

Adapting Wind Map Principles to Urban Transportation Flow

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ABSTRACT

City planners require an effective visualization of urban transportation flow as both a problem-solving and communication tool. However, there are limitations over existing representation of migration flow across transportation networks. In this paper, we propose adapting wind map principles to the new domain of urban transportation flow, by creating new encodings and developing both static and dynamic flow visualizations for the CitiBike NYC dataset. We test the effectiveness of our visualization by collecting a qualitative evaluation of our novel visualization against a baseline evaluation of the control's migration tables. We discuss how our visualization allows a more intuitive, high-level overview of the data and describe the differences in how novices and experts in the transportation field interpret the encodings, data, and make decisions based on our novel visualization.

Author Keywords

Data visualizations; wind maps; city planning; urban transportation; bike networks; flow of people

ACM Classification Keywords

H.5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous.

INTRODUCTION

In the realm of transportation, a visualization is defined as “any progressive means of representing static or temporal spatial and geometric information” [9]. One such type of visualization aims to represent people or migration flows across transportation networks, like subway or bus networks in urban areas. The typical description of migration comes in the form of an array of estimated numbers giving the quantity of movement between known areas. In this paper, we investigate a graphical approach to geographical movement along networks, which adapts the principles found in wind maps to the problem space of urban transportation.

BACKGROUND

City Planner Goals

The former definition of visualization is limited in many respects. In the context of the field of planning of urban environments, however, this definition's problems become much more tangible. At the core of the issue is that this definition, beyond representing a type of data, does not account for the purpose of the representation. In creating a new graphical approach, this aspect is central to our design.

Visualizations in the planner's context is both a problem-solving tool and a communication tool to various stakeholders. Indeed, visualizations allow planners to “communicate problem-solving concepts to the public,” because if the public is unable to understand the planner's vision, convincing them of the necessary financial investment is difficult [9]. Hence, although visualizations are often applied on the project-level, they become useful in many other areas from formation of programs to demonstration of benefits. As such, a visualization must be interpretable by a wide variety of stakeholders and perspectives, facilitating collaborative planning. This aspect of a visualization has numerous benefits beyond better communication, such as earlier identification of problems and objections, better informed decisions that meet a variety of project goals, more buy-in and less resistance [9]. In this way, visualizations must balance expressive power through rigorous rules and processes known by planners and still aid understanding without increasing complexity or confusion [4].

Given this revised purpose-driven definition, we must now return to a short discussion of the form of the visualization that allows to deliver on these goals. Firstly, it is credibility of the visualization that is the greatest impediment to its success as a tool for collaboration. For example, ‘technical stunts’ may wow an audience but make the medium of presentation take on more importance for the audience than the project. Secondly, there are key characteristics that increase the quality of a visualization, including interactivity, context and practicality. For example, interactivity may give users control over what-if scenarios, context may show recognizable landmarks and practicality refers to the use of proven technology.

Applying this to the problem of geographical movement across urban transportation networks, we are able to more clearly delineate the dual purpose of a visualization in this space.

1. Maximize efficiency in the transportation network by better identifying
 1. Flow at different times
 2. Areas where congestion occurs
 3. Flow at different spatial resolutions
 4. How users adapt to changes in the network (i.e. construction)

5. Opportunities for change (higher capacity, different schedule, new route)
2. Demonstrate inputs for decision-making to stakeholders and influence them

Wind Map Principles

The problem of geographical movement across urban networks is one of flow visualization. In speaking of migration, we often use hydrodynamic terms -- an indication that wind map principles may be a powerful means to depict migration [8]. Specifically, wind maps represent the two dimensions of wind direction and wind speed superimposed on a visualized geography.

