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Ocupado: Visualizing Location-Based Counts Over Time Across Buildings

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Figure 1: *Building Recent Interface, overview window. (a) Floor plans sized to all fit within one screen with zone-level superimposed circle symbols showing live device counts. (b) Per-floor aggregate trend charts showing device counts over past 12 hours and prediction for the next 3 hours (red dashed line). (c) Alternative sidebar showing aggregate per-floor usage for typical day vs. current live data.*

Abstract

Understanding how spaces in buildings are being used is vital for optimizing space utilization, for improving resource allocation, and for the design of new facilities. We present a multi-year design study that resulted in Ocupado, a set of visual decision-support tools centered around occupancy data for stakeholders in facilities management and planning. Ocupado uses WiFi devices as a proxy for human presence, capturing location-based counts that preserve privacy without trajectories. We contribute data and task abstractions for studying space utilization for combinations of data granularities in both space and time. In addition, we contribute generalizable design choices for visualizing location-based counts relating to indoor environments. We provide evidence of Ocupado's utility through multiple analysis scenarios with real-world data refined through extensive stakeholder feedback, and discussion of its take-up by our industry partner.

1. Introduction

Efficient space utilization is a challenge for many organizations. Monitoring and analyzing building occupancy over time can lead to valuable insights and data-informed decisions [VvdSK*15; VAL17]. New methods are emerging for implicit and explicit occupancy sensing [MRNC11] and considerable attention has been devoted to using this data for automation in building control systems to reduce energy usage [BXN*13; RKWH15; KSS14]. Better visual data analysis tools would allow these rich spatiotemporal data sources to be leveraged in many new decision-making contexts, but current visual data analysis tools do not suffice to support decision-making about indoor space usage over time.

Previous attempts to visualize occupancy, and other indoor sensor data, are limited to very small regions such as single rooms or floors over relatively short time periods. Building information management systems are tuned for the temporal dynamics of construction, and thus emphasize the 3D structure of a single building that is less relevant for occupancy. These techniques are inapplicable to larger scale settings such as corporate office parks or universities where data exists for many rooms distributed across many buildings. Conversely, systems that focus on time series data related to spatial locations typically emphasize geographic maps, a spatial scale too large to capture room-level usage.

We conducted a multi-year design study with multiple stakeholders in parallel to design and implement visual decision support tools centered around **location-based counts**. Our industry partner, Sensible Building Science (SBS), gathers and uses WiFi device counts as a proxy to estimate space occupancy in large-scale deployments with hundreds of rooms across dozens of buildings. Our goal was to understand the tasks of multiple potential stakeholders in facility planning and operations, select those whose needs align with the characteristics of the occupancy data, and design visualization interfaces to support them. We infer occupancy dynamics from location-based device counts, a datatype that provides strong privacy protection because it prevents the tracking of movements of individual people or device identifiers.

We present three contributions. First, an analysis and abstraction of data and tasks for studying space utilization in the domain of facilities management and planning. Second, the design and implementation of Ocupado, a feature-rich visualization system that addresses multiple levels of data granularity in both space and time. Third, a set of generalizable design choices for visualizing non-trajectory spatiotemporal data relating to large-scale indoor environments. Finally, we present preliminary evidence of Ocupado's utility based on stakeholder feedback and collaborator take-up.

2. Process

The Ocupado tool suite was created in a highly iterative process through many rounds of engagement with multiple stakeholders, with the CEO of our industry partner SBS as the focal and continuous collaborator. The SBS Bridge software tracks the number of active WiFi devices with respect to defineable zones within buildings and feeds this recorded data into an algorithm that interfaces with building automation systems to dynamically adapt the heating, ventilation, and air conditioning (HVAC) to occupant usage [Cor17]. We conjectured that with suitable visualizations, this data could be actively useful for decision-making and resource management, beyond its previous use in fully-automated HVAC control systems.

SBS initially provided us with static example datasets that we investigated through initial data sketches [LD11] created in a rapid prototyping sandbox environment, to support our iterative derivation of data abstractions. In parallel, in pursuit of task abstractions, we conducted nine one-hour informal interviews and brainstorming sessions to elicit domain-specific analysis questions from potential stakeholders across eight different domains who might be interested in monitoring and analyzing space usage. They were identified by the SBS CEO, who also attended these sessions. During this due diligence phase, we evaluated the conformity between stakeholder tasks and data affordances following from the choice of WiFi devices as a proxy for occupants. We ultimately selected five focus domains for continued engagement: space planning, building management, custodial services, classroom management, and data quality control. For the latter, the CEO himself was the intended user, to validate the quality of the data gathered by the Bridge.

As we refined our task and data abstractions [Mun09], our experimental sandbox evolved into a suite of four Ocupado interfaces. We also gained access to a live data stream from a new version of the SBS Bridge. We continued with 12 stakeholder sessions to gain feedback about the evolving tools and abstractions. Sessions with early (potential) and later (focus) stakeholders interleaved showing Ocupado capabilities through chauffeured live demos with informal semi-structured discussions of stakeholder needs, followed up by granting access to prototypes for their direct use. At least two people of our team attended each session to allow detailed note-taking of qualitative feedback during the conversation. The first interview typically provided insights into routine tasks and potential use of Ocupado. Live demos—particularly the analysis of spatial regions stakeholders are familiar with [LD11]—led to a deeper engagement and a larger volume of feedback.

SBS adopted Ocupado as a front end for their Bridge software, so their CEO frequently gave demos to potential customers, sponsors, and partners. In addition to serving as a promoter of Ocupado, he was also an intermediary who relayed information to us about potential stakeholder needs and how they aligned or diverged from the Ocupado prototype capabilities. Other stakeholders also became promoters themselves: stakeholders at the Cisco Innovation Centre began to use Ocupado for chauffeured on-site demos to showcase data from their own building. We discuss the strengths of the extended reach and the limitations of receiving feedback indirectly in § 9. We summarize the full set of stakeholders interviewed by domains and sectors in Supp. p. 4. Ocupado has been deployed at two universities and one corporate office in the course of this 2-year long research project. Continued efforts are needed to create robust implementations and ensure long-term use.

