Unit 2 Case Study – Real-Time Location Systems

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1. Introduction

Due to the surge in growth of wireless networking, being able to dependably track people and things has become a subject of high interest. Such tracking has abundant uses, such as tracking merchandise in stores to prevent theft, recording the location of a medical patient who may have a flight risk, or logging item locations in a warehouse to efficiently ship products. Not only should the movements be recorded, but locating these objects in real-time is often of utmost important. Therefore, real-time location systems (RTLS) have understandably become a substantial topic of research. Specifically, indoor positioning systems (IPS) are the subject of this investigation, as they improve upon the shortcomings of GPS systems and are made possible via now-ubiquitous WiFi signals.

A statistical IPS system was developed for research in a building at the University of Mannheim, and the experiment has been described and analyzed in detail in the Nolan and Lang textbook, *Data Science in R*. We were tasked with expanding the analysis found there to explore possible improvements to the RTLS system. Specifically, we examined their decision to remove a redundant router from the training data, and we also implemented a weighted *k*-Nearest Neighbors (*k*-NN) approach to supplement their conventional *k*-NN method.

Our analysis found that excluding the access point with MAC address ending in c0 yielded better results than excluding the point ending with cd. Using both access points in conjunction did not yield better results. We also found that a weighted *k*-Nearest Neighbors approach did yield increased performance as opposed to the ordinary *k*-Nearest Neighbors methods.

1. Background

This analysis is built upon an RTLS system developed by researchers at the University of Mannheim; it is important to understand the setup of the system in order to grasp the context of the predictions we will be making. First of all, the system was built on the first floor of a building at the university; the building has many internal rooms and walls, which may introduce error but also opportunity for experimentation and improvement. The 15x36 meter floor plan can be seen in Figure 1.

In the design, there are 6 routers, or access points, scattered around the floor denoted by black squares. The grey circles represent “offline” data, i.e. measurements taken with hand-held devices at fixed distances of one meter apart. The offline data coming from these locations provide training data which can be used to predict the location of new devices on this floor. The black circles denote “online” data, a set of randomly collected data points that we will use to test the RTLS system.

The offline and online data provided with this system required rather extensive cleaning to get it into a usable format. This process is documented in the Nolan and Lang text, chapter 1, which we chose to follow. Additionally, extensive exploration of the data was performed in the text, which we followed closely as well in order to understand the structure and characteristics of the data. For brevity we do not include all this work here, but these helpful visuals can be explored in our code base (referenced in Appendix).

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Figure 1. Floor Plan of the Test Environment

The primary aspect of the data exploration to note is that while 6 access point are depicted in the RTLS design, there were actually 7 distinct MAC addresses of routers that recorded signals. It was found that two of these access points actually had the same x and y coordinates within the building, thus they were expected to be redundant. The Nolan and Lang text chose to remove the router address ending with cd rather than the address ending in c0, presumably because there were slightly more signals recorded for the c0 access point. As seen in Figure 2, the behavior of these two routers was not equivalent with respect to orientation of the offline devices, suggesting that including either router may result in differences in predictions. Our objective was to determine whether the correct decision was made in the textbook analysis.

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Figure 2. Orientation vs. Signal Strength for c0 (left) and cd (right) MAC addresses

1. Methodology

The primary method we used to determine which access point(s) to include was the *k*-Nearest Neighbors (*k*-NN) algorithm. In this method, the *k* nearest training points are found for each point in the test set, whose values are averaged to predict the value of the test data point. In our context, we used Euclidean distance (the typical straight-line distance) to measure the similarity between the 6 or 7 signal strengths of an online point to the 6 or 7 signal strengths recorded for the offline points. Then the known (x, y) locations of those closest *k* neighbors were averaged to predict the location of the online device.

The value *k* can be tuned to reduce overfitting or underfitting problems. To determine the optimal value of *k* for our algorithm, we used the Mean Squared Error (MSE) metric to measure the error between the actual and predicted locations. Figure 3 depicts the difference between the actual online points (black circles) and their predicted locations (asterisks) for *k*=1 and *k*=3. When *k* is only 1, the predicted location of an online point is simply predicted to be the location of the closest offline point. As seen on the left, this results in overfitting, as many of the errors (red lines) are very large. The error was substantially reduced by simply increasing *k* to 3, as seen on the right.

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Figure 3. Actual vs. Predicted Locations for *k*=1 (left) and *k*=3 (right)

Additionally, we used 11-fold cross validation in conjunction with the MSE to determine the optimal *k* while excluding the c0 address, excluding the cd address, and preserving both. After comparing the performance of these models, we implemented a weighted *k*-Nearest Neighbors algorithm to try with the best combination of access points. The weighted *k*-NN uses the same concept as normal *k*-NN, but instead of each neighbor having equal “voting” power, the neighbors have weights inversely proportional to their distance (in signal strength) from the point being predicted. In this way, we still incorporate information from all of the *k* closest points, but the closer points will have more influence. For this method we used the formula

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for the weights, as suggested in the Nolan and Lang text.

1. Results

TODO State findings

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Figure 4. Comparison of Learning Curves across Models

Table 1. Model Comparison

|  |  |  |
| --- | --- | --- |
| **Model** | **MSE** | **Optimal *k*** |
| Excluding cd | 1288.55 | 10 |
| Excluding c0 | 1247.37 | 11 |
| Keeping both | 1428.89 | 6 |
| Weighted *k*-NN (excluding c0) | 1237.72 | 11 |

1. Conclusion

TODO Summarize findings and make business recommendations

1. References

* Nolan, D., and Temple Lang, D. (2015), *Data Science in R: A Case Studies Approach to Computational Reasoning and Problem Solving*. Boca Raton, FL: CRC Press (NTL)
* <http://rdatasciencecases.org/>
* TODO ask about adding more

1. Appendix

Our full R code base can be found in a separately submitted Jupyter notebook file, called lJiang\_kRollins\_dDavieau\_Code.ipynb.