Wind maps first appeared in 1656, when Edmond Halley sketched wind patterns on top of a geographical map of the Earth, as seen in Figure 1 [3]. In this static wind account, Halley was imparting upon his readers the surprising dangerousness of certain winds across the world using streamlines. Today, static wind maps like Halley's have evolved for a more specialized audience; thus, interpreting these maps is a learned process. Indeed, today, professional wind visualizations instead show wind speed and direction using a glyph called a wind barb in a grid pattern. This is because, although streamlines better represent flow patterns, these methods are lacking in accurately representing wind speed [7]. As researchers in the transportation space, visualizations must balance pattern-identification (Goals 1a-e) and presentation to stakeholders (Goal 2).



Figure 1. Edmond Halley's historical account of trade winds; pictures is the South American Atlantic Ocean

A central need expressed by city planners is understanding changes in flow across the network temporally. A static map, for this purpose, is limited. At this juncture, we decided to consider how dynamic wind map principles, which use streamlines instead of glyphs, could be adapted to our use case. In dynamic maps, we return to Halley's elegant pen strokes to encode wind direction and speed. More precisely, these repeated pen strokes are called equally-sized vector lines. Direction is operationalized using the angle of the vector, oriented to the flow. However, direction remains ambiguous, and so the front of vector lines is sometimes blunted (as in Halley's diagrams), lines are otherwise given arrowheads or the tails lines fade to

transparency. Wind speed (or strength), on the other hand, has been operationalized in a variety of ways. In glyph-based visualizations, length of the glyph encodes speed [2]. In streamline-based visualization, vector lines are used and it is density or closeness of vectors that encodes wind intensity. As we will discuss soon, we adopt this latter convention for its ease of interpretation off-the-shelf.

Population Flow in Urban Transportation

Understanding geographical movement is critically important in a wide range of areas, from movement of money to material. Here, we focus on the movement of people and visualizations that have gained popularity in the past. This space has become more and more active with more widespread availability of low-cost GPS devices and an ability to analyze large datasets [1]. Integral to these datasets is an underlying structure; the key to visualizing movement of people is to first understand the network. What is the collection of nodes? How are the nodes connected? A transportation network is a collection of nodes and adjoining branches defining connections, where the connection simulate flow from one node (origin) to another (destination).

In the field, migration tables are often used to describe these relationships. Migration tables are matrices where each (i, j) cell is the movement of people exiting node i and arriving at node j, where i and j are nodes or locations. This kind of table can be seen in Figure 2. This type of graphical analysis produces cumulative movement, or the total number of people people from one node to another at a certain time period. As a result of this cumulative nature, they do not reflect the temporal dimension of movement data [1]. In order to tackle this temporal nature, space-time cubes have been used to visualize movement data [5]. The base of the cube represents geography (along the x- and y-axis) and the cube's height (z-axis) represents time. This solution, now, takes care of the temporal aspect of movement, but unlike migration tables, cannot effectively take into account multiple types of routes. For example, in Figure 3, the blue lines describe a single route; if one were to add multiple routes to this cube, the information quality would dilute greatly. As such, we require a visualization that is able to tackle a greater number of routes and cumulative data on a temporal scale.

Stations	1	2
1	0	5
2	2	0

Figure 2. An example migration table for two stations showing cumulative travel data during one day. In this network, no travelers travel to the same station they leave from; 5 travelers leave from station 1 to station 2.

In the context of an urban transportation network, the concept of congestion is important to understanding how to increase efficiency, informing decision-making.

Overwhelmingly, applications aimed at congestion estimation use color to describe congestion intensity [6]. This has reached main-stream usage with Google Maps' traffic layer, where different levels of congestion are calculated and designated with green, yellow and red, corresponding to normal, medium, high congestion. Depending on the network type, it may be that nodes are congested, whereas in other types (driving data on Google Maps), edges are congested instead. These details must be adapted to the network type.

