Dynamic pricing

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Code and presentation can be found here:
https://github.com/tdarcher/pace_interview.git

Existing dynamic price models

- Historical:
  Only consider final number of rooms
  Same day last year, moving average

- Advanced booking
  Only consider the number of reservations
  Additive, booking curve, time series

- Combined:
  Weighted average of historical and advanced

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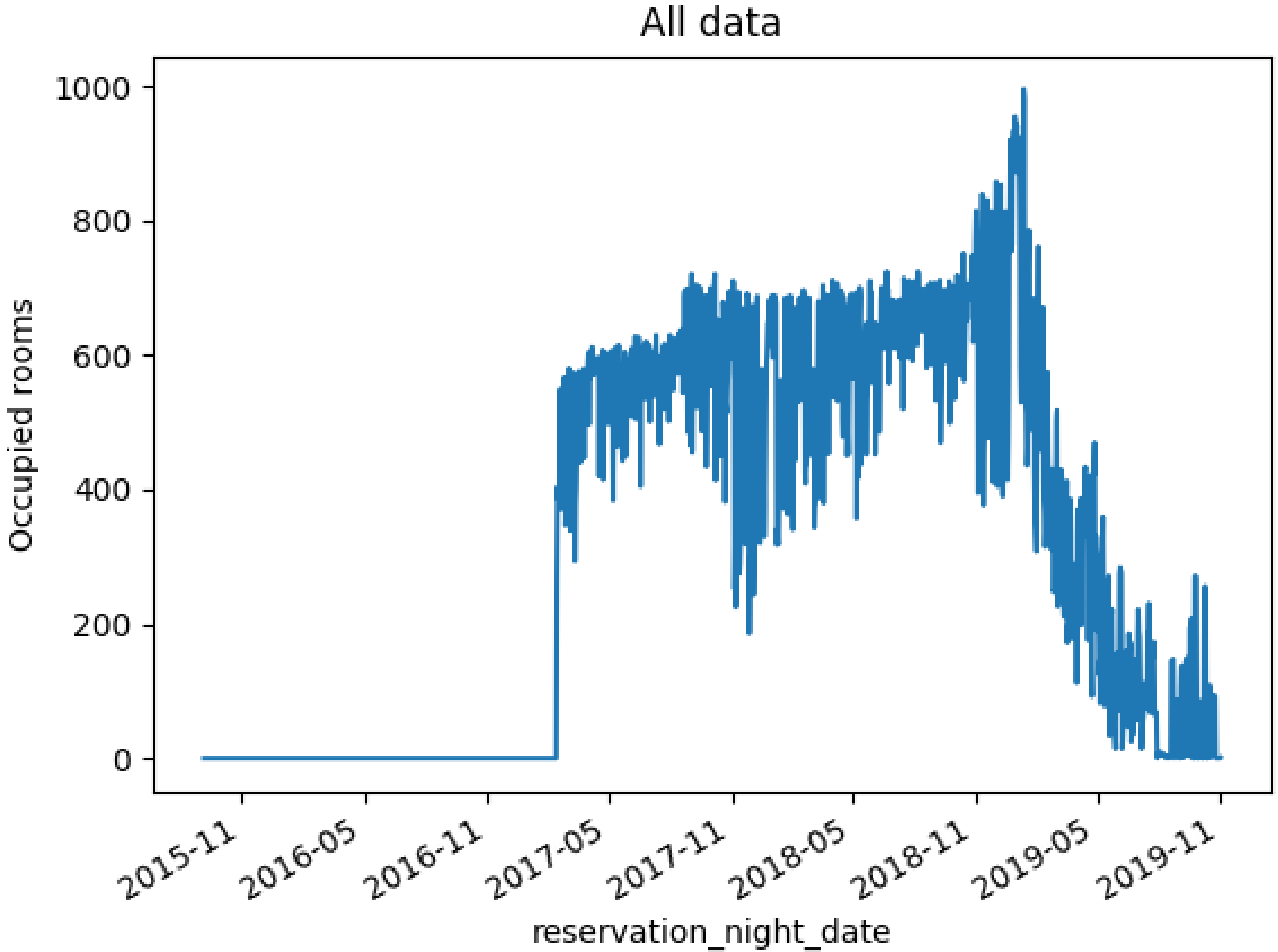
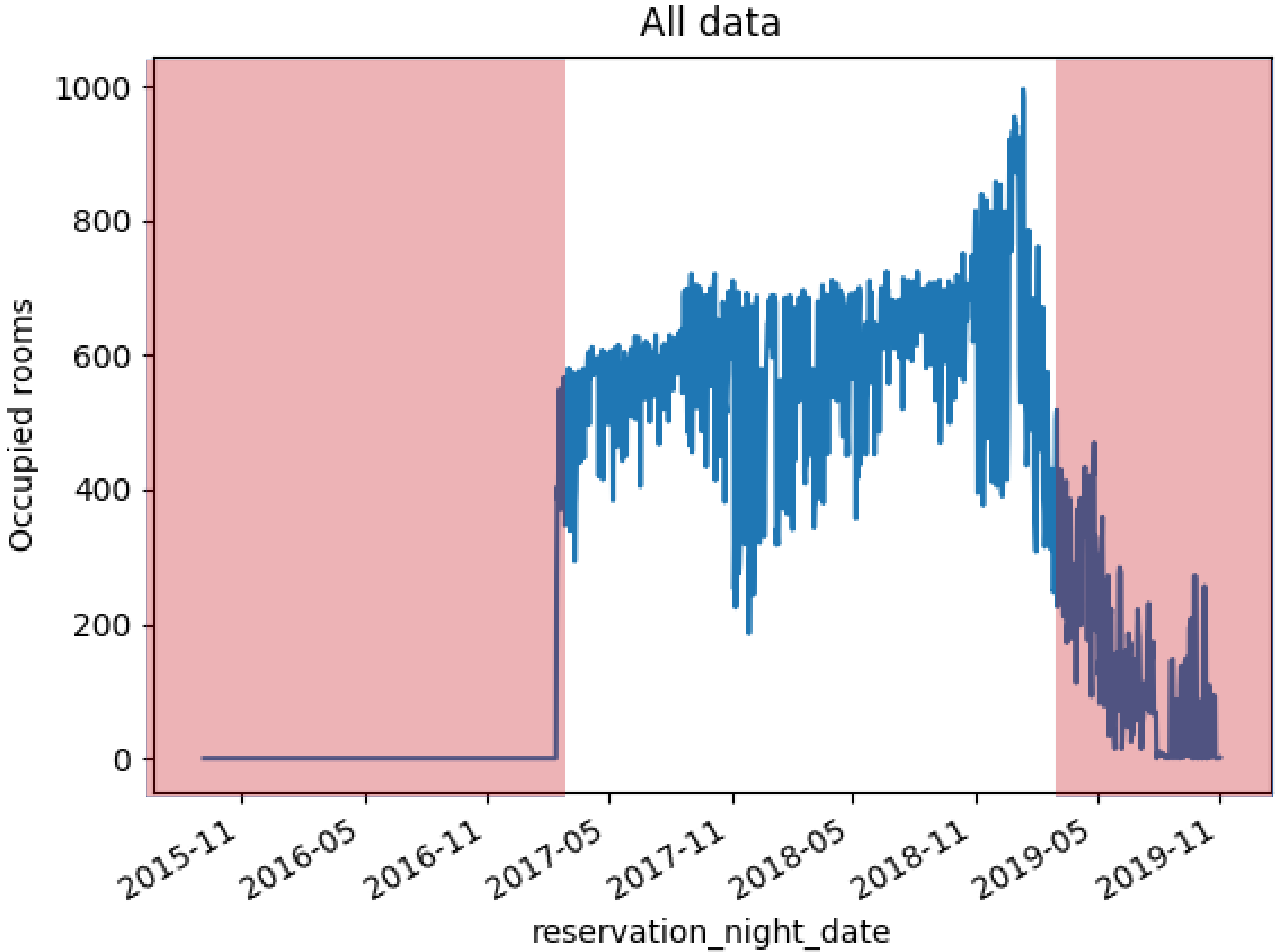
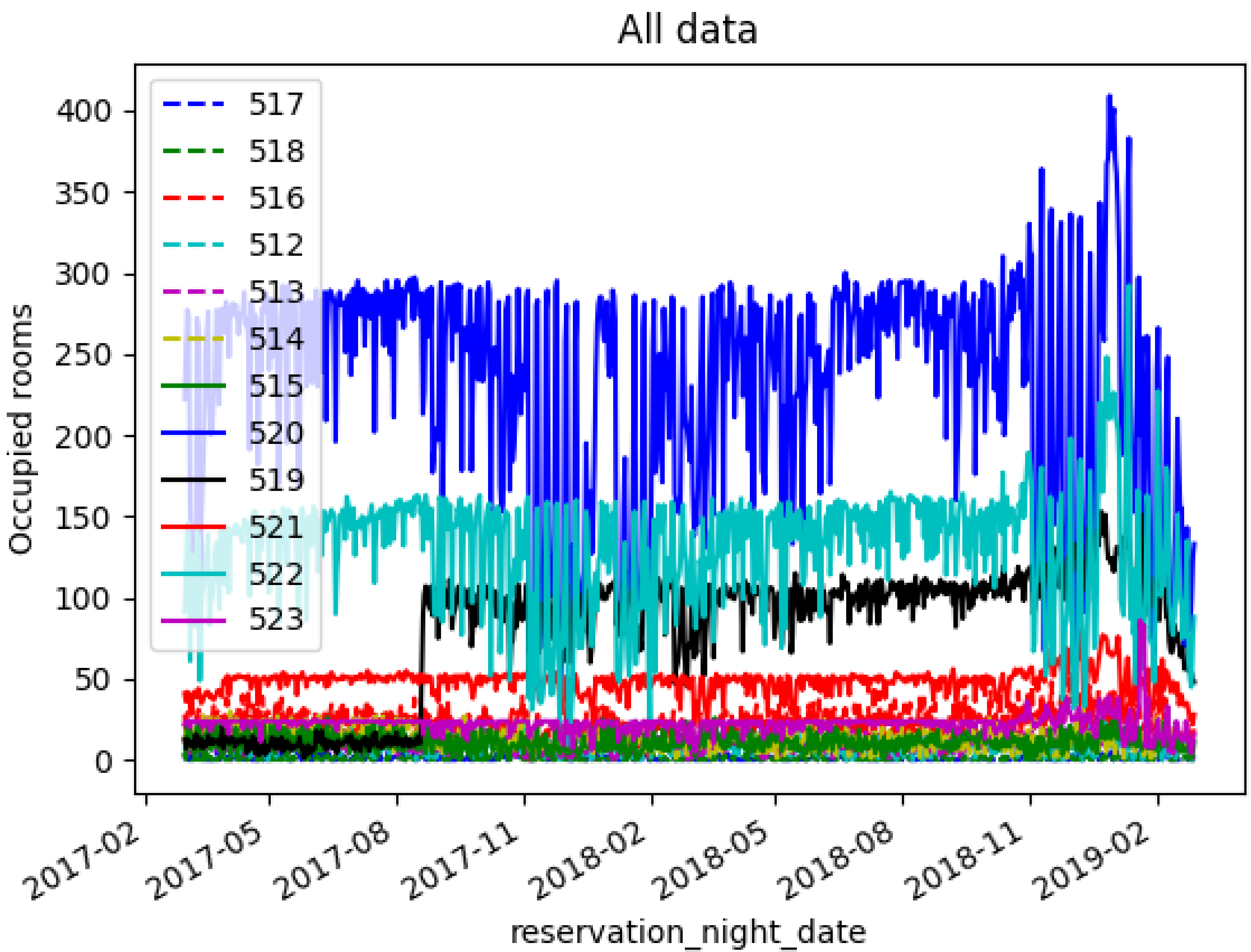