3. Domain Goals and Task Abstraction

The five domains we target with Ocupado can be collectively referred to as facilities planning and operations, where a better understanding of space utilization supports stakeholders to optimize processes and allocate resources.

One goal of **custodial services** is to develop *smart cleaning schedules* to prioritize spaces based on their actual usage instead of following traditional cleaning intervals. We differentiate between *custodial heads* and *custodial managers* as end-users for Ocupado. A custodial head is responsible for the day-to-day operations of a small number of buildings. They would benefit from live or recent short-term data to prioritize regions and assign custodians at the beginning of shifts. Example questions that were elicited in our interviews are *Which rooms are busy now?* or *Which floors were heavily occupied in the past 12 hours but are empty now?* Custodial managers oversee processes across the whole campus, need to balance the workload among hundreds of custodians, make strategic decisions, and communicate them effectively.

Stakeholders in the domain of **space planning**, focused on learning spaces, ask many analysis questions with similarities to custodial managers. In addition, they seek to identify under-capacity usage patterns of facilities. **Classroom management** operates on long-term cycles at the level of entire terms. Both of these stakeholder types engage with the spatial scale of the entire campus.

Building management entails a broad cross-section of questions at a limited spatial scale. A building manager supervises all processes related to one or a few buildings so that the infrastructure meets the needs of the occupants. Interviews with one stakeholder revealed the strong need for temporal comparisons of space usage. Currently, human observation would be necessary to assess the impact of space upgrades or to understand the typical usage of labs; a pain point is the lack of such data.

We selected **data quality control** as a focus domain because WiFi occupancy sensing is a fairly new approach and entails many factors of uncertainty. Besides syntactic quality control checks, SBS seeks to understand more complex issues, such as *What is the minimum size of a zone that can be captured*? or *How are adjacent zones affected by a large number of devices in one room?*

After many rounds of iteration with SBS and five interviews with focus stakeholders, we analyzed the transcripts and narrowed the extensive list of domain-language questions into a smaller core set focused on comparison. We further differentiated these comparison questions into four abstract tasks [Mun09]. We provide a detailed mapping from domain language into abstract form in Supp. p. 5-6; to summarize:

T1 Confirm assumptions or previous observations.
(e.g. do students occupy room in evenings or on weekends)
T2 Monitor the current/recent utilization rate.
(e.g. which rooms are empty/busy)
T3 Communicate space usage and justify decisions.
(e.g. space usage improved after renovation)
T4 Validate the data (quality control).
(e.g. check minimum size of a room that can be captured)

Notably, *exploratory data analysis* is not a target task. Our stakeholders do not need to explore data in their daily routine, and moreover have no training in data analysis; rather, they need information in a clear and concise form to facilitate their decision making.

Our original assumption was that stakeholders could be grouped according to their abstract tasks, and that we would design different interfaces for each group. However, even after substantial attention to task abstraction we did not find a clean breakdown along these lines. Instead, we found that stakeholder concerns could be captured concisely and precisely in terms of comparison with respect to different slices of space and time. We discuss these combinations of spatial and temporal granularity below, since it is most natural to frame them as data abstractions.

4. Data

We use the number of logged WiFi devices to estimate space occupancy at the level of individual rooms across multiple-building environments, such as university campuses. Implicit measuring based on WiFi logging can be implemented relatively easy on a software level and deployed to thousands of rooms without installing additional sensors in any building where routers are already installed [BXN*13; OIAS17; MRNC11]. This crucial cost-effectiveness allowed us to explore many possible use cases with stakeholders. The use of WiFi devices as a proxy for human occupancy does have significant challenges; § 9 discusses their affect on stakeholder selection and our design process.

Although our work centered on WiFi device connections, our methods and visual encodings are sensor-agnostic and thus are transferable to other domains and problem scenarios involving non-trajectory spatiotemporal data.

4.1. Data Acquisition

SBS developed the Bridge software for counting and aggregating WiFi devices which uses the signal strength from access points to triangulate the x/y-location of a device. This method works even for unconnected phones or laptops because almost all WiFi devices continuously broadcast probe requests to find networks that allow connections. SBS records these device coordinates and counts them based on predefined zones that can be created by SBS or its clients. Individual device identifiers are immediately discarded so no trajectories for individual devices can be recovered, and the WiFi triangulation is insufficiently accurate to track small rooms such as single-person offices so de-identifying people is less likely.

At the beginning of this project, SBS shared two static database exports gathered at two university campuses. These datasets, containing several months of data and covering dozens of buildings, were our primary resource while creating data sketches and initial visualization prototypes.

In the second project phase, we switched to using an API provided by SBS that supported near-real-time querying of the logged WiFi connections, where buildings and zones can be added and removed dynamically at any time. We made regular queries every 5 minutes for two organizations: the UBC campus (the same as one of the static databases) with 25 buildings over a time period of 8 months, with a total of 778 zones and more than 62 million timestamped items logged. The second live data stream came from the corporate offices of the Cisco Innovation Centre, inside one story of a large skyscraper with 27 zones in total, producing 2.95 million items over a time period of 13 months.

4.2. Location-Based Counts

We record the number of devices per zone at regular intervals. By taking these snapshots over time, we produce a spatial time series [AA06] for every zone that captures fine-grained occupancy patterns. We call this data type **location-based counts**, and note its non-trajectory nature. These non-trajectory location-based counts allow us to analyze spatiotemporal dynamics but are fundamentally different to trajectory (movement) data that are frequently used in such analyses [OM18]. We note that there are significant and intrinsic privacy advantages for this data type, in contrast to the intrusiveness of the trajectory-based standard approaches. It is notoriously easy to de-anonymize individuals from ostensibly sanitized trajectory data [dMHVB13].

Many tasks are well supported by location-based counts, even though obviously the analysis of movement flows is not. We can compare location-based counts at different time resolutions and identify trends, outliers, and repeating patterns. One benefit of this data type is that we can easily aggregate counts of multiple regions to capture local and global variations, as we discuss below.