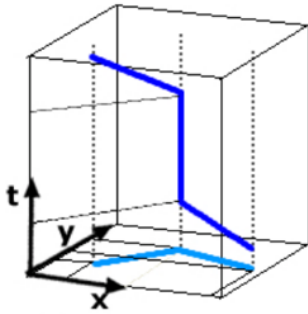


Figure 3. A space-time cube mapping the time it takes (on the z-axis) for an entity to travel the path on the x-y plane.

NEW VISUALIZATION DESIGN

Static Flow Visualization

With knowledge of city planner goals, the prevalent characteristics of wind maps and the available solutions and thus gaps in movement flow visualization for transportation, we were able to more effectively adapt wind maps to our problem space.

Let us first translate wind direction and wind speed into transportation-relevant terms. Wind direction refers to the path taken by a traveller along one or more edges of a graph, called travel path. Wind speed refers to the number of people traveling along the edge of a graph, path density. In Figure 3, we observe Halley's pen strokes from Figure 1's map; these will act as the basis of our visualization. Just as Halley makes use of equally-sized vector lines, we adopt this convention.

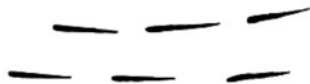


Figure 3. Pen strokes from Edmond Halley (1686) which represent trade winds; they are of roughly equal length and utilize front-blunting to indicate direction.

Now, we adapt wind map characteristics, as described before, to our use-case. In this section, we determine encodings for the following characteristics:

- Travel path and bidirectionality (edges traveled and order traveled in)
- Path density (number of people traveling on a given edge)
- Congestion (comparison of edge/node capacity and number of travelers)
- Travel time (the speed at which people travel an edge)

Travel path, then, is encoded using these equally-sized vector lines. However, like in the case of wind maps, we must also disambiguate direction -- and we choose to fade the vector tails to transparency to indicate forward motion. Unlike wind maps, travel paths within transportation networks can be bidirectional. In order to disambiguate these two directions (or edges) connecting two distinct nodes, we make use of spacing. For two nodes i and j , if there are travelers going in both directions between the nodes, then two 'columns' of vector lines, each traveling in different directions, are present. Path density, or the number of people traveling on a given edge, is encoded using the number of vector lines; the more people using an edge, the more vector lines are used. The denser the path, the busier it is. Note that the flow of different edges (the number of vector lines) may be combined visually depending on the spatial resolution chosen. Congestion is a more complex matter whose representation depends on the transportation network being visualized; as mentioned before, some networks experience congestion on the edges whereas others experience it at the node-level. For the purpose of an experiment, we explore node-level congestion using different shades of red.

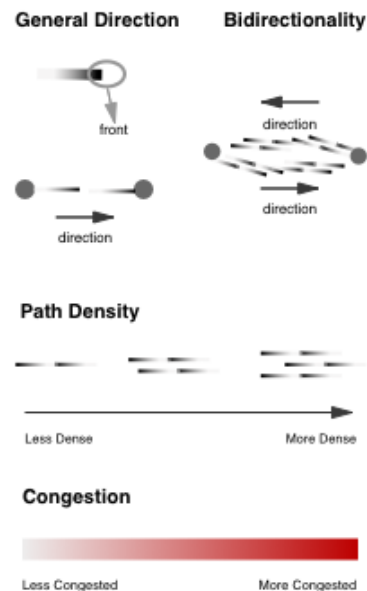


Figure 4. Encodings for the wind-map inspired movement flow visualization for transportation. In

order: general direction, bidirectionality, path density, congestion.



Figure 6. Our static novel visualization, presented to participants describing flow of bikers for a set of bike stations in the Citi New York City bicycle network for the Wednesday 8:30AM to 11:30AM in July 2013 time bracket.

We also take great care to apply the success factors described previously. In our visualizations, for example, we took care to make context clear by highlighting station nodes. We also setup the graphical network using an exact spatial mapping, because planners make use of real-world space to make decisions.

Dynamic Flow Visualization

So far, the description of the visualization encodings allow it to exist statically, representing data for a single time bracket. However, just like migration tables lack a temporal aspect, this visualization requires dynamic functionality in order to represent changes in travel path, path density, congestion and the characteristic yet to be encoded, travel time.

