Finding a place to learn: A mobile study room guide with integrated room occupancy rate indicator

Ramona Renner[1], Steffen Schaffert [1], Bernd Decker[1]

[1]IT Center RWTH Aachen University, Seffenter Weg 23, 52074 Aachen, {renner, schaffert, decker}@itc.rwth-aachen.de

Keywords
Study room, room occupancy rate, collaboration, room occupancy rate forecast, study room guide, hybrid app, mobile, RWTHApp, artificial intelligence, machine learning, user test

1. SUMMARY

An essential part of student life is to study - together and alone. Many students look for a place to study on the university campus to be able to better focus or get assistance from fellow students. However, they have problems finding a suitable spot. Freshmen usually do not yet know common places to study and especially while exam preparation phases, the demand for study rooms is high. At these times, students often do not find a place to study or have to invest a lot of time to find it.

At the request of our students and in cooperation with the students' union executive committee (AStA[1]), we have developed a solution within our university app RWTHApp[2], which tackles the issues above – a user-friendly study room guide with integrated room occupancy rate indicator. It provides an overview of all official study rooms on campus and their features. Furthermore, it displays an indicator for current and predicted future occupancy rates. Students can find study rooms more easily, plan meeting with fellow students beforehand and thereby collaborate better. They can better cope with times of high demand, because they know more places, in particular previously less known ones. This leads to a better overall occupancy rate of available rooms while resulting in more available seats in each individual room.

Recent surveys about our university app showed that the feature was used to find a study room by 50% of all students using the app. Additionally, the data collected in the process helps our student representatives to reason about the need for additional or differently located study rooms.

The focus of this paper lies in the description of the mentioned feature and its implementation.

2. USER INTERFACE

2.1 User Interface Design

Our user interface offers different views to support not only fast scannability, but also spatial orientation with regard to study rooms (see figure 1). Various additional filtering and sorting options simplify and accelerate the search for a suitable room. Besides these overall views, more detailed information about each room is provided on a separate detail page. This prevents the user from getting overwhelmed by too detailed information while searching.

The first part of the app feature, a list of all available study rooms, already existed before our implementation, as a list on the university website. By including it in the official university app and thereby adapting it to a mobile environment, we raised the visibility of this list. The adaptation to the mobile environment was important, as experience and feedback has shown that our students prefer the mobile channel for this specific and comparable activities.

---

[1] The students' union executive committee (AStA) represents the students' interest at RWTH Aachen University.

[2] The RWTHApp is an especially for RWTH Aachen University students designed and developed hybrid app. It offers fast, mobile access to selected information of the most common university tools and other useful features that make daily students' life easier. (Politze & Decker, 2014)

Each list entry shows the name of a study room as well as the address and further location descriptions. Additionally, the time until a room is opened or closed, as well as the occupancy rate, is given. The latter shows either the current or future occupancy, depending on whether the room is currently open or closed. By default, all elements are sorted according to their distance to the user's current location. The occupancy rate and opening hours are provided by both color and text, to support not only faster recognition but also usage by colorblind people.

