three devices.





## Forecasting

### Pros

#### ARIMA

- Well-studied
- Parameters(p, d, q) -> more accurate

### Cons

- Model assumption - stationary
- Parameter tuning

#### ETS

- No requirement for stationarity

- Parameter selection

#### Holt-Winter

- Triple exponential smoothing
- Catch seasonal components

- Model complexity - overfitting

#### LSTM

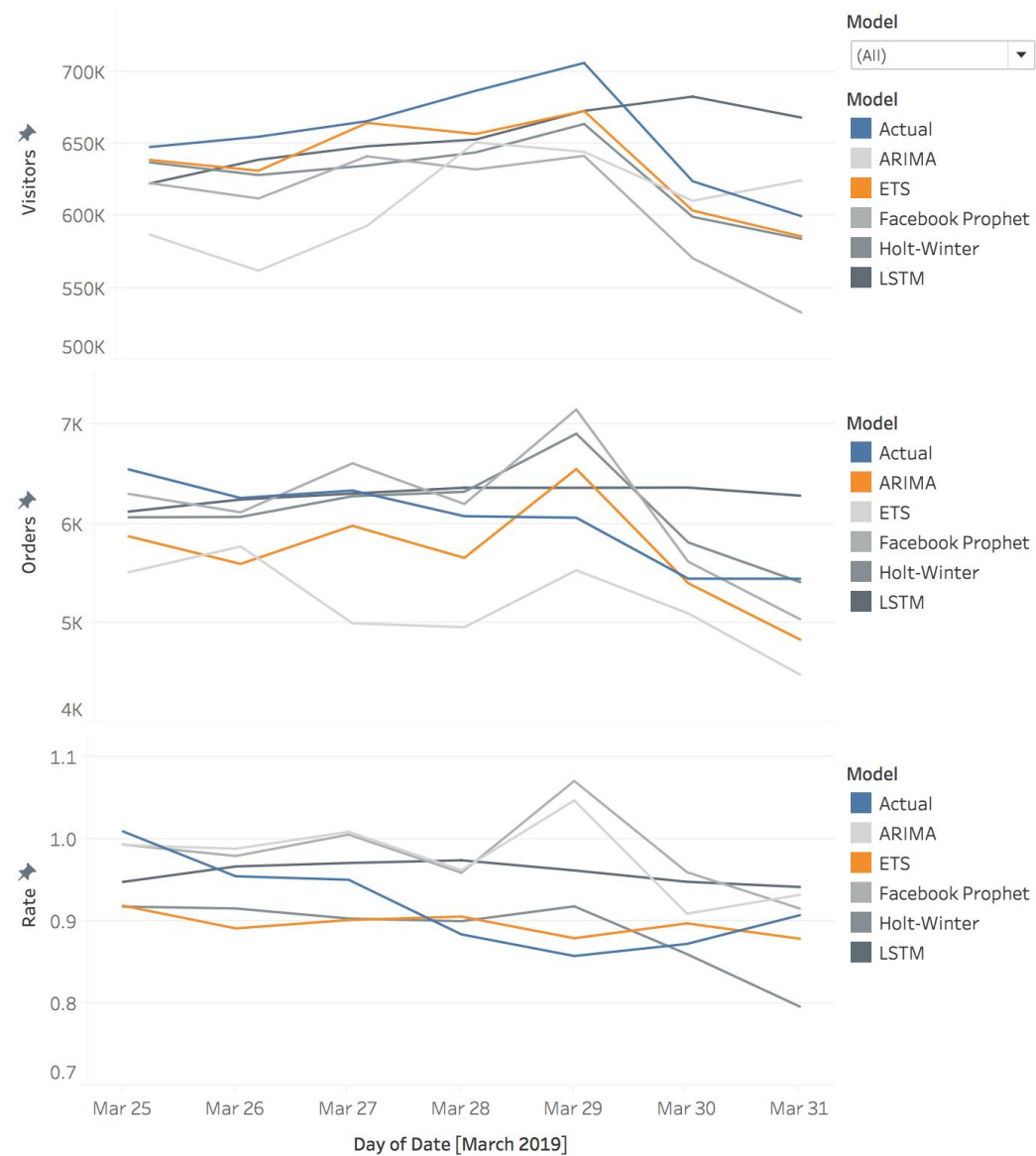
- Time dependency
- Perform well with large data