In the dynamic version of our flow visualization, time is split up into very small discrete units. For every time unit, the state of the transportation flow system is updated as per the underlying data. For example, if more people start traveling westward, then travel density on westward travel paths change dynamically to represent these updated states. Here, we take advantage of vector lines natural affordance; indeed, they can be made to move across the map geography fluidly to represent the movement of people, just as dynamic wind maps do. This dynamic aspect, then, allows us to fill in this required temporal aspect and to also encode travel time. Travel time between two nodes is encoded by speeding up the movement of the vector line across the edge.

RESEARCH QUESTION

Using the flow visualizations described, we wish to investigate the effectiveness of the system. Effectiveness, in our case, looks at three main goals relating to the original purpose of the visualization.

1. Encodings must be easily interpretable by an expert
2. Encodings must be easily interpretable by a novice
3. Data must facilitate decision-making
4. Decisions made must be easily presented and rationalized for an audience

In comparison to other available flow visualizations, it is our belief that our system will perform well, especially when the data needed to be interpreted are large in size. In the remaining parts of this paper, we test whether the described visualization performs better than existing flow visualization tools like migration tables.

Departure Station/ Arrival Station	Broadway & W 49 St	Broadway & W 51 St	Broadway & W 55 St	Central Park S & 6 Ave
Broadway & W 49 St	5	2	3	2
Broadway & W 51 St	8	2	3	4
Broadway & W 55 St	10	8	8	2
Central Park S & 6 Ave	2	3	1	3

Figure 5. A segment of the migration table, presented to participants, describing flow of bikers for a set of bike stations in the Citi New York City bicycle network for Wednesdays 8:30AM to 11:30AM in July 2013.

METHOD

To address our research goals, understanding the effectiveness of our novel visualization in terms of the highlighted purposes, we studied experts and novices in the field of transportation. We released two surveys, a control and experimental versions, which tested three core ideas: interpretation, decision-making and explanation. The control survey presented participants with migration tables as seen in Figure 5, currently being used in practice for

smaller datasets; the experimental survey presented participants our novel visualization, as seen in Figure 6. Both visualizations are an equal representation of data in Citi's New York City Biking transportation network, but presented in two different forms. As such, our surveys offer a qualitative evaluation of the novel visualization using migration tables as a baseline performance metric.

Participants

We ran a total of 11 participants, 5 of whom participated in the control and 6 who participated in the experimental survey. Of the 11 participants, all had varying experiences with transportation data. We released the survey to a company in the Czech Republic called *Leo Express*, which runs a network of buses and trains in the Central European region. A majority of participants worked in the field and had relative fluency and experience dealing with this kind of data.

Experimental Conditions

Participants were randomly assigned to either the control or experimental surveys, where the control presented data using migration tables and the experimental presented the same data via our novel visualization. Each survey has similar experience distributions. In this way, this was a between subjects design, thus avoiding the carryover effects that may have occurred in a within subjects design.

Procedure

Participants, both experts and relative novices, were randomly assigned to a control or experimental survey. In this survey, participants were presented with a visualization of fabricated data from *Citi Bike*, New York City's on-the-go rental biking network. Participants analyzed visualizations that represent average flow using aggregate data from Wednesdays in July 2013 in the 8:30AM to 11:30AM time bracket. The survey was split up into multiple areas each testing previously-articulated goals. The areas are as follows:

1. Interpretation of visualization encodings
2. Interpretation of flow data
3. Decision-making based on flow data
4. Presenting rationalization for a decision

The first section asked participants to 'learn' the visualization via multiple-answer questions. For each encoding (direction, number of people, congestion, speed), participants could select a series of pre-made responses. The following three areas tested both our static and 'dynamic' visualization on the grounds of data-interpretation, decision-making and presentation. A 'dynamic' visualization, in this case, is a set of two static visualizations which show flow changes across the geography: one for the 8:30AM to 11:30AM time bracket and one covering the 11:30AM to 2:30PM time bracket. More specifically, the second section asked participants to interpret flow data; for example, we asked participants which was the busiest station and how flow changes through various stations. In the combined third and fourth

section, we explore decision-making, asking participants to choose where to increase the capacity of a station and where to add a station -- both activities a planner would need to consider in the face of congestion -- and to explain their rationale.