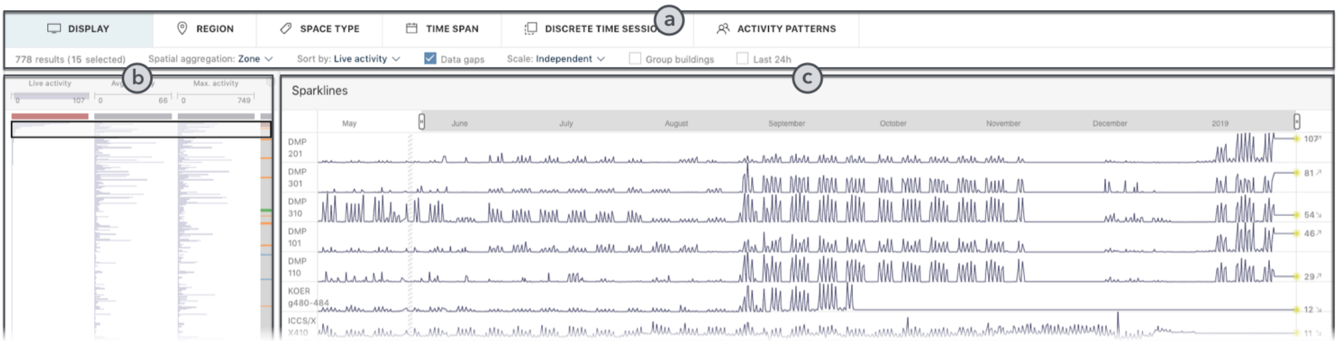

Figure 2: *Campus Explorer Interface. (a) Control panel for filter and display settings. (b) High-level region overview shown as quantitative and categorical data stripes. (c) Region subset view providing mid-level details for regions selected in the region overview; users can choose between different visual encodings for it. Clicking on one region opens a modal region detail window with low-level details.*

4.3. Spatial and Temporal Data Granularity

We decompose spatial regions into hierarchical layers. The lowest-level unit is a **zone**, roughly corresponding to the room level, which is customized for the stakeholder context. Examples of zones include research labs, classrooms, hallways, and multiple-office groups. Each zone consists of one or more complex shapes and is linked to a specific floor and building. Zones can include further attributes, such as room size or space type.

The higher-level layers in the hierarchy are floor, building, and campus. A floor usually contains several zones, has a corresponding floor plan and is associated to a building. The metadata for a building contains geographic coordinates (latitude/longitude), a list of floors, and a building name. Currently, the highest spatial layer is a campus containing dozens of buildings in a roughly contiguous spatial neighborhood. We use the generic term **region** to subsume zones, floors, and buildings.

The spatial data that pertains to a task includes not only regions but also their spatial **context** (see Fig. 3). Tasks have different **cardinality**: some may concern all zones on a floor, others concern a few zones distributed across a campus, or only a single region.

We decompose time into a short-term or long-term **period**. We also distinguish temporal **rollup** via aggregation from the use of individual measures. For example, a custodial head wants to compare a region's average daily utilization with the current rate (*T2 Monitor*), while a building manager wants to see individual counts over time to compare long-term trends and patterns (*T3 Communicate*). In addition to the usual contiguous time ranges, we also support non-contiguous time slices for use cases such as a custodial manager who needs to check all morning shifts (6am - 2pm) on weekdays during the last winter term (*T1 Confirm*).

To precisely describe these spatiotemporal data granularities and link them to interfaces, design decisions, and analysis scenarios, we use the notation for *space:time* combinations shown in Fig. 3. For example, *ZF-All:SA* (compare all zones on a floor : short-term aggregated) applies to the scenario *A custodial head wants to monitor the average utilization of all the rooms on the first floor in the past 6 hours*. The asterisk (*) symbol indicates a wildcard that can be replaced by any of the available options, such as *ZB-** for one, few, or all zones in a building.

Space	**Region** ←	{ ***Z**one*, ***F**loor*, ***B**uilding* }
	Context ←	{ ***F**loor*, ***B**uilding*, ***C**ampus* }
	Cardinality ←	{ ***One***, ***Few***, ***All*** } Regions
Time	**Period** ←	{ ***S**hort-Term*, ***L**ong-Term* }
	Rollup ←	{ ***A**ggregate*, ***I**ndividual* } Counts

Figure 3: *Spatial and temporal data granularities.*

5. Ocupado Interfaces

We started by implementing a sandbox prototyping environment to rapidly explore and evaluate the design space of visual encodings, in a similar spirit to efforts by Brehmer et al. [BNTM16]. Screenshots and detailed descriptions of all design iterations are included in Supp. p. 17-32.

After obtaining a more precise understanding of our focus domains and access to a live data stream, we created four interfaces that are based on a shared underlying infrastructure but can be deployed independently. We call them interfaces rather than dashboards because they are fully interactive systems with multiple subpages and dynamic data sources [SCB*19].

From the very start, we implemented all visualizations as independent components that can be linked, enhanced, and exchanged. This design process supported highly dynamic prototyping and allowed us to reuse components in different interfaces and to engineer for an easy transition from static to streaming data.

Campus Explorer Interface. The goal for our first interface was to implement a general-purpose tool centered around location-based counts that would serve the needs of multiple stakeholders who focus on analysis. Although it has considerable functionality and a product-like look, it is a technology probe [HMW*03] and was intended to be a vehicle for continued iteration on visualization designs and continued task elicitation. The interface facilitates cross-building analyses, provides global filter options that can be applied to all views, and enables users to look at the data from different angles and levels of detail (*T1-T4*).