All data
Occupied rooms
1000
800
600
400
200
0
2015-11
2016-05
2016-11
2017-05
2017-11
2018-05
2018-11
2019-05
2019-11
reservation_night_date

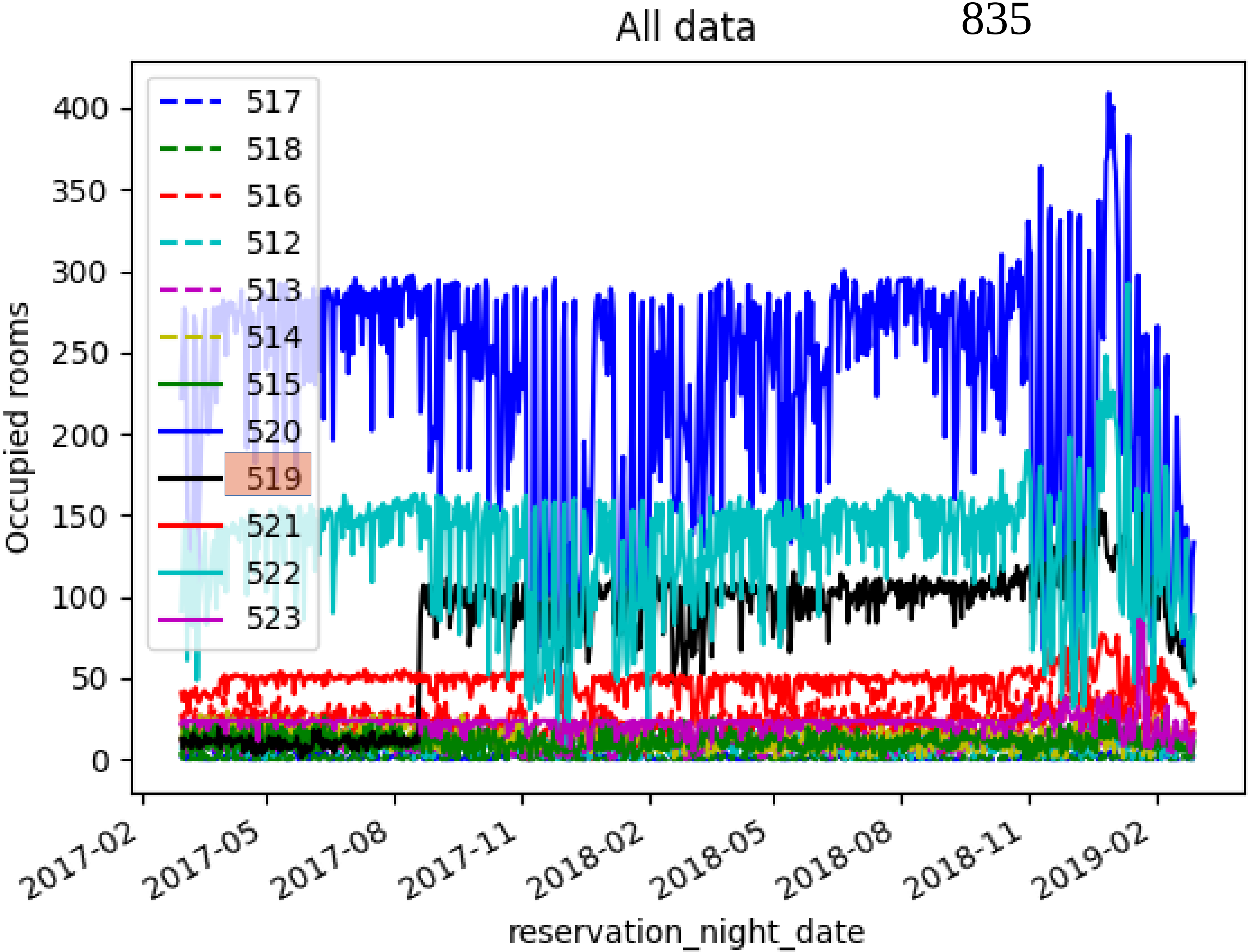
1 Occupancy prediction

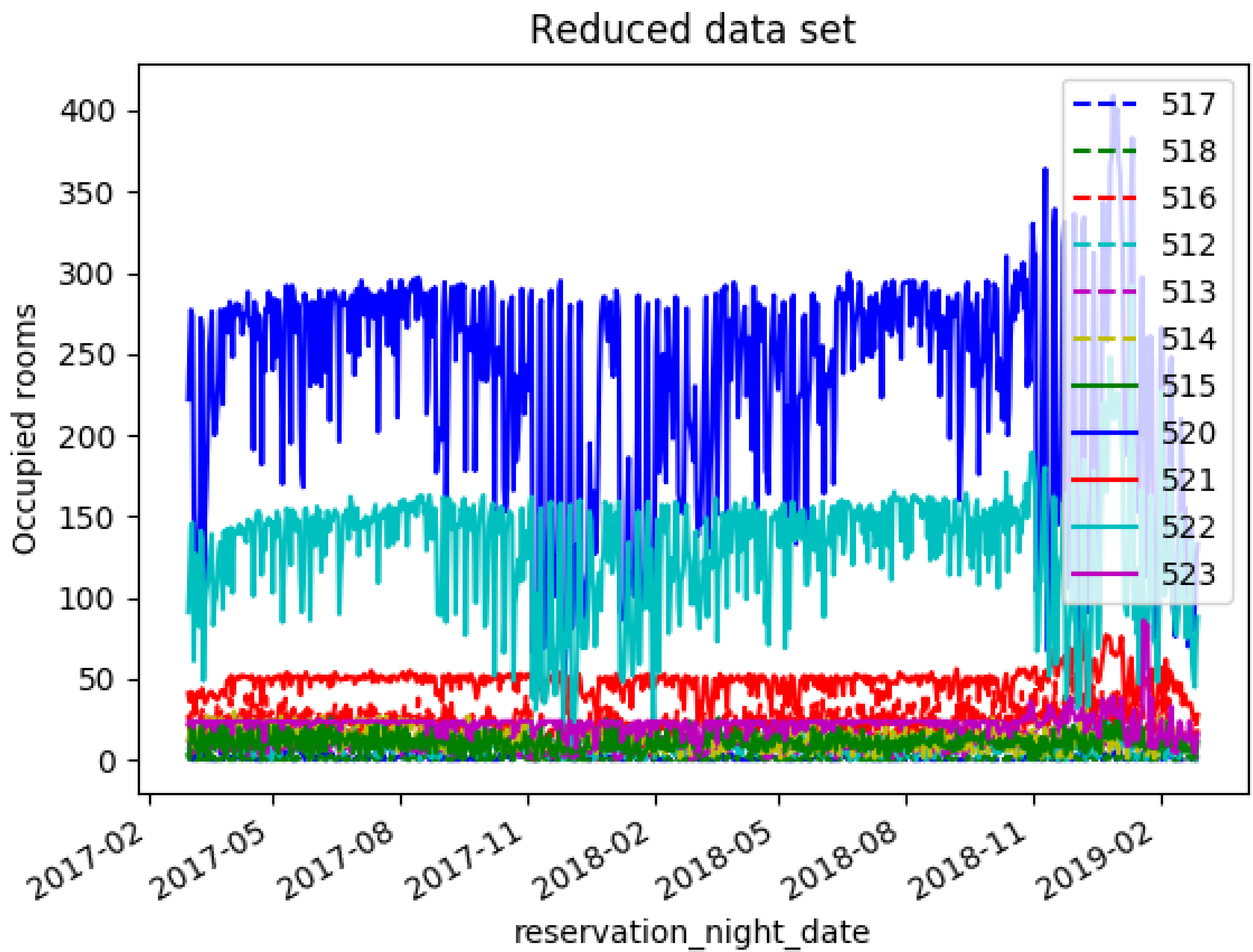

All data
Occupied rooms
1000
800
600
400
200
0
2015-11
2016-05
2016-11