- Hyper parameter tuning
- Require large data

#### Facebook Prophet

- Strong seasonal effects
- Robust to missing data and outliers

- Overfitting
- Require large data



## Metric Evaluation

### Visitors

Model	Metric		
	MAPE	MASE	RMSE
ARIMA	7.35%	0.51	132365
ETS	2.94%	0.21	57044.3
FB	7.91%	0.54	132491
Holt-Winter	4.36%	0.45	78978.5
LSTM	6.22%	0.45	109967

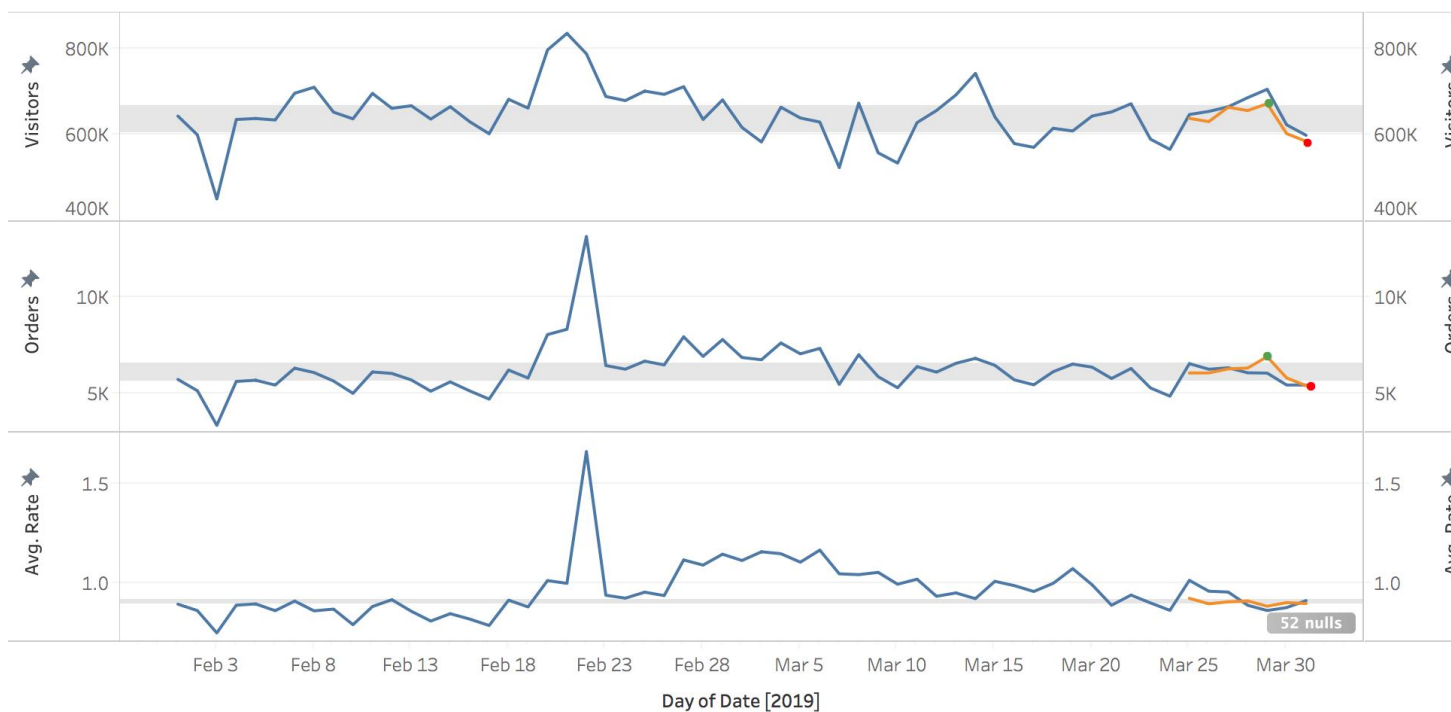
### Orders

Model	Metric		
	MAPE	MASE	RMSE
ARIMA	16.30%	1.59	2376.38
ETS	8.22%	0.89	1343.48
FB	5.22%	0.67	1242.65
Holt-Winter	4.99%	0.6	1083.92
LSTM	6.36%	0.77	1373.22

### Rate

Model	Metric		
	MAPE	MASE	RMSE
ARIMA	4.76%	0.48	1.3E-03
ETS	6.26%	0.69	2.10E-03
FB	7.66%	0.76	2.5E-03
Holt-Winter	6.19%	0.69	1.69E-03
LSTM	5.94%	0.63	1.7E-03

### Anomalies in Forecast



\* Anomalies: points lie out of  $\pm 1$  standard deviation, which includes 65% data.