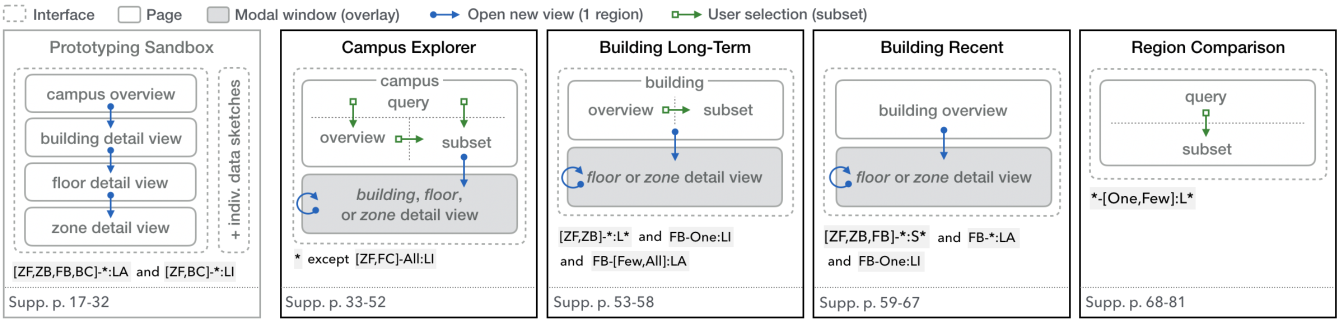

Figure 4: *Schematic diagrams to illustrate the view composition and interrelations of all Ocupado interfaces. Each drilldown transition in the sandbox requires a page reload. This static navigation path between pages impede transitions between overview and details and make comparisons between regions difficult. All subsequent interfaces address this limitation by allowing users to switch between views seamlessly and to create dynamic filter queries.*

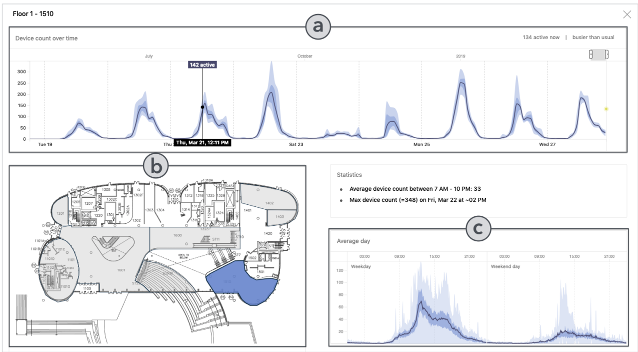

Figure 5: *Region detail view. (a) Zoomable binned time series chart. (b) Floor plan for spatial context and navigation. (c) Typical day profiles.*

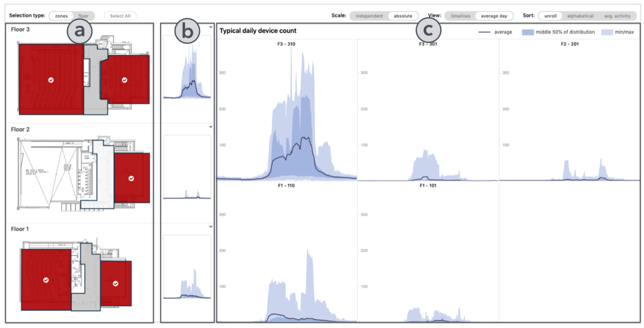

Figure 6: *Building Long-Term Interface. (a) Interactive floor plans for selecting regions of interest. (b) Per-floor rollups showing average utilization. (c) Each selected zone shown as typical day profiles or sparklines.*

The interface is flexible and powerful, as it supports a cross-cut of data granularities in space and time (** except [ZC,FC]-All:LI*), but it is quite complex. Over the course of many interviews and brainstorming sessions, it became clear that some common domain questions would be easier to address with a simpler interface, especially for users who monitor only a small subset of regions and are not trained data analysts.

Our first foray into simplifying the sometimes-overwhelming Campus Explorer was in the form of *application presets* that provide single-click access to any combination of actions that could be accomplished through the interactive interface. One example is *Select all regions that are associated with the Computer Science department, rank them in descending order based on the current device count compared to the maximum activity during the last 12 hours, and show the top 10 as sparklines*. (*ZB-Few:LI*; Supp. p. 40)

Building Long-Term Interface. Many questions concern only zones within a single building, even for stakeholders who are responsible for regions across a whole campus. To enable a more target-oriented analysis, we created an interface that lets users inspect location-based counts in a similar way as in the Campus Explorer but only for a specific building (*[ZF,ZB]-*:L**, *FB-One:LI*, *FB-[Few,All]:LA*; Fig. 6).

Building Recent Interface. Some stakeholder questions are focused on live or recent short-term data where historical data is distracting. The Building Recent Interface, shown in Fig. 1, explicitly tackles *T2 Monitor* and facilitates a holistic short-term view of one building (*[ZF,ZB,FB]-*:S**, *FB-*:LA*, *FB-One:LI*).

Region Comparison Interface. Comparing a small subset of regions or time periods in detail is relevant for all tasks except *T2 Monitor*; stakeholder examples include analyzing the impact of space upgrades, comparing summer vs. winter use, and assessing the custodial workload of different floors (**-[One,Few]:L**). The other interfaces only support this task to a limited extent because the faceting approach can hinder direct local comparison [JME10]. In the Region Comparison Interface, we display data from multiple regions in the same space, superimposed.

5.1. Implementation

We follow common practice by separating front-end interactive visualizations from back-end data processing. The front ends are implemented in JavaScript and use D3 for interaction and rendering. The back end, responsible for data preprocessing querying the PostgreSQL database, and for providing a RESTful API, is based on Python and the web framework Django.

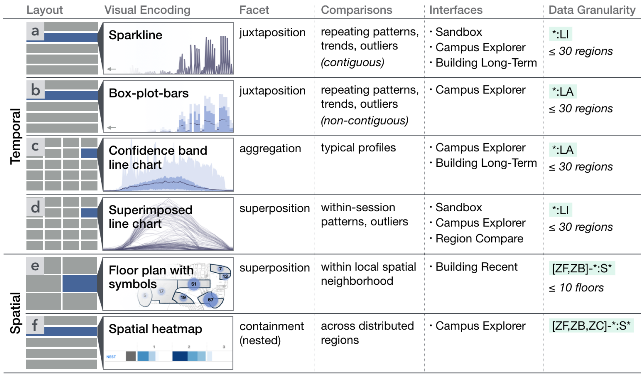

Figure 7: *Visualization components for region subset views, emphasizing either temporal or spatial aspects, to facilitate comparisons between contiguous regions, such as rooms on a floor, or between a subset of regions that are distributed across a campus.*

6. Ocupado Design

We now describe the individual components of our visualization prototypes, and then discuss the rationale for visual encodings and interaction techniques with respect to our data and task abstractions. The accompanying video shows the look and feel of the interactive interfaces (michaeloppermann.com/files/ocupado.mp4).

