Analysing the footfall in Leeds city centre using street cameras

1 Introduction

Understanding the movement of pedestrians is crucial for council and police personnel. It assists them in planning for security, to be ready for potential crowd trouble, managing the litter etc. Information about peak hours, major locations is of interest of commercial organisations to plan the promotional and cultural events. For this Leeds City Council has placed 8 CCTV cameras in various locations of the city centre. To monitor the footfall hourly information has been retrieved from these cameras.

In this report we will be understanding in depth about various factors affecting this footfall via visualisations and discuss performance of several models developed to forecast the number of pedestrians.

2 Data and Variables

Eight CCTV cameras have been placed around Leeds City Centre which record hourly number of pedestrians in 8 locations indicated in Figure 1. Information about hourly weather conditions, minimum and maximum temperature, humidity and wind speed were also leveraged to comprehend if weather conditions impact the number of walkers.

3 Understanding through visualisations

Figure 2 illustrates the total footfall in all the 8 locations over several years. A declining trend can be observed which indicates that number of pedestrians in

Figure 1: The positions of 8 cameras across Leeds city centre

the city centre are reducing over time. December experiences highest footfall while, the number of pedestrians plunge in January.

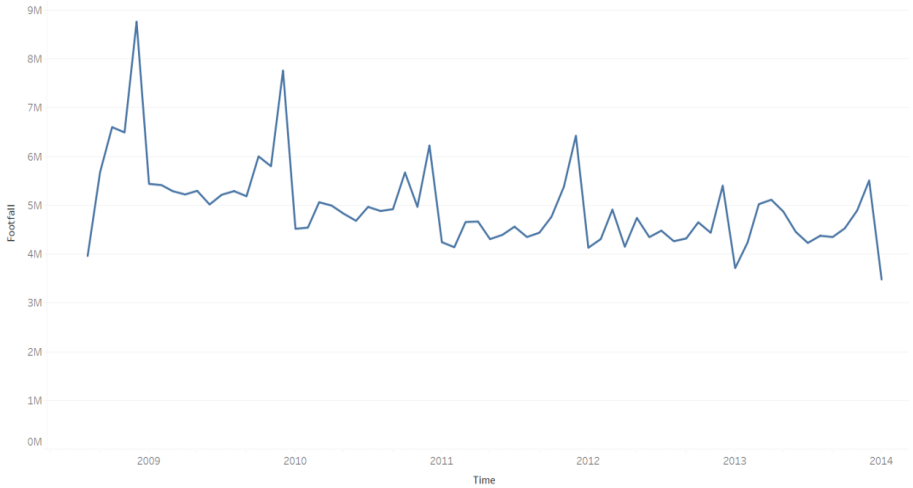


Figure 2: Number of pedestrians in Leeds city centre over time

On exploring further (Figure 3) it was witnessed that all the locations but Dortmund Square witness an increase in footfall in second half of the year. In last quarter of the year, Albion Street South, Briggate and Commercial Street at Lush are famous locations amongst people.