2017-05
2017-11
2018-05
2018-11
2019-05
2019-11
reservation_night_date

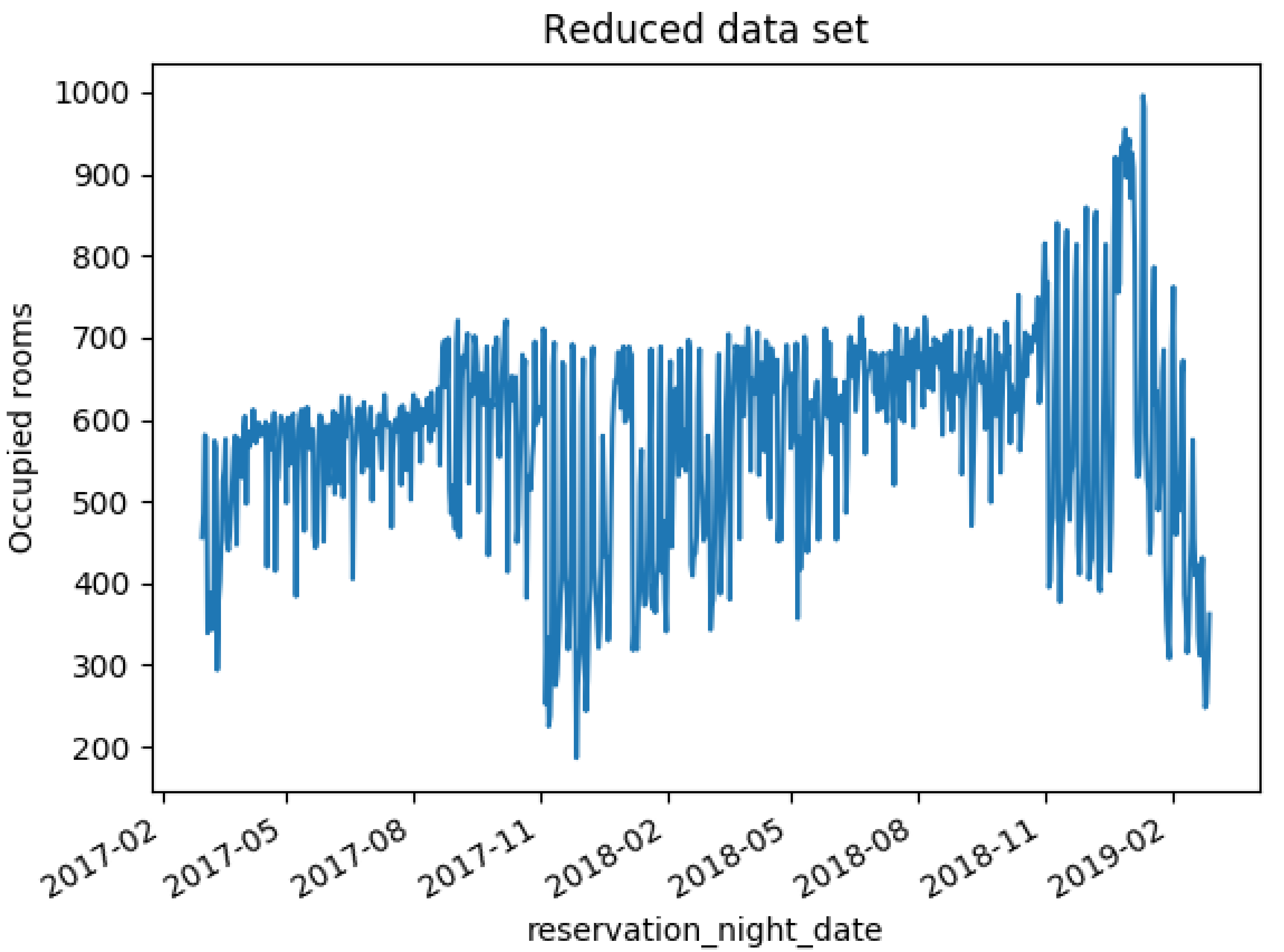


All data
Occupied rooms
reservation_night_date
517
518
516
512
513
514
515
520
519
521
522
523
0
50
100
150
200
250
300
350
400
2017-02
2017-05
2017-08
2017-11
2018-02
2018-05
2018-08
2018-11
2019-02