6.1. View coordination and layout

Fig. 4 shows a schematic overview of the sandbox and the four Ocupado interfaces, which feature carefully designed linkages between multiple coordinated views.

The sandbox starts with a campus-level overview of all buildings on a single page, with drill-down navigation into the spatial hierarchy where clicking on a region selects it to see in more detail. Each drilldown transition to a building-level page, a floor-level page, or a zone-level page requires a page reload. This static navigation path between pages impedes transitions between overview and details and make comparisons between regions difficult. All subsequent Ocupado interfaces address this limitation by allowing users to switch between views seamlessly.

The Campus Explorer and Building Long-Term interfaces incorporate a two-column layout with the region selector (high-level) on the left and the region subset view (mid-level) on the right. The region selectors are shown in Fig. 2b for the Campus Explorer and in Fig. 6a for the Building Long-Term Interface. Selected subsets are shown in Fig. 2c and Fig. 6c; different visual encodings for region subset views can be selected depending on the task, as we describe in § 6.2.

The Campus Explorer provides a control panel at the top, as shown in in Fig. 2a, that allows users to narrow down the results and to customize the display settings. Activity patterns provide shortcuts to complex combinations of actions, as described in § 5.

A click on a specific region opens a modal window that contains the region details (low-level), as shown in Fig. 5. All the selections and display settings remain active until the user returns to the overview visualizations to continue the analysis. This multi-tier approach [ABS*14] in the Campus Explorer and Building Long-Term Interface facilitates fluent transitions between three levels of data granularity without page reloads and loss of active selections. The Building Recent interface also integrates an on-click detail view, for users who want to inspect a specific region more closely and beyond the 12 hour short-term time window.

The Region Comparison Interface is an exception and does not provide any overview or detail pages. Users begin the analysis by choosing regions and time periods of interest, similarly as with the Campus Explorer control panel, and the results are displayed in multiple visualizations within the same page.

6.2. Visualization Components

We now discuss the visualization components used in the selectors, the subset views, and the detail views.

6.2.1. Region Selector

Region selectors provide a high-level overview and enable users to select a subset of regions based on their location or utilization (Supp. p. 9). In the Campus Explorer, we use a simplified version of the LineUp visualization [GLG*13] that we call **data stripes** as an abstract sortable representation of many regions, as shown in Fig. 2b (**:[S*,LA]*). Depending on the selected region level, a row corresponds to a zone, floor or building and each column encodes a categorical or quantitative attribute, such as *average device count*. The selection window (black bordered) can be dragged across the rows to pick a region subset. The Building Long-Term Interface uses interactive **floor plans** as selectors to show the whole building while preserving spatial contiguity, as shown in Fig. 6a. Users can click on individual zones or select whole floors.

6.2.2. Region Subset View

We divide the visual components for analyzing region subsets into two groups, emphasizing either temporal or spatial aspects. Fig. 7 shows all subset components and their characteristics.

The **wall of sparklines** (see Fig. 2c for an example instantiation within the Campus Explorer) shows location-based counts to quickly scan long-term patterns, to identify data gaps (encoded with grey diagonal stripes), and to compare regions at the overview level. It works well for contiguous time periods (**:LI*, $\leq$ 30 regions). The explicit indication of missing data by the grey stripes was an iterative improvement over our first attempt, which relied on analysts to notice anomalous plateaus and make conjectures [SS18].

Some analysis questions focus on very specific, non-contiguous time slices. A user may want to analyze the activity in multiple regions during Friday evenings. We use **box-plot-bars** [BSM04] to visualize these time slices while also retaining the underlying continuous time line. The light blue area shows the min-max range, the blue area shows the interquartile range (IQR; between the 25% and 75% percentile), and the dark blue line indicates the average device count (**:LA*, $\leq$ 30 regions).

We use **confidence-band line charts** to visualize aggregated days and time slices to help analysts reason about typical activity, such as *When do people usually leave on Friday evenings?* (**:LA*, $\leq$ 30 regions) Despite the confidence bands, aggregating all device counts hides important details that are crucial for certain domain questions, such as identifying outliers or unusual patterns on one of the days. We added another view that supports these local time-slice comparisons by showing **individual line charts superimposed**, as illustrated in Fig. 7d (**:LI*, $\leq$ 30 regions).

Users can globally choose between independent and absolute y-scales that are applied to all temporal visualizations. Independent y-scales emphasize temporal patterns despite widely differing region sizes and utilization rates. Absolute scales ensure consistent axes and enable direct comparisons of device counts between regions.

We use floor plans and spatial heatmaps to visualize current device counts and aggregated metrics in the spatial context of one building or the whole campus. **Floor plans with circle symbols** are the core component of the Building Recent Interface and present an at-a-glance view of all regions within a building (*[ZF,ZB]-*:S**, $\leq$ 10 floors). The **spatial heatmap** is an abstract campus representation, where each row corresponds to one building; it is a concise depiction of multiple floor plans that preserves spatial contiguity at the building level (*[ZF,ZB,ZC]-*:S**).

6.2.3. Region Detail View

All the detail views contain a **zoomable binned time series chart** that shows the device count over time at different levels of granularity. As with the line charts, we use confidence bands to show the min-max interval and interquartile range for these dynamically sized time windows (temporal bins). Initially, the bands around the average line are wide but the further a user zooms in, the narrower they get, until the dark blue line represents the actual device count and the bands disappear. This transition is illustrated in Fig. 8.

This view also includes charts presenting the average daily utilization on weekdays and weekends as line charts with confidence bands, similarly to Fig. 7c.

At the floor or zone level, an interactive floor plan is displayed as a side-by-side view (see Fig. 5b). It helps users to navigate between regions and to get a sense of the physical location and structure of a zone. The detail view of a building shows instead all floor plans, similarly to Fig. 1 but without circle symbols (Supp. p. 50).

6.3. Design Rationale

Why data stripes? Data stripes can show multiple attributes of several hundred regions in a compact view (**:[S*,LA]*). Enhanced with an interactive selection window and ranking options, it serves as an overview in a linked-view. In the sandbox environment, we experimented with a geographical building map as a selector but quickly rejected it because it cannot show the rooms and floor levels of the spatial hierarchy.