At the end, we asked respondents to describe their professional interactions with transportation data, the perceived purpose of the visualization they evaluated, perceived needed additional features and their experience answering the questions in terms of difficulty.

RESULTS

From our aforementioned experimental design, our aim was to collect a qualitative evaluation of our novel visualization against a baseline evaluation of the control's migration tables. An initial analysis of results showed that participants' responses were shorter than expected, as such, it is more difficult to draw conclusive results from sections 2 and 4. A first pass over the results, however, reveal a widely differing approach to flow data between control and experimental participants. Here, we will dive into those results per section, making note of the differences for novice and experts concurrently.

Interpreting Visualization Encodings

The first step for participants was to interpret the visualizations' encodings. Respondents were able to identify the correct encodings at a high rate of success. This rate of success was higher (100% for all questions except one) for the control's migration table - which is testament to the simplicity of the data representation -- there is no symbolic processing to be done by participants. Migration tables only presented challenges in representing congestion; it was less clear what the relationship between station capacity and flow was to create an equation for congestion. For our novel representation, there was significantly more symbolic processing to be done, and as such, the rate of error was higher. Questions were set up to sometimes have multiple correct answers, but across the board, participants were not able to successfully notice this. For example, the corresponding congestion question in the experimental version provided two correct answers but only one out of six (16%) respondents correctly identified this. In the following section, we will discuss our survey design choices further. Moreover, one respondent incorrectly stated that length encoded speed although speed was not represented. Interestingly, a novice versus expert analysis showed there was no difference in ability to interpret encodings.

Interpreting Flow Data

In this section, the survey asked participants to record which station was the busiest, whether it was a sink or source, change of flow in a specific station and change of flow in the network itself. For station-specific questions, performance was roughly the same across the control and experimental versions. Most participants interpreted "busiest" to mean highest traffic flow (5 of 6 in experimental; 5 of 5 in control), and as such, disregarded congestion information. Thus, they were able to identify that West 56th Street and 6th Avenue has the most traffic

flow. Identifying change of flow in the station itself was successful in both versions (100% correct answers). However, the quality of answers identifying change of flow in the network itself (collective of all stations) using the ‘dynamic’ visualizations was much higher in the experimental version. In the experimental version, participants made greater allusion to interactions between stations and geographies (“North”, “West”); in the control version, change of flow was limited to station-specific comments. A novice versus expert analysis showed there was no difference in ability to interpret flow data (except for a network-wide analysis, where a novice had more difficulty describing flow change).

City Planning Decisions

In this section, we asked participants to make increase the capacity of a station and add a station to the network. This is where the experimental version outdid the control in the most marked manner.

Let us first discuss the experimental version. In deciding where to add capacity, responses were varied but once again took advantage of proximity data seen thanks to map data; for example, one participant noted the limited capacity of one station (Central Park South & 6th Avenue) whose use was currently limited but was next to a highly congested station. For the additional station decision, all 6 participants in the experimental version noticed that there was an underserved area where flow source was concentrated and three congested stations were located, as seen in Figure 7. These two positive results are indeed the most striking of our investigation.

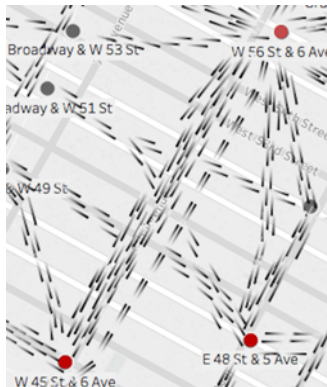


Figure 7. An underserved area of the map in between three congested stations, mapped on the experimental novel visualization.