$\frac{733}{835}$ Rooms remaining

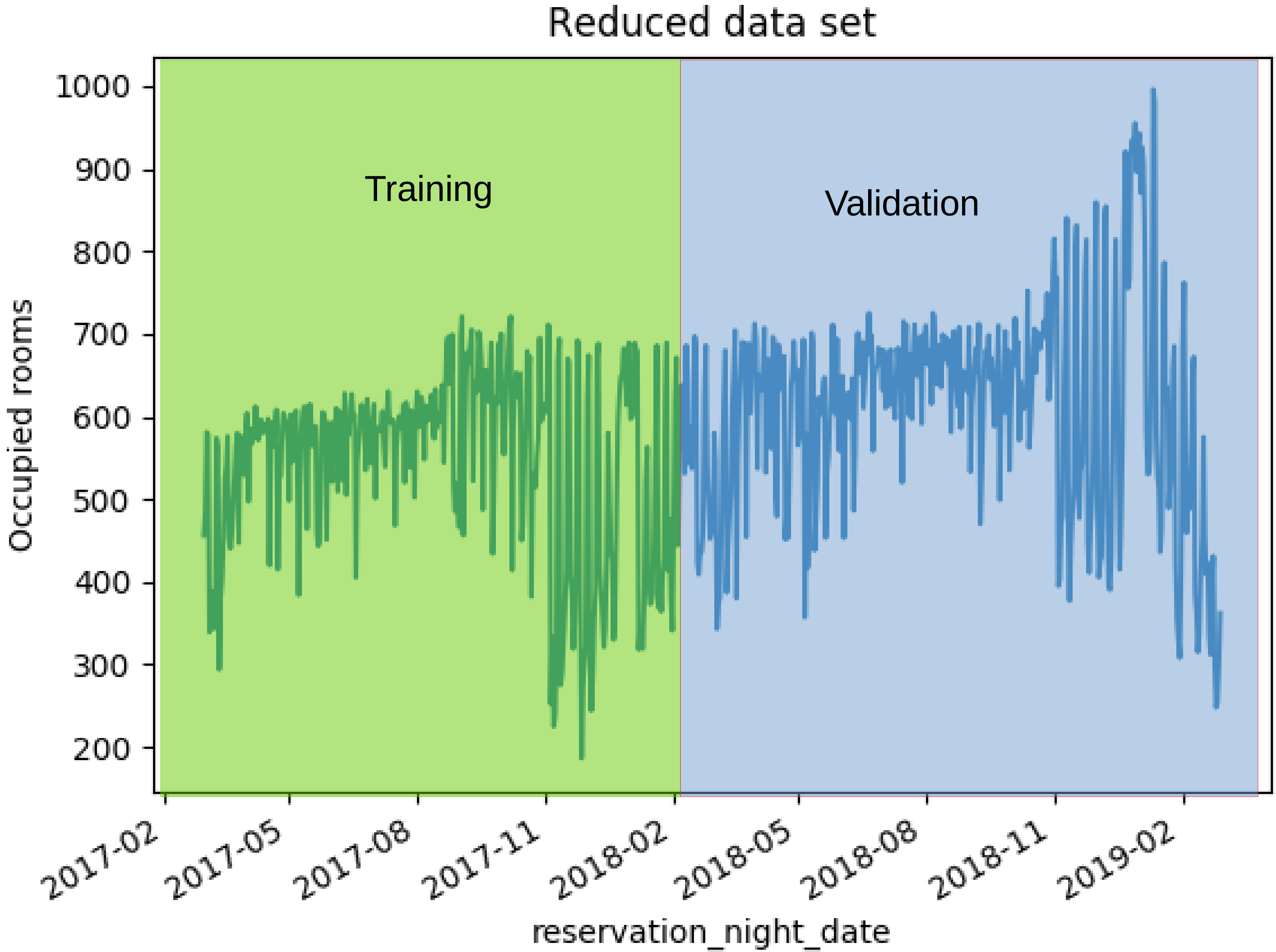


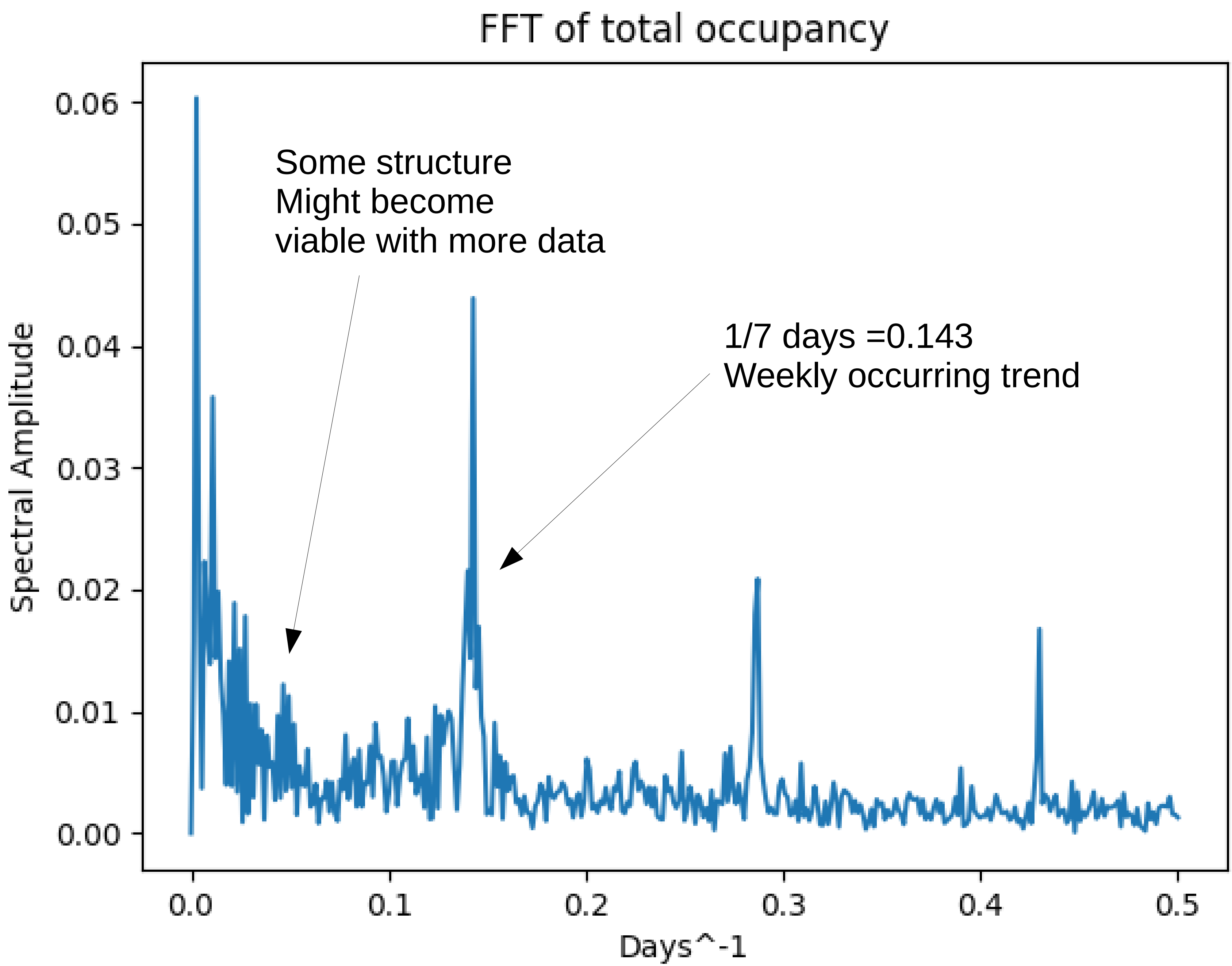

Reduced data set
Occupied rooms
reservation_night_date
400
350
300
250
200
150
100
50
0
2017-02
2017-05
2017-08
2017-11
2018-02
2018-05
2018-08
2018-11
2019-02
517
518
516
512
513
514
515
520
521
522
523