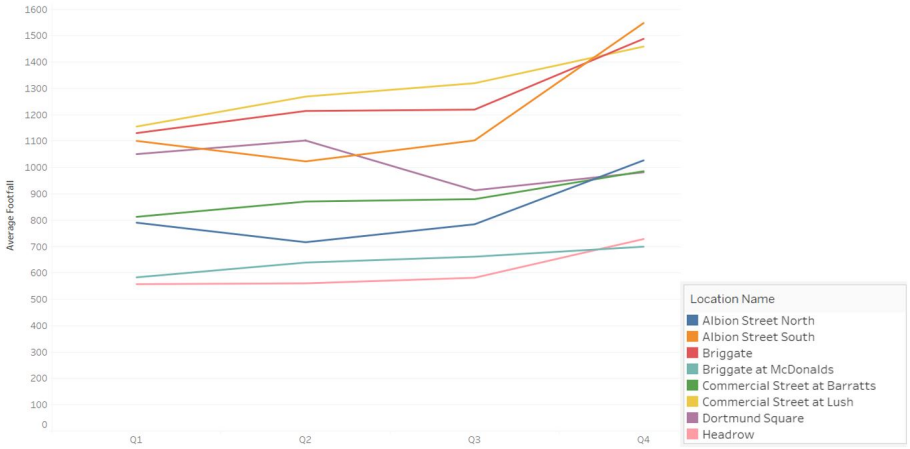


Figure 3: Quarter-wise average footfall for 8 locations

On comparing the weekly average footfall at top 2 locations(Albion Street South and Briggate) and Dortmund Square, closer inspection of Figure 4 indicates that during the second half of the year top locations are witnessing increased footfall from week 27 while in Dortmund Square the footfall is dropping. However, during the last 3 weeks of the year, like any other location Dortmund Square is also experiencing a growth in the number of pedestrians.

Figure 4: Week-wise average footfall

3.1 Peak hours and popular locations

The figure below reveals that most of the visitors are present between 10am - 6pm and 11am - 3pm are the peak hours. Thus Leeds City Council can use this information to employ more personnel for litter management. It is

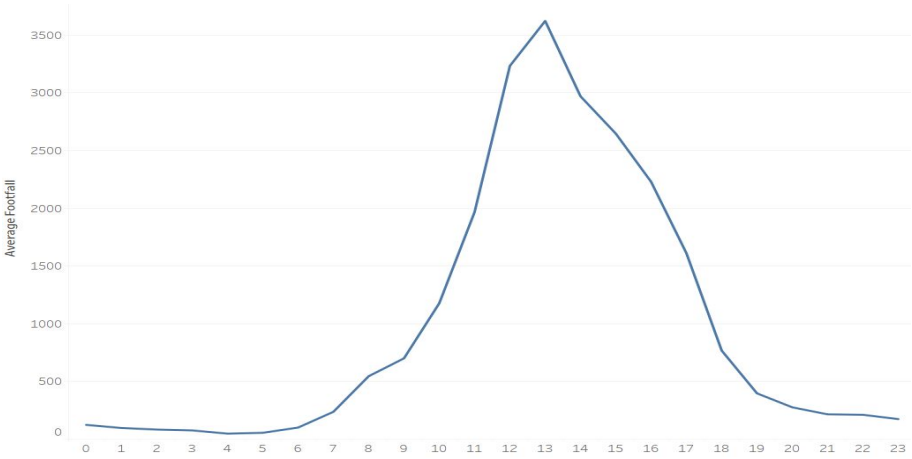


Figure 5: Peak hours at Leeds City Centre

apparent from Figure 6 that Commercial Street at Lush, Briggate and Albion south street are most crowded locations, as it was echoed in 3. Being the most popular locations there is a possibility of crowd trouble thus police authorities should be more conscious. Furthermore, Headrow and Briggate at McDonald's are the locations witnessing least footfall.

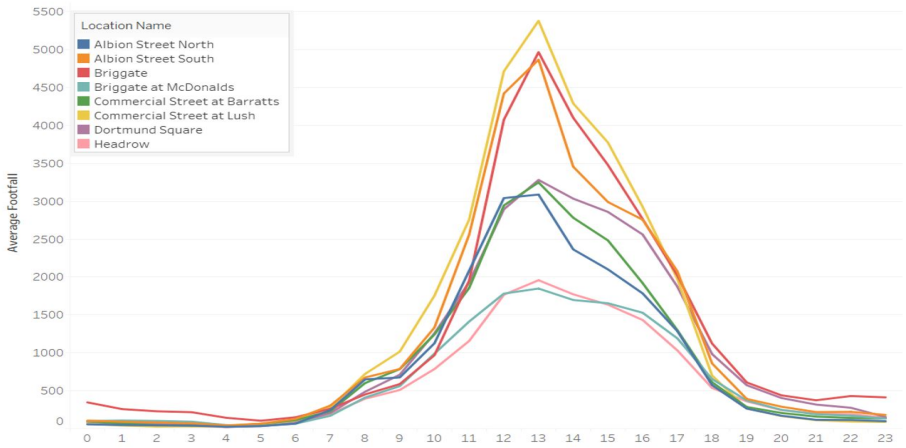


Figure 6: Most crowded locations by time of the day at Leeds City Centre

3.2 Assessing the impact of weekends

Weekends are a time where people prefer to have a break from monotony and involve in recreational activities. Using this assumption it was tried to ascertain if the footfall is more during the weekends. At an overall level Figure 7 highlights that there is a slight rise in the footfall, but on going further interestingly, it was found that this increase is primarily due to locations like Briggate and Commercial streets. Not much significant difference in the footfall was present during the weekends.