The control version, on the other hand, had more mixed results. In deciding where to add capacity, responses were more consistent and proposed new bikes at congested areas (in both the static and dynamic cases). In fact, in deciding where to add a new station, responses were overlapping -- often suggesting added capacity and a new station at and near West 56th Street and 6th Avenue (3 of 5 responses). This, however, is not the most optimal solution. As will be discussed in the next section, this result suggests that

context (geographical, in this case) is important to making decisions.

Once again, a novice versus expert analysis showed there was no difference in ability to make decisions for an updated network.

Presenting Information

Throughout sections 2 to 4, participants were asked to submit reasoning for their responses. Results for this goal are less evident because responses were in most cases quite short, and in some cases, limited to less than five words. However, one striking result occurred in section 3. Rationalizations of decision-making in the control version made greater use of underlying data and alluded to single station statistics; rationalizations in the experimental versions made greater use of interactions across stations in the network, using a higher-level analysis.

DISCUSSION

Survey Format Downfalls

Our team pursued a qualitative research study using an online survey format. In this survey, participants were asked to answer multiple-choice and short-answer questions. However, there were unexpected effects of using this format. Firstly, despite being instructed of this, participants did not seem aware that questions could have more than one multiple-choice answer. Secondly, short-answer responses were typically very short, making it difficult for us to develop conclusions about presentation of information. In this way, an online survey may not have been the best format for this research study. Instead, a guided in-person interview may have produced more substantial data for our team to analyze.

Novice vs. Expert Ability

One of the goals of our novel visualization was to facilitate flow understanding for many stakeholders, including both experts and novices. Of our 11 participants, 7 had experience with transportation data (at least 6 out of 10 on a scale). However, we were surprised to see that ability to interpret encodings and flow data did not differ for novices. Although this kind of conclusion is difficult to make given our small sample size, it remains a surprising finding.

However, we expected to see differences between novices and experts when it came to decision-making. However, even then, there was no difference. In analyzing difficulty level experienced for the survey, most participants reported that the survey was moderately easy (5 out of 10) across both experimental conditions. Our team believes that the scenarios presented to the participants, as represented by data in the visualizations, made answers evident. For example, one of the stations had a much greater amount of traffic than others. As seen in Figure 7, correct answers existed.

Interpreting Flow Data via Context

Beyond the reasoning above to explain no novice to expert differences, we also decided to explore what factors shape data interpretation ability in the context of urban flow, and perhaps how this can inform this novice versus expert

discussion. Interpreting information is based on several factors, including:

1. Comfort with visualization types in the space
2. Comfort with the underlying geography
3. Comfort with the nature of the data (type of transportation network)

The first and second factors are the ones which shapes novice versus expert ability. In the previous section, we argued that relative ease of our questions made the novice/expert distinction unpronounced, thus eliminating the influence of both these factors. For example, for factor 1, there was no real learning curve for both the control and experimental visualizations; for factor 3, clear-cut data facilitated question answering.

This leaves us with the second factor, which describes how understanding of the underlying geography can aid understanding. Walker claims that “[including] the existing context—that is, the present-day landscape, corridors, and buildings in the project area—to help the viewer orient to the scene and build a mental connection between the model and the real world” can be a powerful aid [9]. The experimental visualization’s use of context is evident; it superimposes data on top of a geographical map of New York City; the control, on the other hand, requires participants to go through the extra step of mentally (or otherwise) plotting data from the migration table onto a map. As a result of this, we observed that participants in the experimental version could better interpret network-wide flow. This finding highlights how important context can be to understanding flow, since flow is an inherently fluid, transitive, geographically interactive phenomenon.