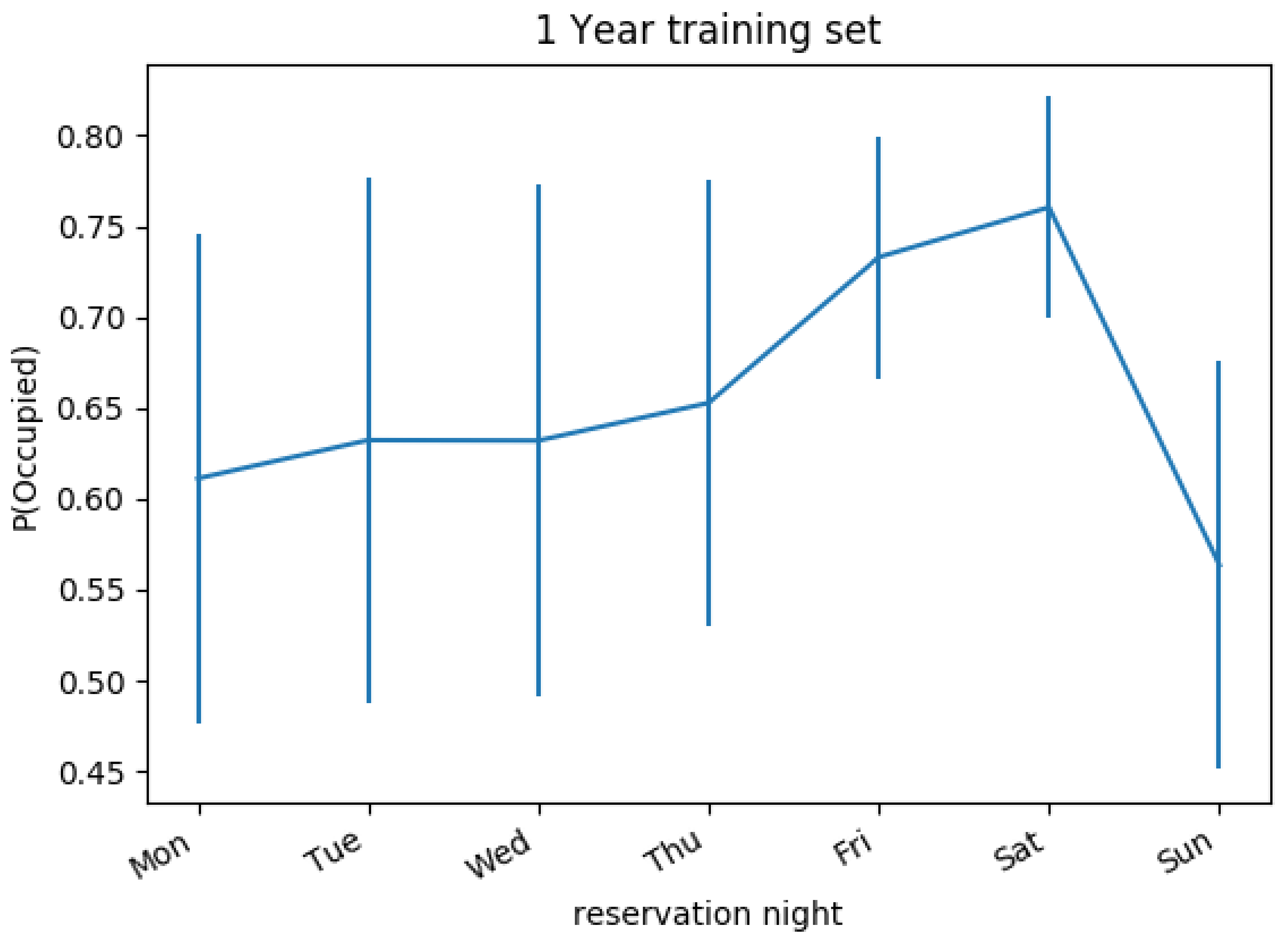

Reduced data set
Occupied rooms
1000
900
800
700
600
500
400
300
200
2017-02
2017-05
2017-08
2017-11
2018-02
2018-05
2018-08
2018-11
2019-02
reservation_night_date

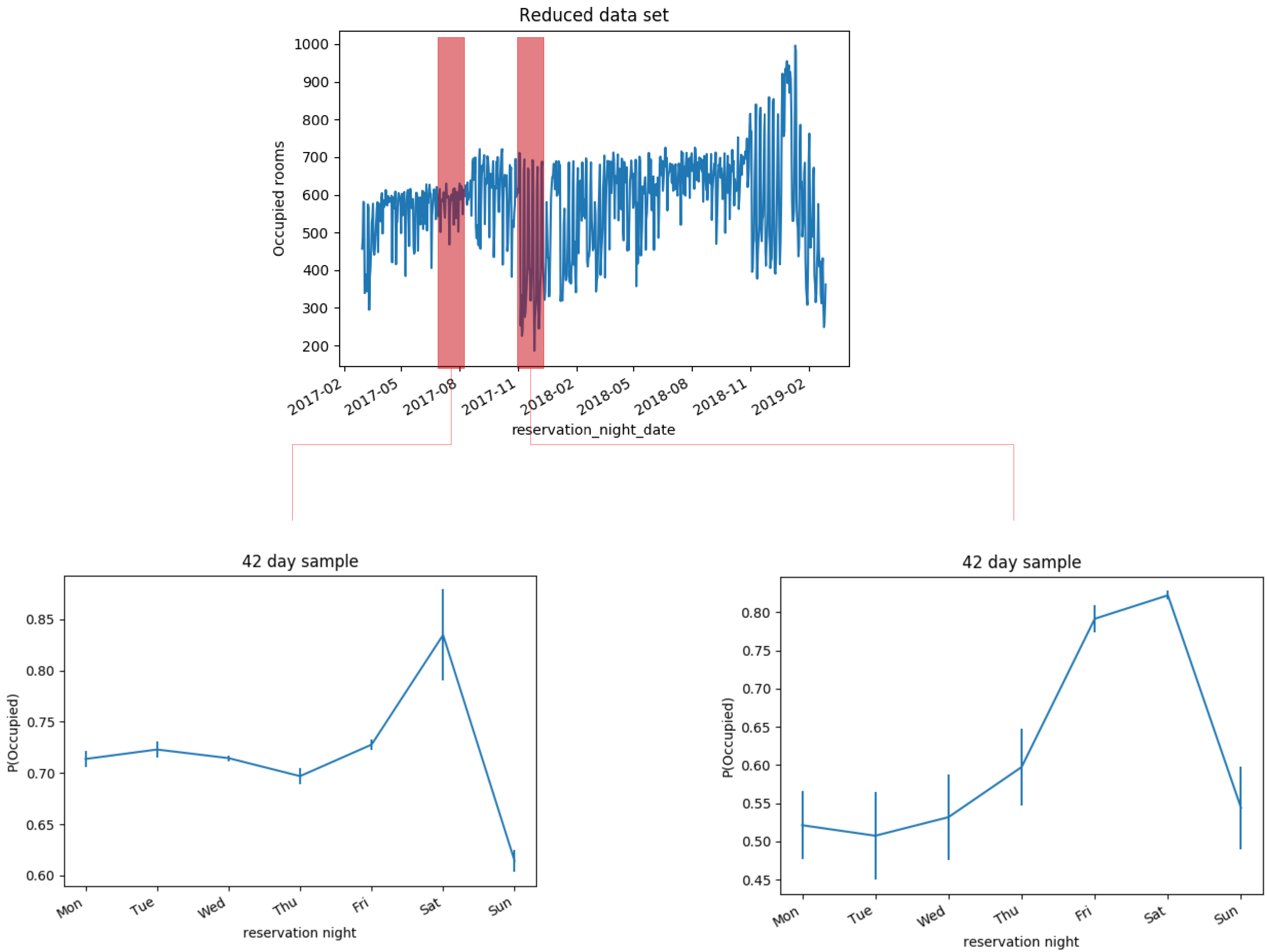
Analysis of Historical trends

Predicting demand

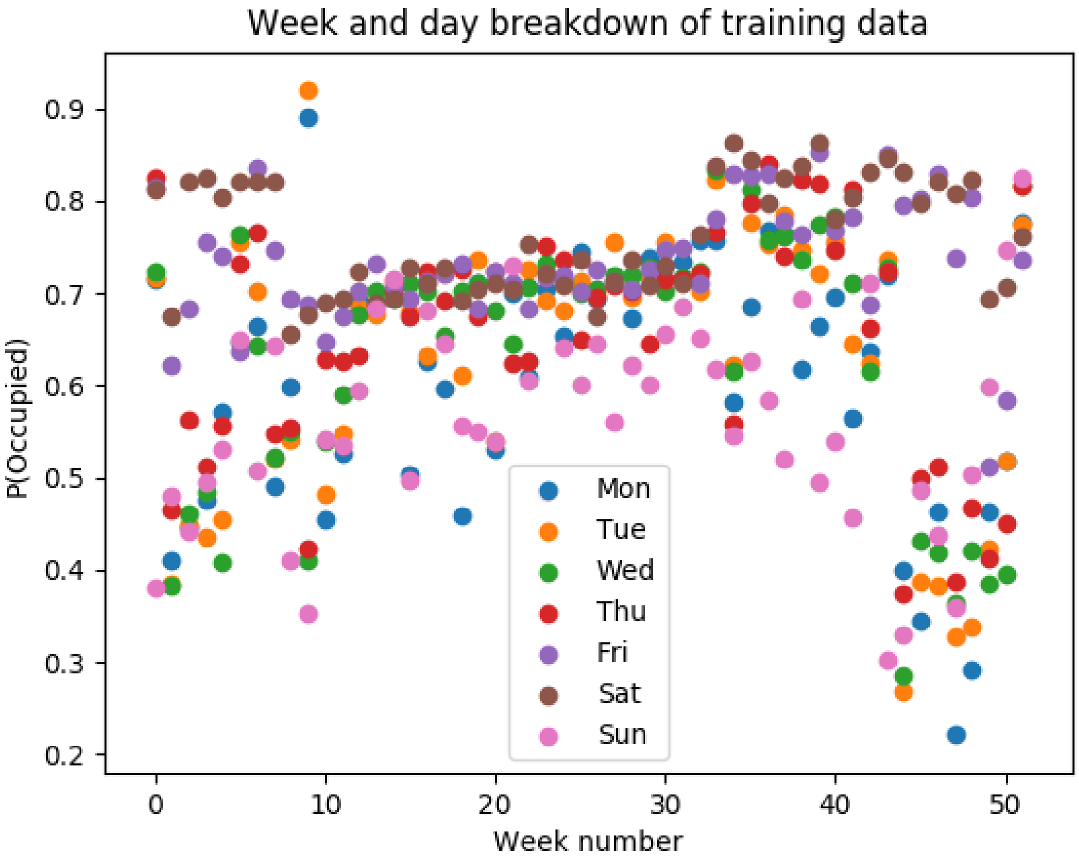

Reduced data set
Training
Validation
Occupied rooms
1000
900
800
700
600
500
400
300
200
2017-02
2017-05
2017-08
2017-11
2018-02
2018-05
2018-08
2018-11
2019-02
reservation_night_date