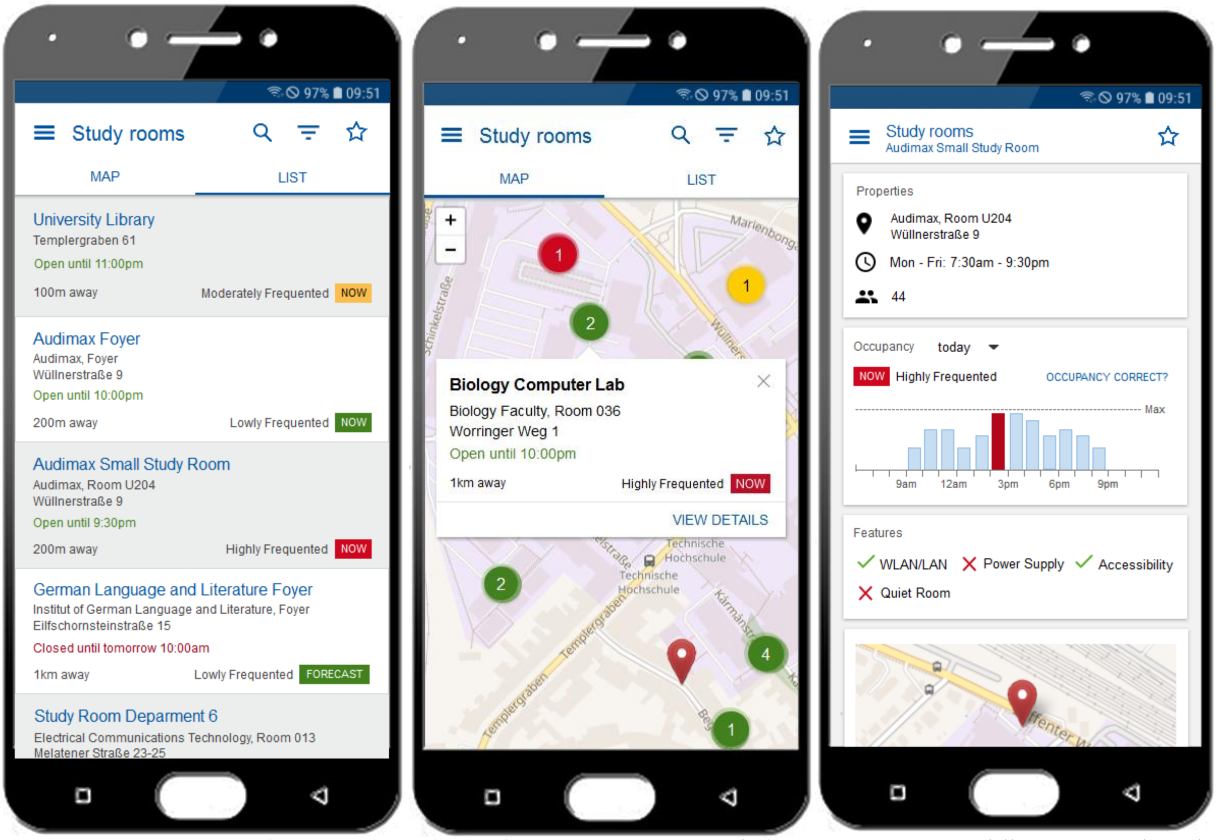

Figure 1: User Interface Design of app feature: List view (left), map view (middle), room detail view (right)

The second view in figure 1 is a map view, which enables students to view their own location and relative the position of study rooms at a glance. Moreover, it displays the current occupancy rate and opening status of a room by color, e.g. a room lowly frequented and open is displayed in green while a closed or highly frequented room is displayed in red. Each study room marker provides the same information as an entry in the list view, when clicked.

As mentioned, both views offer various filtering and sorting options for users to efficiently find a fitting and currently open study room with available seats. It allows filtering by room features such as Wi-Fi connectivity, accessibility, available power supply and room type (e.g. discussion room). Sorting by distance is also possible.

In both the list and map view, it is possible to go to a details page for each study room. The room detail page (see figure 1) reveals different room characteristics like an overview of the room features, the opening hours and a map view of the study room location and its near surroundings. To allow the user to easily access navigation, this image and a separate flat button serve as a link to open an external map application. Moreover, the view provides detailed information about the occupancy rates of the current day and a 2-day forecast.
To improve the reliability of the displayed occupancy rates, we also provide a feedback modal. It can be accessed from the room detail page and offers various predefined feedback options as well as the possibility to report the exact number of students currenty in a room.

2.2 Design and test process

The design process of our app feature focused on the users' needs when it comes to finding a suitable study room. In detail, it supports various scenarios like finding a suitable room near the user's current location or finding a room near a specific area to meet with fellow students in the near future. The design was planned and implemented based on such user-centered scenarios.

The user interface design was tested by a small number of users who belong to our target group. We conducted multiple studies with few participants each time instead of one study with all participants, as recommended by (Nielsen, 2012). This means that we adapted the user interface after each user test based on the findings conducted and thereby were able to carry out multiple design and test iterations.

Each observational user test was structured as described in (Krug, 2014). After a short introduction, the user independently performed various tasks with an interactive, high fidelity prototype[3]. All users were asked to use the speaking aloud method to share their thoughts while using the prototype. To facilitate the evaluation, the sound was recorded during each session and notes on observations were taken. At the end of the session, chosen observations were discussed and additional feedback of the participant was written down.

Based on the user tests, several usability issues were identified and fixed before the actual implementation of the feature. In the first test runs, for example, the participants had difficulties due to the naming of some elements. The identified problems were solved in further design iterations. As a result, the participants of the later tests were able to solve the test tasks quickly and without any noteworthy difficulties.

Further feedback, through our in-app feedback channel and a user survey, was collected after the release of the app feature. Small feature additions have already been implemented based on that information.

3. ROOM OCCUPANCY RATE

3.1 Determination of current and future room occupancy rate

Nowadays almost every student carries one or more mobile devices. Most of these devices are permanently connected to the internet. While students are on the university campus, they usually use the university Wi-Fi, in our case eduroam[4]. This enables us to estimate the current occupancy rate of study rooms based on the number of currently connected devices near a particular room. This number of devices can then be used to get an estimation of the number of students currently in a room.