Why juxtaposed sparklines? Sparklines provide a high-level overview of many regions over extensive time periods within one view (**:LI*). We can display about 30 sparklines and more than one year of data with a sufficient level of detail on standard displays. Location-based counts are averaged based on three hour windows to avoid occlusion and latency. We ruled out superposition

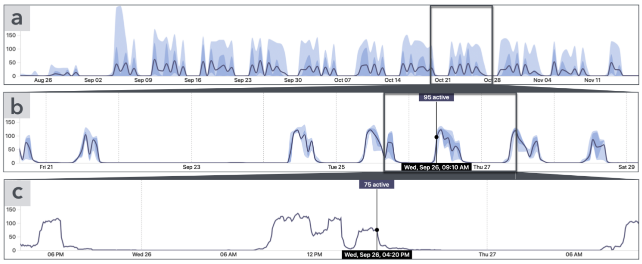

Figure 8: *Binned time series chart at different zoom levels. (a) 13 weeks of high frequency data are aggregated and displayed with confidence bands to avoid visual clutter. (b) Zoomed in to reveal more details, with narrower confidence bands. (c) At maximum zoom, confidence bands disappear and the line represents the original device count.*

because distinguishing the identity of individual lines is too challenging with a large number of regions [JME10]. We tried interactive heatmaps, but ruled them out quickly: the higher precision of the positional vs. the color channel for visual encoding was indeed crucial in this case, as discussed with Pathline [MWS*10] and studied by Lam et al. [LMK07]. See Supp. p. 23 for direct comparison.

Why binned time series? We use a temporal binning approach to avoid visual clutter and rendering latency due to high-frequency data. In contrast to data aggregation approaches that lead to compact time series representations [LKLC03], we support dynamic binning through user interaction. When users zoom in, the visible time frame (bin) gets smaller to reveal more details.

Why not use spatially embedded time series? We investigated spatially embedded time series and cartograms, for instance as used by Wood et al. [WSD11] in geographic small multiples to study bike sharing dynamics, as a viable option to visualize location-based counts. We ruled it out because of the indoor spatial data model and the highly varied region sizes, which would require trade-offs that affect the statistical or spatial accuracy.

Why all floor plans side by side? Stakeholders in facility planning and operations work with printed floor plans on a regular basis, for example, to assign shifts or to communicate renovations, so this depiction of spatial context is both familiar and highly relevant for many use cases. Whenever possible, we integrate floor plans to capture the spatial context, providing a spatial overview and allowing users to look up and compare zones. On the right side of Building Recent and the left side of Building Long-Term, we automatically size the plans so that all floors fit onto a single screen without scrolling on a standard desktop display. This approach works well for buildings with up to ten floors, which is the limit of our example datasets. Campus-wide analyses and cross-building comparisons (*[ZC,FC,BC]-**) necessitate a higher level of abstraction, as is provided by the data stripes.

Why not use exploded views (3D building model)? Exploded views [LACS08] are a common technique to visualize multiple floors of a building, particularly in architecture and interior design. We ruled out this option because of the myriad limitations of 3D visualizations. The side-by-side layout of 2D floor plans provides a bird's eye view on a building without occlusion.

Why circle symbols on top of floor plans? Our stakeholders strongly expected to see absolute numbers for device counts (*T2 Monitoring*). We did experiment with color-coding zones within floor plans as choropleths [YE14], which suffered from the known problems that small zones containing large absolute numbers were not salient. After several design iterations we chose superimposed circle symbols (size coded by radius), augmented with a numeric label, where the symbol can extend beyond the zone boundaries. The circle scale is automatically adjusted to the size of the largest zone in the building. This choice leaves open the future option of color-coding zones based on tags such as space types.

Why order regions according to floor plans (linearization)? When using data stripes as the selector in the Campus Explorer, the order of the stripes controls the order of the regions in the subset view, so they are completely divorced from any spatial context and stakeholders found it hard to reason about them (Supp. p. 51). In the Building Long-Term Interface, we devise an order for regions in the subset view that preserves important aspects of spatial contiguity within each building by **linearizing** a traversal of its floor plans, preserving floor-level structure and ensuring that spatially nearby zones are close to each other in the display (Supp. p. 58). Linear representations are often used to display multivariate data, particularly graphs, at scale [PGS*16; NGCL18]. Decisions between abstraction and spatial contiguity pervade many aspects of the Ocupado design and are primarily driven by scalability issues. Our stakeholders strongly signalled their comfort with and preference for using floor plans many times, but these cannot be the principal medium to disseminate all information because of the very limited spatial extent of each zone at building-level scales. While we can encode one or two numbers with circle symbols or glyphs, we cannot show the many data points contained within sparklines or line charts. Our linearization approach attempts to combine the benefits of both in a middle ground. We use a similar automatic sizing as above to fit all selected zones in a single screen.

Why modal windows? We use modal windows for region details instead of a focus+context technique [ZCPB11] to provide different perspectives, such as the floor layout and the zoomable time line, to not overwhelm users with too many linked views. The region selector and region subset view are shown side by side and a third layer, with region-level details, would subdivide the page layout even further. Seeing all levels of details within one multi-view visualization is not required for the given tasks. To guarantee fluent transitions, all the selections and display settings remain active until the user returns to the overview visualizations to continue the analysis.

7. Analysis Scenarios

We illustrate the capabilities of Ocupado in three analysis scenarios conducted by one of the authors using real data, based on themes that emerged repeatedly in sessions with stakeholders.

7.1. Data Quality Control

The most central task for our SBS collaborator is to identify inaccurate records and to analyze issues that affect data integrity (*T4 Validate*). In this scenario, an analyst uses all four Ocupado interfaces and is able to detect four types of quality issues:

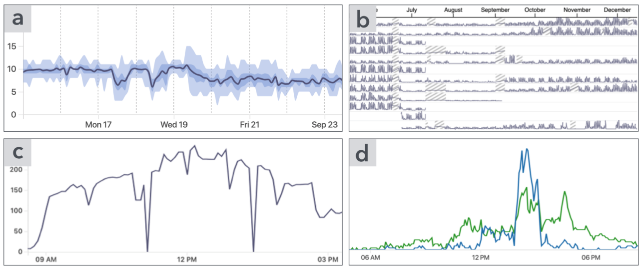

Figure 9: *Example quality issues: (a) static devices add noise; (b) sparklines uncover data gaps; (c) random sudden drops for single data points that are filtered out; (d) direct comparison of two regions confirms human observation that an event on floor leads to an increase of devices in adjacent floors.*

Static devices (e.g., printers) that are continuously sending signals. This problem was expected as one of the limitations of using WiFi counts as a proxy variable. The confidence-band line charts (subset view) and the zoomable timeline (detail) make the shifted baseline for device counts immediately visible, as shown in Fig. 9a.