FFT of total occupancy
Some structure
Might become
viable with more data
1/7 days =0.143
Weekly occurring trend
Spectral Amplitude
Days^-1
0.00
0.01
0.02
0.03
0.04
0.05
0.06
0.0
0.1
0.2
0.3
0.4
0.5


1 Year training set
P(Occupied)
0.80
0.75
0.70
0.65
0.60
0.55
0.50
0.45
Mon
Tue
Wed
Thu
Fri
Sat
Sun
reservation night


Reduced data set
Occupied rooms
1000
900
800
700
600
500
400
300
200
2017-02
2017-05
2017-08
2017-11
2018-02
2018-05
2018-08
2018-11
2019-02
reservation_night_date
42 day sample
P(Occupied)
0.85
0.80
0.75
0.70
0.65
0.60
Mon
Tue
Wed
Thu
Fri
Sat
Sun
reservation night
42 day sample
P(Occupied)
0.80
0.75
0.70
0.65
0.60
0.55
0.50
0.45
Mon
Tue
Wed
Thu
Fri
Sat
Sun
reservation night

Initial model



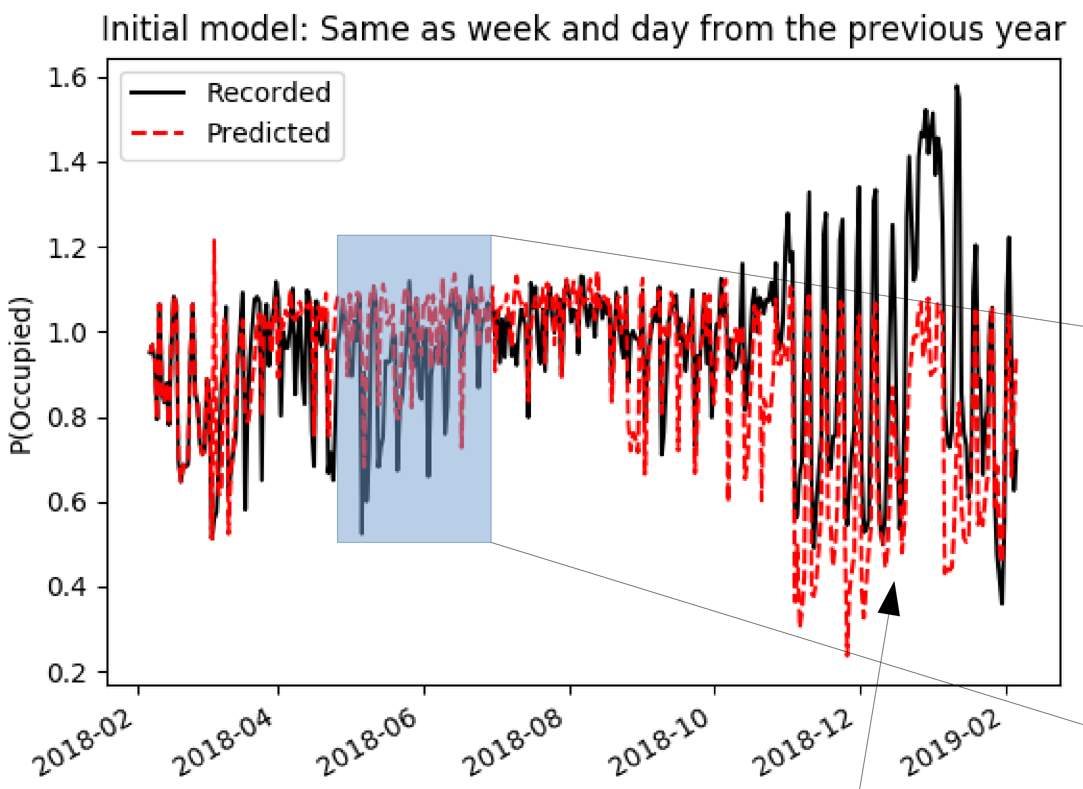
- Data broken down into week number and day
- Demand estimated to be the same as previous year

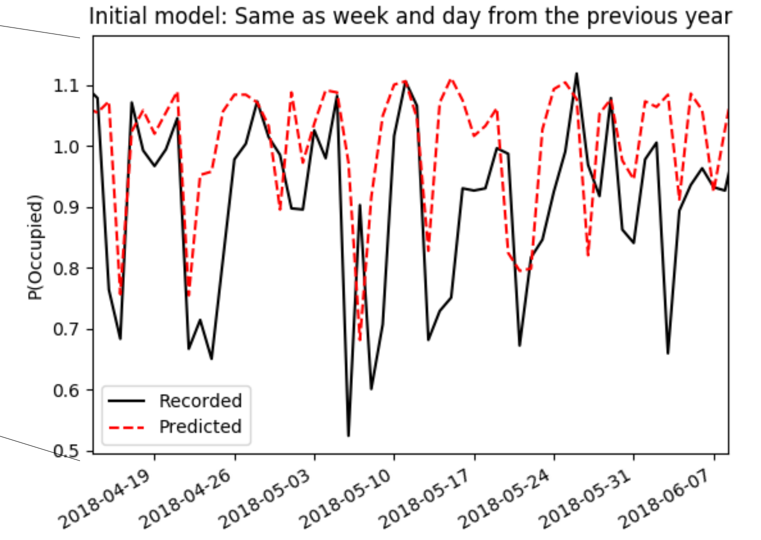
Predict occupancy from historical data

- Historical occupancy taken from day and week of previous year.

Works well for the fitted data:
- Need to refit for each hotel
- No variation with improved performance of the hotel

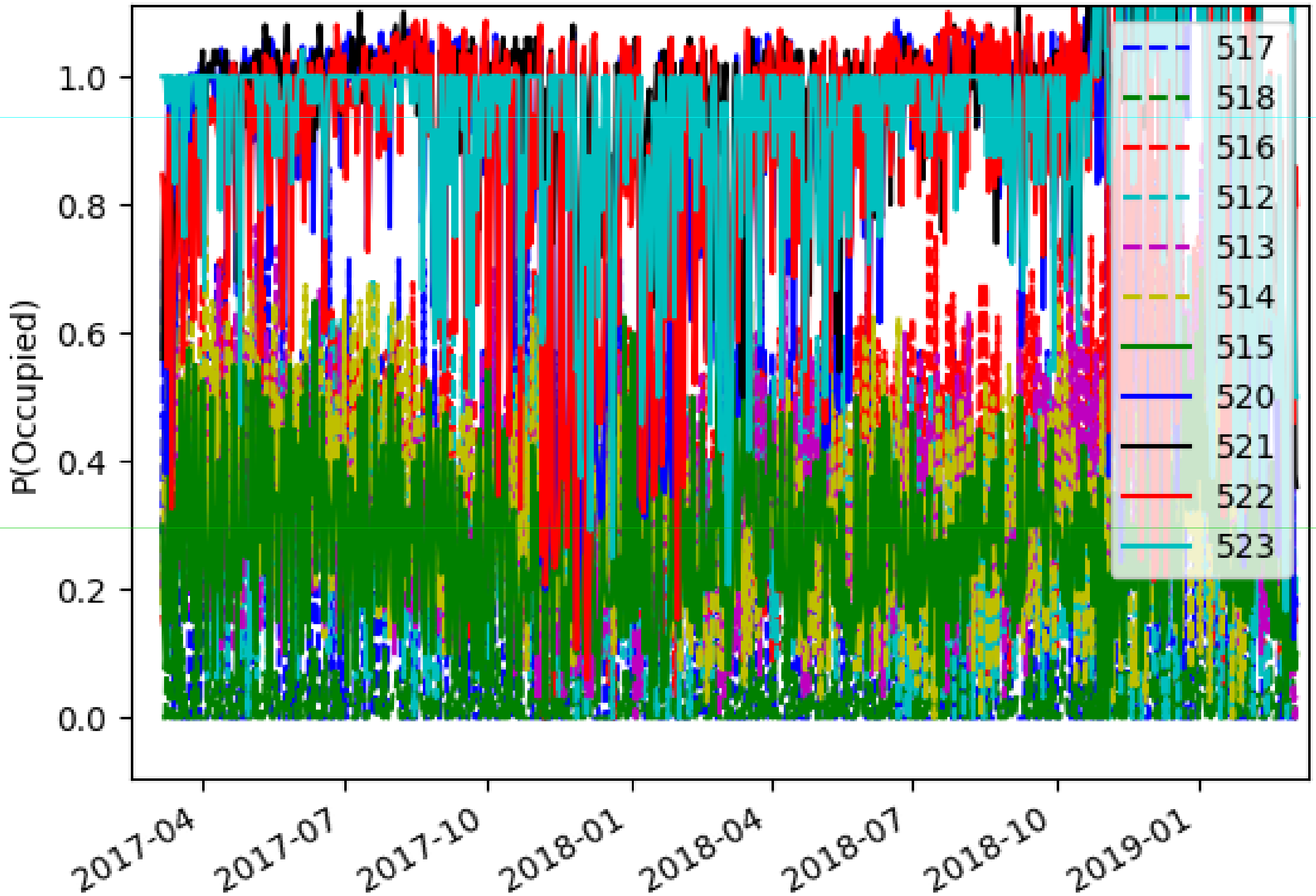
$$Residual = \sum_{Day=1,N} \frac{\left|P_{Day} - P_{Day}^{fitted}\right|}{N} = 0.13$$