Decision-Making Facilitated by Context

In the same vein as the interpretation of data, we expected there to be a gulf in ability to make the ‘right’ decisions between novices and experts. This was not the case, and this was once again as a result of reduced influence of factor 1 and 3. Instead, it seems factor 2 influenced the result the most once more, as seen by the novel visualization’s superior performance in this survey section. As revealed in our results, the experimental visualization facilitated the identification of the correct answers.

For the additional capacity question, the experimental versions had a wider variety of responses; the control had the same responses. The additional capacity question did not have a clear-cut answer, and so these results are striking. This shows us that the experimental visualization does not only map number of travelers but also effectively maps the connections between stations -- in a geographically contextualized manner. This gives participants the ability to come to more responses, and allows for creativity to be applied. With more information, you are empowered to produce better responses. Moreover, 4 of 6 participants noted the “red” stations in their answer, showing how a simple congestion encoding can act as a substantial aid. On the other hand, control responses were homogenous, indicating that as a result of lack of

geographical context, participants focused on where congestion was currently occurring. Lack of context, then, limits divergent thinking.

For the additional station question, the experimental version once again performed well. A map-based visualization reveals which geographic location had most traffic, congestion and a station-vacuum. This, as seen in Figure 7, is in between 3 main congested stations. Although control and experimental answers were similar (added station near West 56th Street/6th Avenue), the rationalization for this response was different for each experimental condition.

In general, the quality of decisions is more accurate for the map-based visualizations. Participants have a better higher-level overview of what is happening. As a result, flow understanding on the global geography was made easier with the wind-map because there isn’t an extra step required for users to plot/associate numbers to the map of New York. Moreover, congestion colors are helpful and created the biggest difference in understanding traffic.

Rationalization Differences

Although the survey format limited our ability to make substantial conclusions in this arena, as a result of shortened answers, it is clear to us that the form of the visualization impacts the way that participants rationalize and therefore present their conclusions. This, of course, is understandable. So, as reviewed in the results section, the experimental condition produced more rationalizations alluding to interactions between stations (i.e. clusters) whereas the control condition produced more rationalizations with numerical data specific to single stations and not interactions. Again, this makes sense given the nature of the visualizations. In migration tables, you make much greater reference to underlying data; it is more specific to one station. In the experimental visualization, you do not — instead you make use of more higher-level interactions between geographies. Interestingly, from our feedback form, we found that some participants in the experimental condition would have preferred to have greater access to the underlying data. This, however, should be done in a balanced manner. Walker notes that “engineers often want to include details... to illustrate diligence and depth of understanding, and to convey the most information possible.” Instead, a lot of time should be invested into “placing priority on objects that are material to the discussion” [9].

PROTOTYPE

The prototype of the dynamic, interactive visualization can be seen [here](#). It uses Citibike trip data from February 2014 to show the movement of people through time. When the visualization is played, lines are drawn from the start to stop locations indicating each rider’s overall direction of travel. The paths are drawn as straight lines from the start to end locations, as the dataset does not contain the actual path the rider took. The visualization moves through time, incrementing in 15-minute intervals, to show how ridership changes through the day. We used d3 geo libraries to build a street map of New York City and display the locations and

movement on top of the map. This prototype was a first step for us plotting data dynamically and interactively; although it does not use the encodings of our novel visualization, it is a proof of concept on which to continue building.



Figure 7. An image of the dynamic prototype displaying movement of Citibike users in NYC at 12:45 AM.

FUTURE WORK

Much work can be done to further the work begun on the prototype, including work on improving encodings, adding more contextual information, and adding additional features. Taking into consideration the results from our survey, we can encode congestion, which is currently not shown in our dynamic prototype. Additional helpful features, such as a slider so the user can manually scrub through different time periods, could also be implemented. Because of the feedback from transportation experts wanting the capability to focus in on a particular section, but also see all the data as a whole, creating a zooming feature which would display different levels of information depending on the scale, would be a necessary future step.

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