Missing data records were also expected because the UBC campus is a test environment for the underlying Bridge data collection and preprocessing pipeline. Nevertheless, the duration and number of system outages was an important new insight surfaced by juxtaposed sparklines, shown in Fig. 9b, which provided a dense overview of the recording periods and outages of up to 40 buildings on one screen. The analyst uses the data stripes in the Campus Explorer to rank zones based on average device count in order to locate constantly empty regions (*ZC-All:R*, Supp. p. 89). All interfaces allow live monitoring and ensure early detection of any system failures.

Sudden drops are artifacts caused by the WiFi recording. The device count drops to zero for a single data point before it is up again at a normal level. This unexpected behavior is different from missing data values where nothing at all is recorded. This type of failure is particularly noticeable in the binned timeline, as shown in Fig. 9c. The overview visualizations conceal the drops due to the binning over the long recording periods. The analyst observes this issue in different zones across many buildings. To avoid confusion, new versions of Ocupado interfaces allow the interpolation of correct values by default [BFG*15].

Incorrect zone allocations were unexpected and pose a challenge for WiFi occupancy sensing. Inaccurate device coordinates and floor bleed-through —a large event on one floor results in a rapid increase of devices on the floor directly below or above— can lead to wrong inferences. Possible causes are triangulation problems because of a small number of WiFi routers, wall attenuations, and uncalibrated networks. This problem is difficult to debug without human observation to cross-check. Ocupado supports the analysis by displaying the actual device coordinates on floor plans for debugging. Analysts can immediately see if coordinates are plausible, for example, if they are within the floor plan boundaries. In the Region Comparison Interface, the analyst can compare multiple regions to investigate effects such as floor bleed-through

(*FB-Few:L**). Fig. 9d illustrates how a rapid increase in one room (blue) affected the device count in an adjacent room (green).

7.2. Recent Utilization Patterns

Custodial heads need to assign custodians to regions at the beginning of shifts, a recurring task (*T2 Monitoring*) with difficulties due to absences, one-off events, and other factors that influence the schedule. Custodial managers reported the prioritization of regions as an important task for custodial heads, where the scope is usually limited to one building at a time. The Building Recent Interface can be used to inform these decisions.

The analyst opens the interface and live activity of all zones in the Forest Science building is superimposed on floor plans, as shown in Fig. 1a (*ZB-All:SI*). Two major hotspots in the main floor stand out immediately. The left sidebar shows the device count during the last 12 hours aggregated per floor (*FB-All:SI*). A dashed line indicates how the utilization might change during the next three hours based on averages for that day of the week. They switch to *typical day* and notes that the device count in the first floor is much higher than usual at this time (*FB-All:LA*).

The analyst wants to know more about these two hotspots and selects *mean* instead of *live* in the menu bar (Supp. p. 64), and adjusts the time range slider. The symbols overlaid on floor plans now show the mean value during the selected time window and are updated automatically (*ZB-All:SA*). They ascertain that these two zones got busy recently and instead other zones on the same floor were occupied before and are empty now. In this case, custodians can be assigned to the empty zones.

7.3. Campus-Wide Situational Awareness

Cross-building analysis was required by some of our stakeholders and is supported by the Campus Explorer. For example, the question *What is going on around the campus?* (*T1 Confirm*, *[ZC,FC,BC]-*:S**) has been repeatedly articulated. Accompanying screenshots for this analysis scenario are in Supp. p. 82-87.

The analyst selects the *Campus, live overview* activity pattern from the control panel. The interface automatically sorts zones based on live activity in descending order, selects the top 70, and visualizes them in a spatial heatmap (*ZC-Few:SI*). The analyst runs this query on the weekend, and they are unsurprised to see high activity in NEST, a student union building. However, the high device counts in DMP are surprising in a building primarily used for lectures. In the control panel, they filter on DMP to exclude all other buildings (Supp. p. 85) and changes the view to superimposed line charts (*ZB-Few:LI*, Fig. 7d). Since each line denotes one day, clear patterns are not discernible due to the long (8-month) recording period. The analyst selects only weekends with the discrete time sessions menu, and sees five outlier days stand out from the other near-zero lines, seeing that occasional after-hours use does occur.

8. Related Work

We review relevant previous work on spatiotemporal visualizations in general, without trajectories in specific, and space usage.

8.1. General Spatiotemporal Data Visualization

Techniques to visualize time-oriented data have been well studied in recent years [AMST11; BLB*17]. Our more specific focus is on spatiotemporal data [AAB*09]. The many techniques to visualize geographical trajectory or origin-destination data include Flow Map Layout [PXYH05], Space Time Cubes [Kra03; DV10], or Flowstrates [BBBL11]. In contrast, the concern with Ocupado is on non-trajectory, event-based data. We facilitate the analysis and comparison of spatial regions across multiple temporal resolutions, not visualization of movements per se.

Visualization techniques for time series data are often applicable to scenarios that involve spatiotemporal data. Wijk's approach to visual time series clustering [VV99] provided inspiration for our superimposed line chart component (see Fig. 7d).

8.2. Non-Trajectory Spatiotemporal Data Visualization

Spatiotemporal datasets are often event-based and consist solely of geo-referenced timestamped items without trajectory information. Our data abstraction of location-based counts is one instance of such data, but in particular comes with guarantees that we collect data regularly from the same locations over time.

Kim et al. [KJW*18] proposed a flow extraction model based on kernel density estimation to visualize flow patterns without having an explicit notion of movement. In contrast, we do not attempt to reconstruct flows from the recorded location-based counts; our underlying data collection infrastructure was designed expressly to preclude such usage.