Over occupancy/more rooms on line?

Can we introduce transferability?



Average occupancy of 523 close to 100%

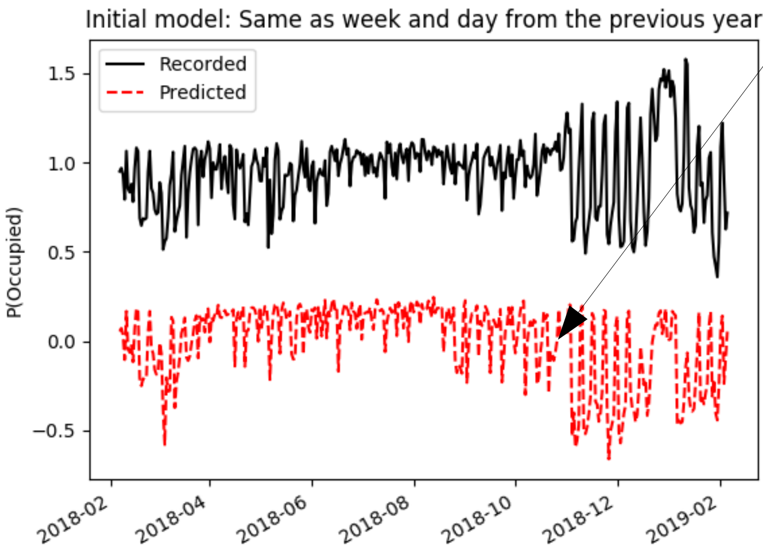
Average occupancy of 515 only 30%

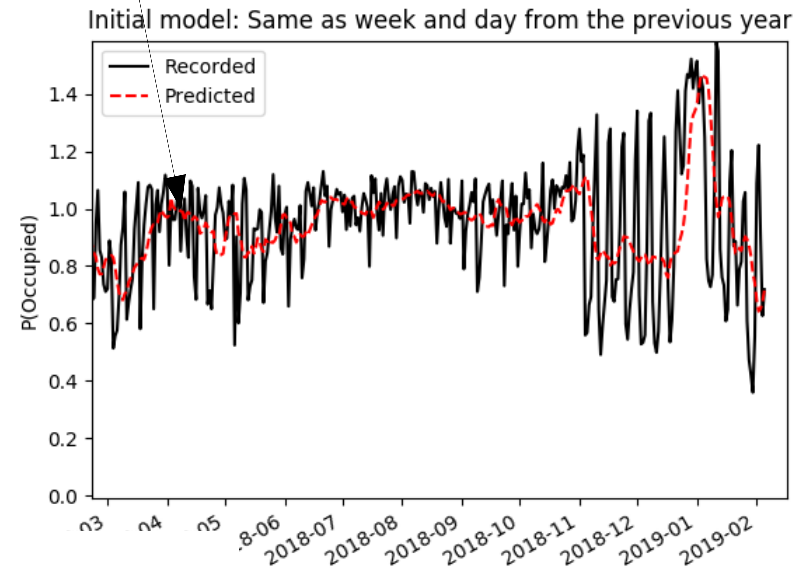
Similar demand curve for each room id, but a systematic shift present

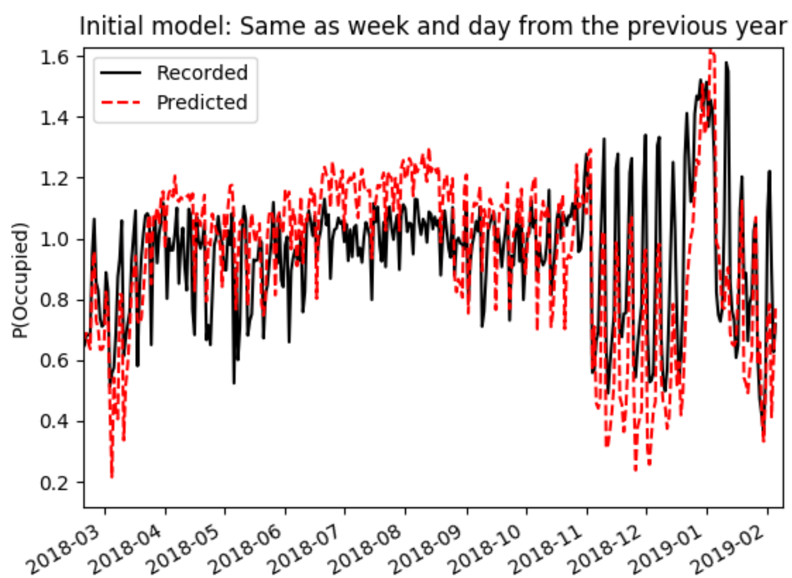
Normalized demand

Hotel performance

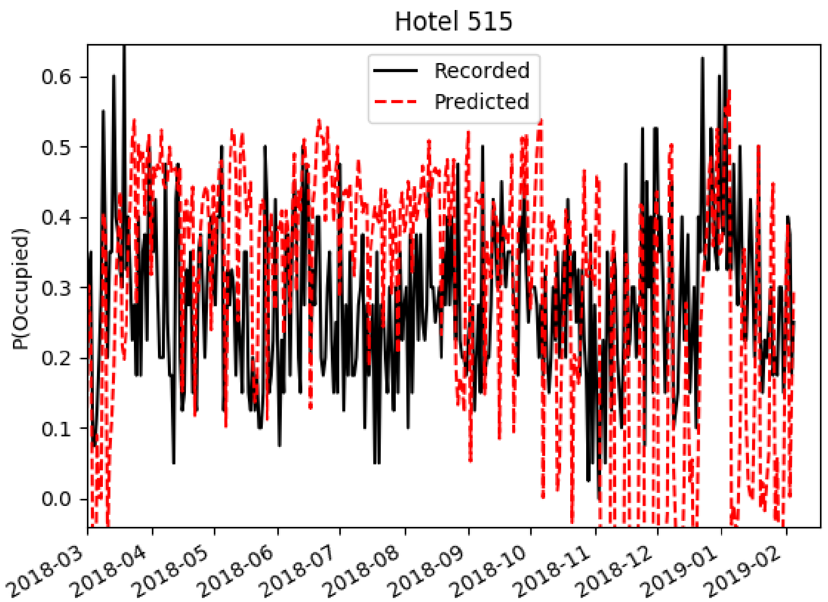
$$P = P_{Occupied\,.\,Historical} - \overline{P_{Occupied\,.\,Historical}} + \sum_{Night-8}^{Night-1} P_{Occupied}$$