The number of connected devices is queried every ten minutes for each access point. Past data is stored to enable better predictions and to give an indication about the occupancy history of the current day. The time of ten minutes provides a good mix of gathering enough data to smooth out noise while not putting the system under too much load from constant data updates. If the time between measurements is too long, short studying sessions could go unnoticed, as these students would not be recorded in the counts. From experience, most students use more than ten minutes to study when in a study room. On the other hand, it is possible that students only have time between two lectures. With time slots at university typically being 45 minutes, this would probably be the maximum for a viable period between measurements.

With the number of connected devices for each access point, device counts for individual study rooms can be estimated. In the easiest case, this means that the counts from all access points available inside a single study room are summed up. In reality, access points being accessible from different rooms or even from outside of the building introduce inaccuracies. In our current model, access points are assigned to the room from which the strongest Wi-Fi signal can be received.

To get an estimate of how many users are inside a study room instead of how many devices, the calculated numbers are converted. In our model, this currently uses the average number of devices

[3] The prototype was created with Axure RP.

[4] https://www.eduroam.org/

that users are registered to eduroam with. This number is around two, as most students bring a laptop as well as a smartphone with them. This number was retrieved from our eduroam device manager (Decker, Politze, & Renner, 2017), which generates individual eduroam credentials for each device of a user.

For reasons of data protection, all mentioned metrics do not entail any personal information. Because of this, the user count has to be estimated and cannot be directly retrieved. Retrieving additional or different information could make certain aspects of the study room guide more exact, for example if access points would already give information about the number of unique users currently connected there.

Another feature is the prediction of future occupancy rates. For this part, the queried information about connected devices is put into a machine learning algorithm, which estimates future values. The steps to estimate users per room remain the same, so data from individual access points is aggregated based on rooms and then translated into user counts.

3.2 Prediction algorithm

A central part of the occupancy rate feature is the algorithm to predict the number of devices connected to an access point for a certain point in the future. The algorithm is described in detail in (Selzer, Asteriadis, & Politze, 2017).

The prediction is performed for each access point individually. The number of connected devices produces a continuous series of measurements, from the start of measurement, in our case in 2017, to the present point in time. Each measurement entails a timestamp and the number of connected devices at this point in time. A combination of Kalman filter (Kalman, 1960) and Gradient Boosting Regression (GBR) (Friedman, 2001) is used to predict future values.

In preparation to use these machine learning algorithms, features are extracted from the measurements, more specifically from the timestamp of the measurements. These features are then used by the algorithm to find relations between different points in time. This is visualized in figure 2.

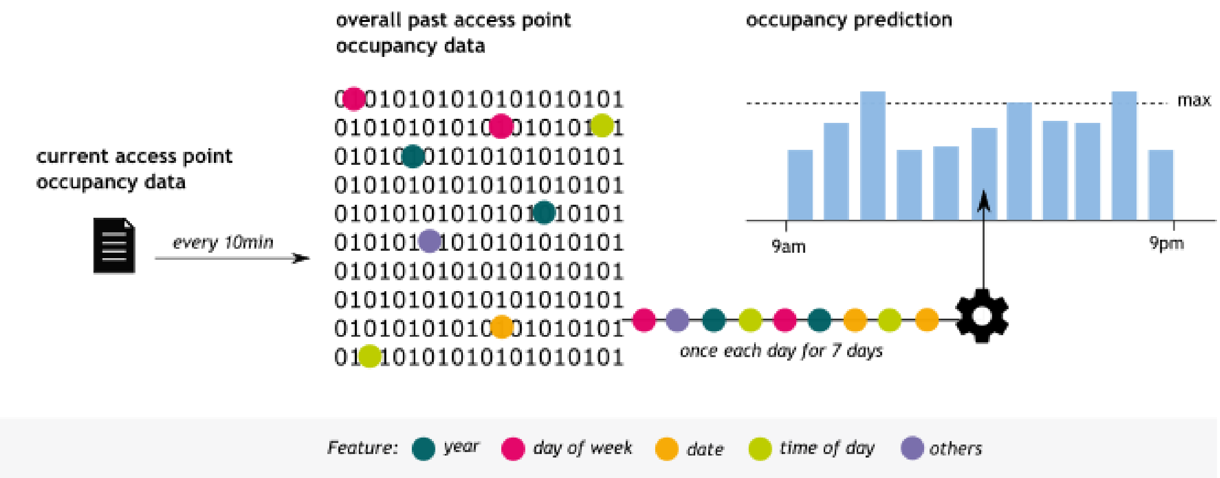

Figure 2: Prediction process

The time of day is the first feature, as most patterns will repeat daily over the course of the day. The second feature is the day of week, as patterns of the same weekday will probably be more similar due to most activities at university following a weekly schedule. The third feature is the date, which uses the fact that semester events mostly occur at similar dates, so this factor helps detecting exam phases for example. The last feature is the year, which is used as an indicator of how current the measurement is.