Many previous systems aggregate and visualize dynamic one-off locations, such as GPS coordinates that are assigned to social media posts [CTB*12] or crime incident reports [MRH*10]. Miranda et al. [MDL*17] defined the concept of an *urban pulse* to capture the spatiotemporal activity in a city based on geo-located Tweets and Flickr uploads. The goal of these systems is to identify and visualize geographical hotspots while our work is focused on counts from very specific indoor zones.

More closely related to our work are systems that visualize data that is collected regularly at the same spots, such as weather stations [VBA*12] or ocean observing systems [BDP08]. Oppermann et al. [OMS18] used linked views to visualize spatiotemporal changes in bike sharing networks based on station fill levels. These methods have temporal resolution restricted to predefined periods, and rely on large-scale geographic maps as their fundamental approach which is inappropriate for indoor spatial data. In contrast, our data model has a spatial hierarchy comprised of buildings, floors, and rooms, requiring an alternative approach.

8.3. Space Usage Visualization

Several studies specifically address the visual analysis of space usage. Ivanov et al. [IWSK07] proposed an occupancy detection system based on motion sensors and video cameras. In a side-by-side view, users can watch the video footage and analyze the recorded movements and occupancy. In recent years there has been a growing interest in visualizations of museum visitor flows [SSNS15;

MMF*17]. Kuutti et al. [KSS14] proposed a real time activity visualization in addition to a demand-controlled ventilation system. Occupancy is estimated via infrared sensors and overlaid on a floor plan to support live monitoring. Although these systems do inform about space occupancy in small regions, their primary mission is the analysis of movements; they do not support in-depth analysis of non-trajectory data.

Building management systems have been proposed that visualize occupancy to study energy-related behavior [PDB*18; CLHL17]. Most closely related to our approach is the work from Verbree et al. [VvdSK*15] who also worked with facility managers at a university to analyze usage patterns based on WiFi signals. They created a visualization dashboard as part of their study but the proof of concept is based on a 1-week time frame and a small number of rooms. Ocupado allows users to explore much larger-scale environments, with hundreds of zones and months of recordings.

Our collaboration partner SBS had an existing interactive interface for monitoring one single floor at a time. It did not support comparisons, extensive analyses, or any of the abstract tasks in full.

Google's popular times histogram [Goo19] helps users to estimate wait times.We use a similar technique in the Building Recent Interface to show per-floor usage for a typical day.

9. Discussion

We discuss granularity, feedback channels, and proxy measures.

Interfaces by Data Granularity. We implemented four interfaces each target different combinations of spatial and temporal data granularities. The same stakeholder might use different interfaces for different tasks but does not switch off between all four routinely. We originally envisioned interfaces tailored to each focus domain, but the process of data and task abstraction led us to realize that data granularity is a better grouping strategy than stakeholder domain. In particular, constraining the data dimensions allowed us to significantly reduce the complexity of the Building Long-Term, Building Recent, and Region Comparison Interface to increase ease of use.

Combining individual visualization components deemed to be effective into a holistic and deployable system, while maintaining a fluidity of use, is a challenging and often neglected endeavour in visualization design studies (see Pitfalls 24-25 in Design Study Methodology [SMM12]). We invested this level of engineering effort to achieve deployable software in hope of observing real-world use by our collaborator and third-party customers.

Multiple Feedback Channels. In an iterative process with multiple parallel stakeholders, comparable with the multiple channels of discourse by Wood et al. [WBD14], we discussed domain-specific questions, presented ideas, and gathered feedback over the course of more than two years. While we personally conducted interviews primarily with stakeholders on a university campus, the SBS CEO took the role of a *promoter* and made vigorous efforts to present Ocupado and to assess potential usage scenarios with external clients. In total, he gave 24 demos to potential stakeholders for whom direct contact with us was not feasible. This type of outreach resulted in a new feedback channel. Instead of directly attending or leading demos, we received high-level informal feedback from our industry partner. Although the feedback was filtered and summarized, it was actively useful in the core design and implementation stages. Despite the potential limitations that an intermediary could mischaracterize actual needs, we found that the additional feedback channel provided valuable insights. This *promoter* role may be a useful addition to the other design study methodology roles identified in previous work [SMM12].

Closely related is the use of Ocupado by SBS and Cisco's Innovation Centre to *showcase* their back-end data collection pipeline on live data. While the human-in-the-loop occupancy analysis is just one possible use case for their product, they decided to use Ocupado extensively to demonstrate their technology in a real-world setting. This non-analytical task was unexpected but an additional validation of the effectiveness of our visualization design.

Proxy Measures are often required to stand in for variables that cannot be directly measured or if the acquisition is prohibitively expensive; the choice to use them is part of the *operationalization* process [FM17]. We conjectured that using WiFi devices as a proxy for human occupancy would be good enough for some use cases but exclude others. Initial talks with potential stakeholders confirmed this assumption. The major threat with proxy measures is a lack of correlation with the variable of interest that would entice analysts to draw wrong conclusions. Previous studies [BXN*13; OIAS17] ascertained that WiFi counts can estimate occupancy with a relatively high degree of accuracy and laid the groundwork for Ocupado. In addition to stating that the visualizations show device counts and not head counts, we deliberately chose not to visualize headcount capacity limits in rooms to remove the temptation of direct comparisons. Nevertheless, we ourselves sometimes fell prey to confusion on this front, so it may remain a hazard for users.

A useful area for future work would be a dynamic, data-driven estimate of the headcount-devicecount ratio suitable for a specific context. A single static formula would not suffice, since the number of logged WiFi devices per person may vary dramatically; further data analysis using Ocupado could inform future studies.

10. Conclusion

The Ocupado visual decision-support tools show space usage patterns with a privacy-preserving architecture based on location-based counts to support analysis across several hundred zones in dozens of buildings. Interviews and feedback from many stakeholder domains engaged in facilities planning and operations were incorporated into data and task abstractions, exposing the need for visualization interfaces that support flexible combinations of data granularities in both space and time. We contributed generalizable design rationales to visualize non-trajectory spatiotemporal data related to indoor environments and discussed the adoption of Ocupado by our industry collaborator.

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