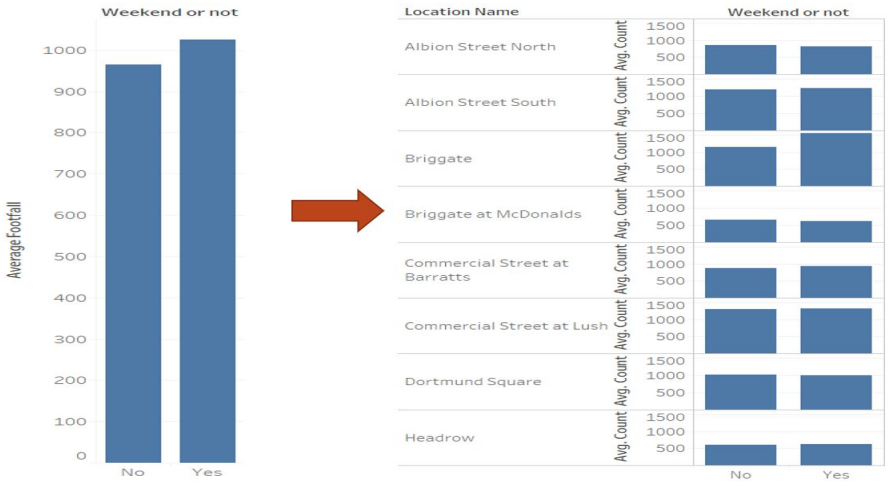


Figure 7: Bar plot for footfall during weekends

3.3 Understanding the role of weather conditions on footfall

It was tried to explore the relationship between weather factors (maximum temperature and wind speed) and footfall. As can be seen from Figure 8, there seems to be no impact of weather conditions on the number of visitors. January and December record for least and highest footfall respectively.

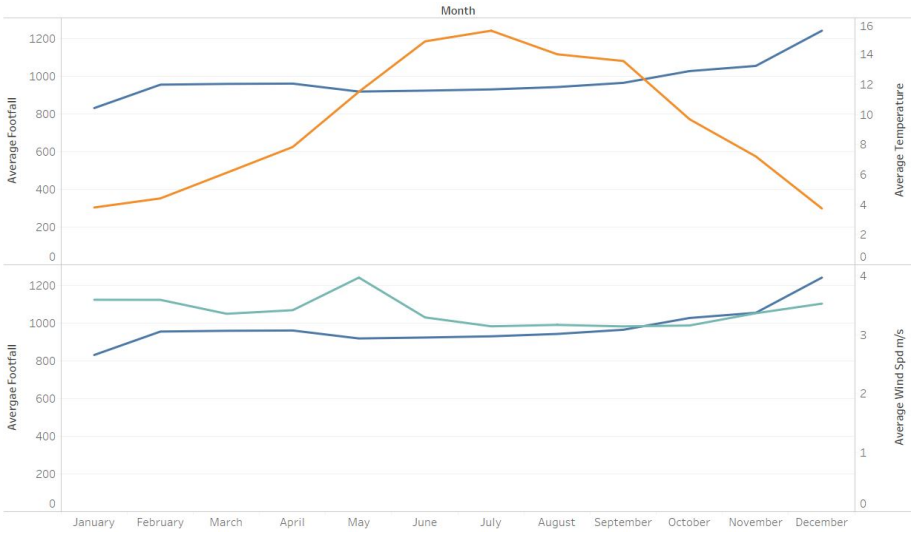


Figure 8: Impact of weather conditions on footfall

4 Correlation between different cameras

In this section we have tried to establish the relationship between different cameras.

Table 1 provides the correlation between footfall for different cameras. All of the numbers are indicative of highly positive correlation. Correlation amongst Albion streets and Commercial streets are extremely high (more than 0.9). This might be possible due to the fact that these 4 locations are closely located (1).