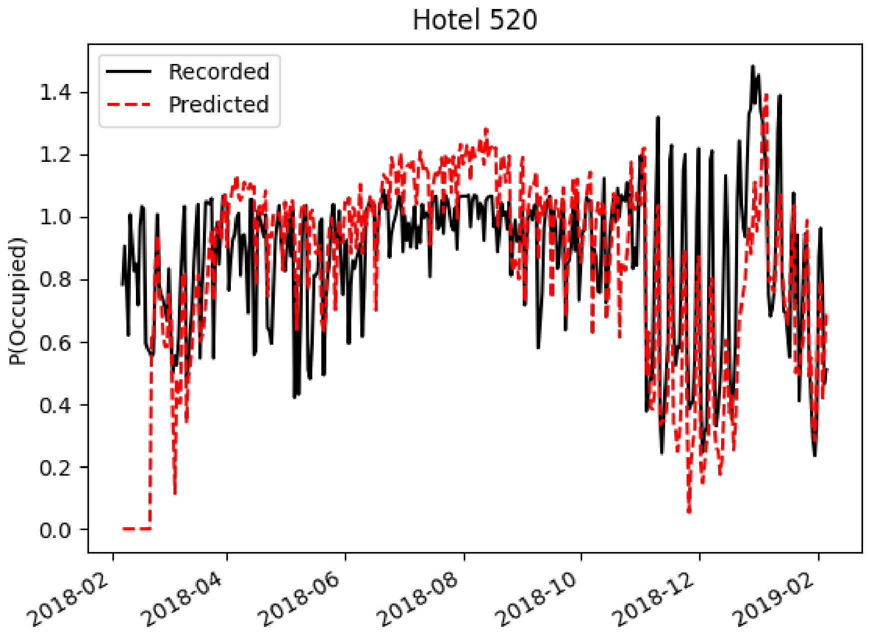






Applying model to different hotels





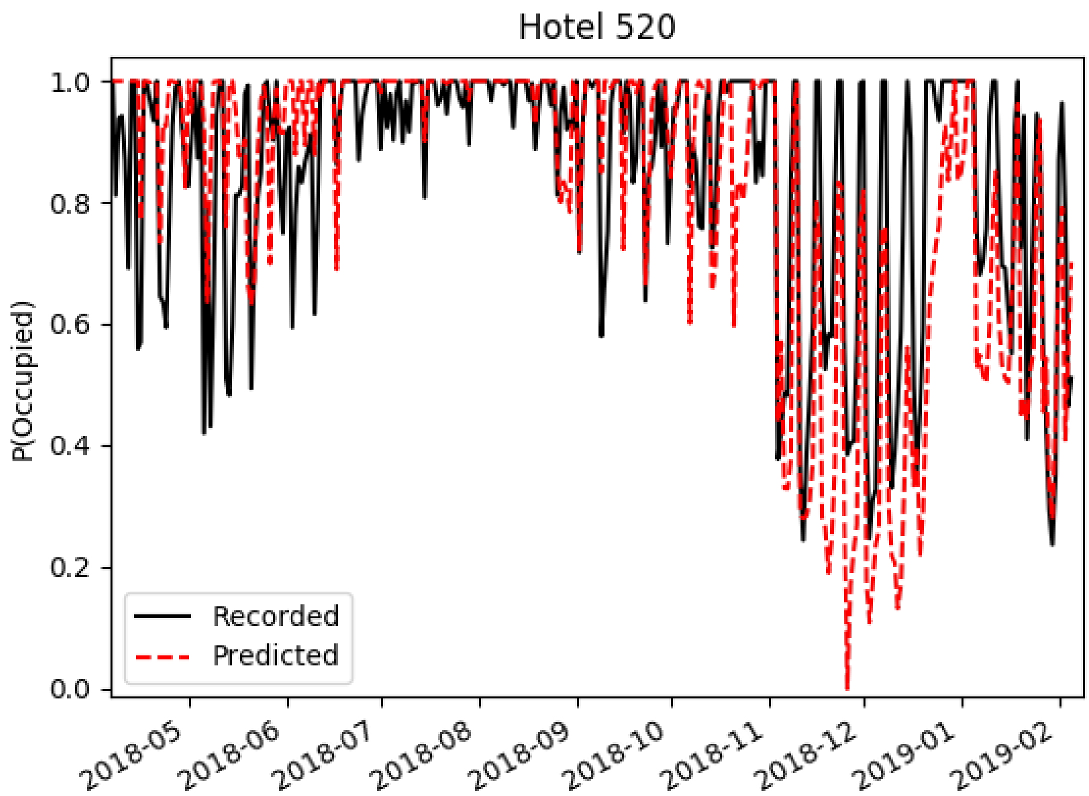
$$Residual = \sum_{Day=1,N} \frac{\left|P_{Day} - P_{Day}^{fitted}\right|}{N} = 0.13$$

Residual=0.17

Residual=0.14

2.Revenue

Revenue

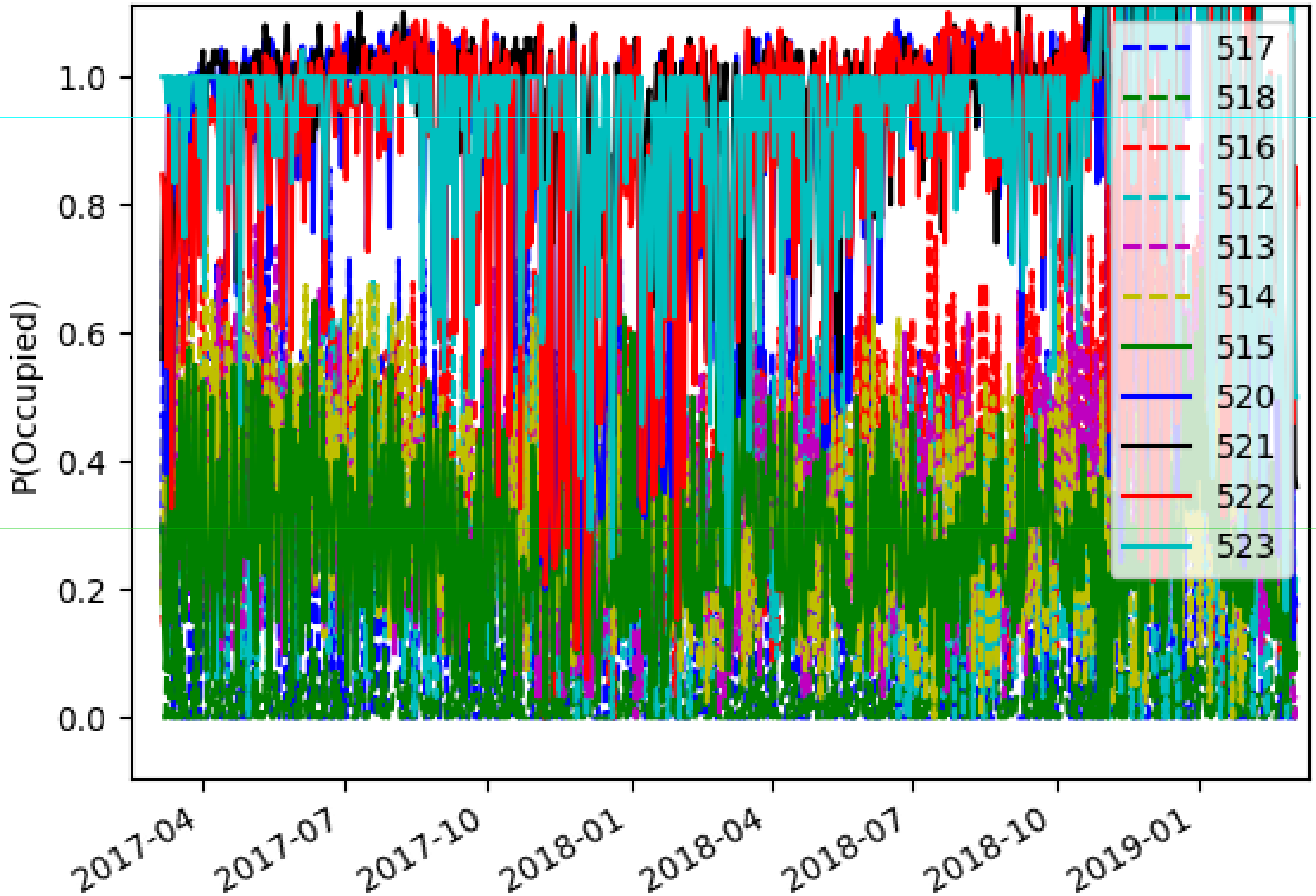


P>1 is not a real, the prediction must be truncated

$$Revnue = Rooms \times Cost\ per\ room \times P_{Occupancy}$$

However the occupancy probability is a function of price which will create feedback if the price is changed

3.Price recommendation



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Hotels which are fully occupied most of the year could benefit from a price increase, e.g. 523,520,522

Hotels which have extra capacity could try a price decrease

Considerations

$$P_{Occupancy}(Room\,Price\,,Romm\,abundance\,,location\ldots.)$$

Feed back between changing the price and the occupancy is unknown

Small changes the the price could be made to probe how the occupancy responds.

Rooms could be divided up into price bands to
– promote constant occupation keeping the workload consistent

Thank you

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