Although measurements are performed every ten minutes, the predictions are only generated for every full hour. This is done to smooth out possible peaks in connected devices that are not related to study room occupancy. The most prominent case for this would be students passing by a study room on their way to a lecture. Especially if study rooms are near the entrance of a building, this will cause short peaks.

4. INFRASTRUCTURE

One thing that many universities have in common is that information is distributed over many different systems. A big challenge for this project was to gather all this information in an effort to create a simple-to-use application. The data collection for our university is depicted in figure 3.

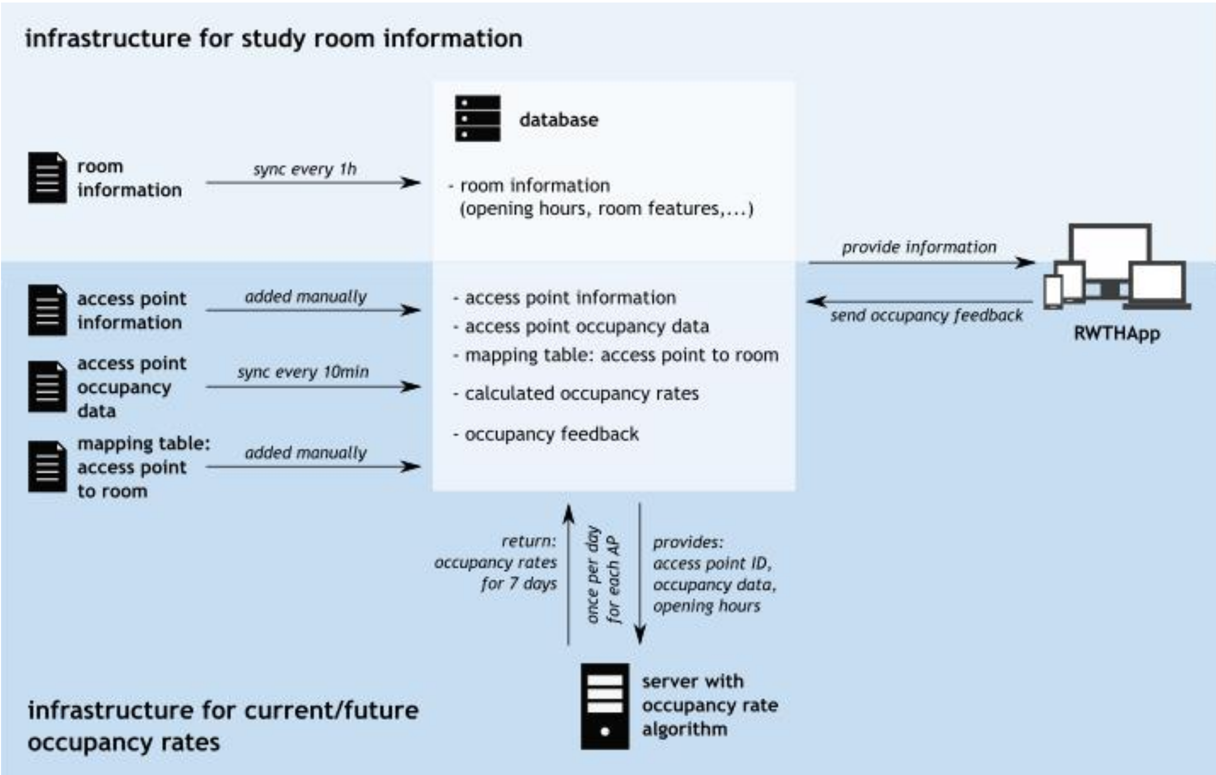

Figure 3: Infrastructure for providing study room information and current and future occupancy rates

The most important piece to this is the list of available study rooms. This list includes general room information, like a room number and the address of the room's building. Study room specific metadata, like opening times and capacity information, is also included. In our case, this information is retrieved from our university website in regular intervals.

The number of devices currently connected to a specific access point in our university Wi-Fi is supplied by a webservice provided by our network group and is retrieved every ten minutes. As described in the last section, this information is then used to determine the number of users in a study room.