Table 1: Correlation between footfall in different locations at same time

	Albion Street North	Albion Street South	Briggate	Briggate at McDonalds	Commercial Street at Barratts	Commercial Street at Lush	Dortmund Square	Headrow
Albion Street North	1.00	0.94	0.81	0.86	0.93	0.93	0.87	0.91
Albion Street South	0.94	1.00	0.81	0.83	0.91	0.92	0.85	0.88
Briggate	0.81	0.81	1.00	0.78	0.86	0.84	0.84	0.88
Briggate at McDonalds	0.86	0.83	0.78	1.00	0.88	0.86	0.87	0.91
Commercial Street at Barratts	0.93	0.91	0.86	0.88	1.00	0.97	0.90	0.96
Commercial Street at Lush	0.93	0.92	0.84	0.86	0.97	1.00	0.89	0.93
Dortmund Square	0.87	0.85	0.84	0.87	0.90	0.89	1.00	0.91
Headrow	0.91	0.88	0.88	0.91	0.96	0.93	0.91	1.00

5 Forecasting the footfall

For forecasting the footfall and to test the accuracy of our models we have divided the data into training and test sets, where training set comprised of data till June 2013, while test set contained the data from July 2013 to January 2014.

5.1 Using Facebook's prophet package

There are plethora of models available to analyse the time series, namely ARIMA, AR, MA, LSTM, Exponential Smoothing etc. It might be tedious to try all of them, noting that they require a lot of customisation and fine tuning. Facebook has built an API to forecast different time series which performs all the fine tuning automatically: FB Prophet. We have leveraged Facebook's Python API for FBProphet and a snippet of the code is available in Figure 9

For this we have used additive seasonality, and are encountering for seasonality at daily, weekly, monthly, and annual level.

```
model = Prophet(seasonality_mode= 'additive',seasonality_prior_scale= 15, daily_seasonality= False,
                weekly_seasonality = False,
                yearly_seasonality=False).add_seasonality(
                name = 'weekly',
                period = 7,
                fourier_order = 7).add_seasonality(
                name = 'daily',
                period = 1,
                fourier_order = 2).add_seasonality(
                name = 'yearly',
                period = 365,
                fourier_order = 5).add_seasonality(
                name = 'monthly',
                period = 30,
                fourier_order = 12)
```

Figure 9: Code snippet for FBProphet

For Albion Street North, in Figure 10 we can see how our time series has been

decomposed into trend and seasonality. Looking at the trend line, our assertion of reduction in footfall is supported.

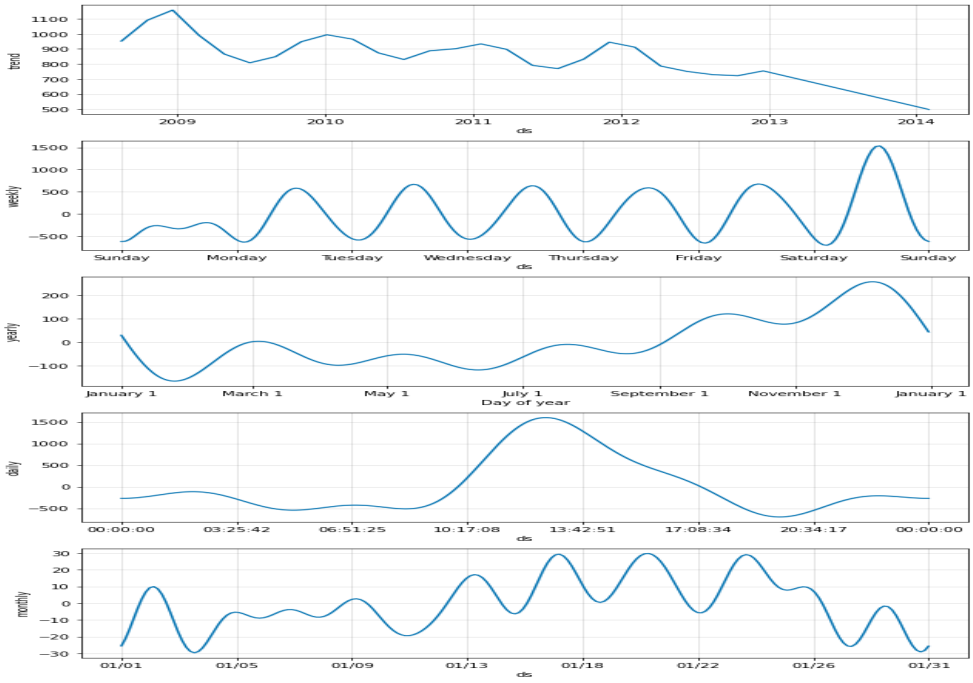


Figure 10: Decomposition of footfall by FBProphet for Albion Street North

To understand how well our model fits our data, Figure 11 shows the actual and forecasts for a part of observations in our test set for Albion Street North. The model seems to be performing well. It can be seen from table 2 that mean absolute percentage error (MAPE) ranges from 17% to 25% for all the locations.

5.2 Various machine learning models

We have tried fitting various machine learning models to our data: Linear Regression, Random Forest (regressors), XGBoost and Stochastic Gradient Descent (SGD) Regressors. Results for them for Albion Street North are present in table 3. Ensemble algorithms (Random Forests and XGBoost regressors) have led the highest R square of nearly 95% and least errors as compared to other two algorithms.

Table 2: Overall results by FBProphet for each of the 8 locations

Camera	MAE	MAPE
Albion North	159	21
Albion South	533	33
Briggate	454	19
Briggate McD	238	23
Commercial Street at Barratts	203	27
Commercial Street at Lush	278	24
Dortmund Square	600	35
Headrow	107	17

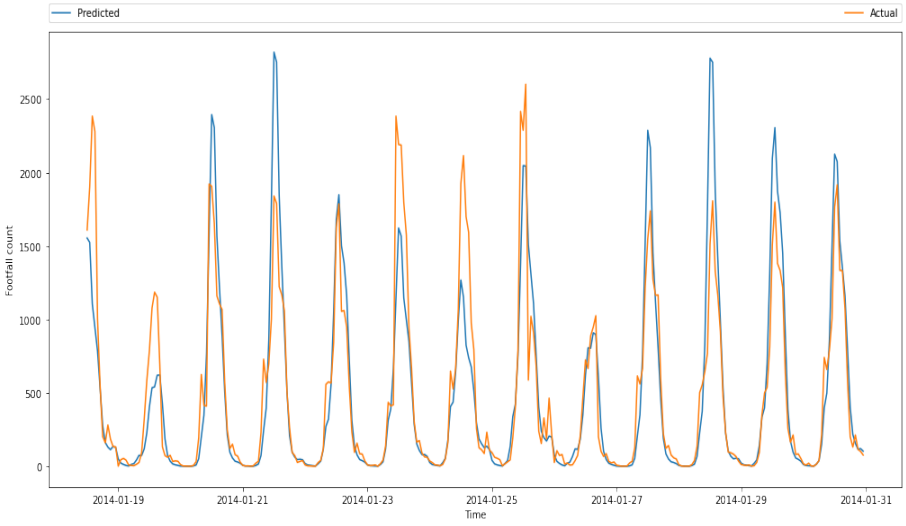
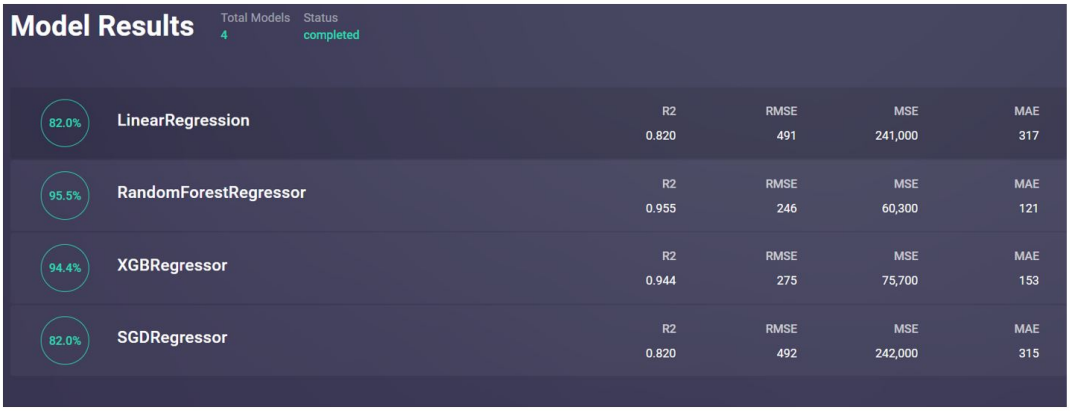