To aggregate the occupancy for a room, the mapping from access points to rooms is necessary. If there is information available about where access points are located, this can be used for the mapping. The alternative is to gather this information manually by scanning available access points in each study room. This manual process can also provide better information about how access points may overlap or be reachable from multiple rooms. In our case, we chose to collect this information manually, as the available data was not complete for every access point.

Predictions are generated from the available data once per day for a week in advance by the algorithm described in the previous chapter.

Most of this information is stored in a central database to improve access time and the reliability of the system. Because many different systems are involved, it is realistic that at least one of these systems may be unreachable. Additionally, old occupancy numbers from access points can be used for better predictions. These predictions are also stored in the database, as calculating them is expensive. More recent predictions simply overwrite older ones.

5. OUTLOOK

There are aspects that we plan to improve. The number of devices currently connected to an access point, as described above, is an exact number. Inaccuracies come into the algorithm when converting this to the number of users and relating this data to a specific room. Currently, this calculation uses a constant conversion factor. By using feedback provided by users, it should be possible to improve the conversion with the help of additional machine learning algorithms. We already collect occupancy feedback, but have not yet processed the feedback. So far it is only stored for later use.

The displayed study room information is curated manually on our university website. This leads to duplicate data, especially when it comes to the base information of a room like its location. In the past, this lead to inconsistencies when rooms were removed as study rooms in the internal system but not on the public study room list. In the long-term, the study room feature will instead use data offered by the university-wide room management system. This, however, requires changes in the management system.

Similar systems to the one presented in this paper exist from commercial providers as well. The main difference is that these systems usually need a tracking application on the device of the user. This enables the collection of additional metrics like time spend at a certain place but comes at the cost of the user’s privacy.

There are also plans to extend the general idea of occupancy tracking to other areas. We recently started planning a similar feature for our canteens. By giving students and employees an indication of how long the wait time for a specific canteen is at a certain point in time, they can better plan ahead. This could potentially decrease peak waiting times and increase the number of customers in lesser-known canteens. Similarly, our approach can be extended to different fields for which capacity information is useful. This includes for example lecture room occupancy or room management in general.

The approach described in this paper should also be applicable to other universities. Even the base version with having a well-curated list of study rooms with filtering and a potential map view can help students with discovering new and lesser-known study rooms. This list can then be refined by including occupancy information. This may be acquired from access point data, but there are alternative means. By using technologies like Bluetooth beacons for indoor navigation, it should be possible to enable better navigation within university buildings as well as use information from these beacons to get a user count for specific rooms. There is plenty of data potentially already available, the challenge is to process it and make it available in an easy to use way.

6. REFERENCES

Decker, B., Politze, M., & Renner, R. (2017). Device specific credentials to protect from identity theft in Eduroam. *23rd Annual EUNIS Congress*. Münster, Germany.

Friedman, J. (2001). Greedy function approximation: A gradient boosting machine. *Ann. Statist. 29, no. 5*, pp. 1189-1232.

Kalman, R. (1960). A new approach to linear filtering and prediction problems. *Transactions of the ASME-Journal of Basic Engineering, 82 (Series D)*, pp. 35-45.

Krug, S. (2014). *Don't Make Me Think* (3 ed.). mitp Verlag GmbH & Co. KG.

Nielsen, J. (2012, June 4). *How Many Test Users in a Usability Study?* Retrieved May 1, 2019, from Nielsen Norman Group: https://www.nngroup.com/articles/how-many-test-users/

Politze, M., & Decker, B. (2014). RWTHApp: from a requirements analysis to a service oriented architecture for secure mobile access to personalized data. In J. Bergström. Umeå, Sweden.

Selzer, S., Asteriadis, S., & Politze, M. (2017). Prediction of learning space occupation through WLAN access point data using Kalman filter and gradient boosting regression. IEEE.

7. AUTHORS' BIOGRAPHIES

Ramona Renner studied Media Computer Science with focus on Human-Computer Interaction, Accessibility, Media Technology and Art & Design. She received her Diploma from Technische Universität Dresden in 2016. Since July 2016, she works at the IT Center of RWTH Aachen University as Interaction Designer & Front-End Developer.

Steffen Schaffert finished his studies in Artificial Intelligence at Maastricht University in 2017. Currently, he is working at the IT Center of RWTH Aachen University as a software developer in the field of E-Learning.

Bernd Decker is deputy head of division of IT process support division at IT Center RWTH Aachen University since 2011. From 2006 to 2009 he worked at IT Center as Software Developer and since 2009 as lead of the development group. His work is focused on IT solutions for processes in the field of E-Learning, E-Services and campus management systems.