Figure 11: Graph representing forecasted and actual footfall for Albion Street North

Table 3: Results by different machine learning models for Albion Street North



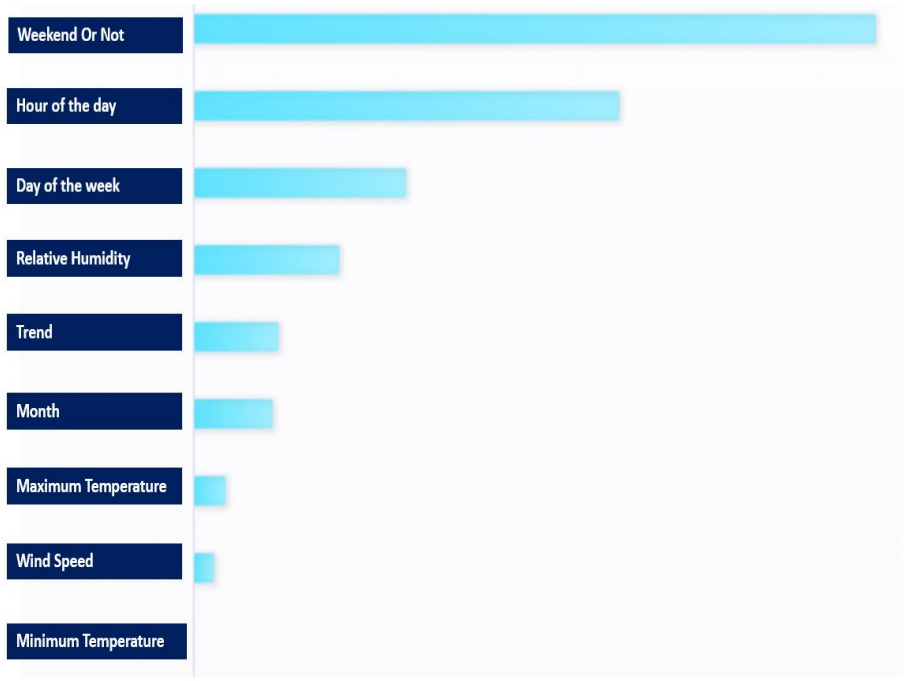


Figure 12: Feature Importance

Random forests have the potential to help us decide which features are important. By changing the permutation of a predictor's values, it gets the predictions for OOB observations and checks for the difference in the difference using original values. The average of this difference is taken for all the trees and is then normalised. If the score is high, then the variable is more important as changing the values of the predictor is leading to worse prediction.

Figure 12 provides the importance of such features for Albion Street North. Our binary variable indicating the day is a weekend or not is extremely important, followed by hour of the day and day of the week. Interestingly, random forests gave trend a very low importance.

6 Conclusion

The main goal of this report was to understand the factors affecting the footfall at Leeds City Centre for various locations. This study has identified that over

the time footfall has been reducing in most of the locations, except Briggate. During last part of the year, the footfall is highest in all the locations. Weekends have slight impact on the footfall; impact of weekends is more pronounced in Briggate. Peak hours in the city centre are during 11am - 3pm. Thus, during this time and specially on weekends, for locations like Commercial streets, Albion south street and Briggate special provisions should be made for litter management and maintaining peace and security. Astonishingly, it was discovered that weather conditions do not impact the number of pedestrians.

Ensemble techniques (random forests and XGBoost) are providing good results for forecasting the footfall. For locations like Headrow and Albion Street North, Facebook's Prophet API is having quite low errors.

References

[1] Chatfield, C. *The analysis of time series*. 5^{th} edition. London, UK: Chapman & Hall

[2] Bhalla, D. (2014). *A COMPLETE GUIDE TO RANDOM FOREST IN R.*, Listendata, https://www.listendata.com/2014/11/random-forest-with-r.html