Understanding the Dynamics of Timeliness: A Data-Driven Approach to Daily Commutes

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Understanding Timeliness

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University students in Calgary often move between lectures, social events, and home across a large city, usually under time pressure. All of us have experienced showing up late and only afterwards trying to guess why. Was it traffic, a slow bus, poor planning, weather, mood, or just bad luck? It is rare that anyone actually measures those patterns over time.

For this project, our group collected a shared dataset of our real commutes over several weeks. For each qualifying trip, we recorded:

- When it happened (date).
- What the trip was for (activities include Appointment, Errand, Exams, Home, Lecture, Social, Study, or Tutorial).
- How we travelled via primary and secondary modes (if used) with fixed categories of Bike, Bus, Drove, Train, and Walk.
- What time we wanted to arrive and what time we actually arrived.
- How we felt (mood) and what the environmental conditions were like (weather).

Each member logged trips that had a meaningful destination and a desired arrival time, such as getting to class, a meeting, or a social event. We did not include tiny intra-campus movements or random short walks where punctuality is not meaningful. Entries were recorded on the same day in a shared spreadsheet, using a 24-hour time format and consistent attributes with a fixed list aof categories where necessary.

Our main goal was to understand timeliness in a more objective way. Instead of saying a commute was “bad” or “fine,” we wanted to see how many minutes late or early we actually were, and how that relates to mode of transport, activity type, and mood. We also wanted the final dashboard to be something we ourselves would actually use as a personal “punctuality mirror,” not just a static class assignment.

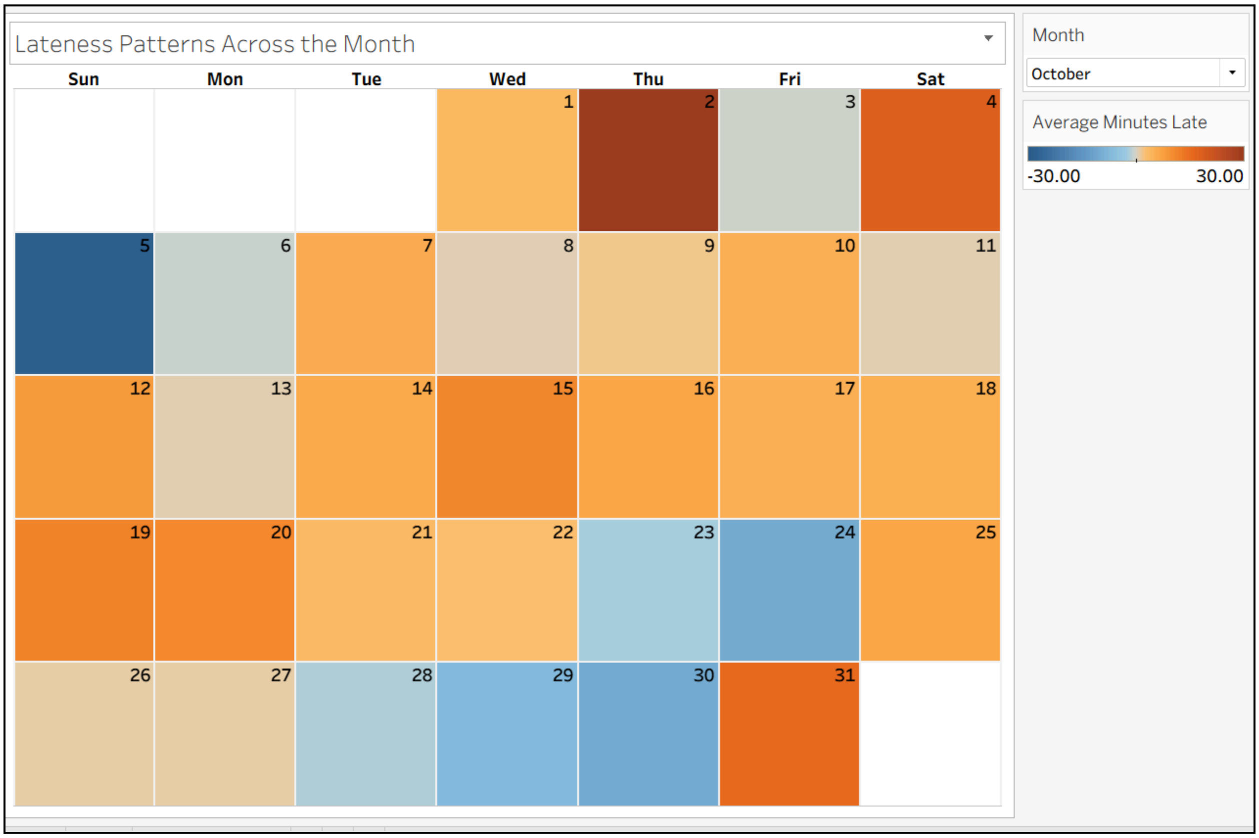
From our proposal and preliminary discussions, we focused on answering the following questions within our visualizations:

1. For which activity types is lateness more socially acceptable?
2. Does our general mood beforehand during our commute affect our timeliness?
3. Do different transport modes help or hurt our ability to hit our planned arrival times?
4. Are we typically earlier or later on specific days of the week?
5. Does the scheduled time of an activity affect how likely we are to be on time?
6. At a high level, what practical recommendations would we give a student who wants to be more on time?

The final dashboard brings together each team member’s visualization into one place so that users can switch between high-level patterns and detailed examples of individual commutes.

Visualizations

Visual 1: Calendar Heatmap



Questions

The calendar heatmap was created to examine broader patterns in punctuality across the dataset. The key questions guiding its design included:

1. Which days in each month exhibit the most severe lateness?
2. Are weekdays associated with greater lateness than weekends?
3. Do clusters of high or low punctuality emerge within specific weeks of the month?
4. How does lateness vary at a month-level compared to individual trip-level variation?

These questions emphasized the need to summarize commute performance at a daily level to reveal broader patterns of lateness across the month.

Description

The calendar heatmap displays each day of a month as a single square, with color encoding the aggregated *Minutes Late* value for that date. A diverging palette ranging from blue (early arrival) to orange (late arrival) is applied. The color scale is fixed across all months using a range of -30 to +30. This consistency allows month-to-month comparisons and prevents the misleading shifts that occur when colors auto-adjust per sheet.

Day numbers are displayed as labels inside each square, and tooltips provide additional details of *Average Minutes Late* and the *Total Number of Commutes* recorded on that day. This design makes it easy to see how punctuality varies throughout the month. Clusters of late or early days become visible, and it is straightforward to compare weekdays with weekends or notice outlier dates. The heatmap provides a clear month-level overview while still allowing viewers to inspect specific days when needed.

Implementation

The visualization was implemented in Tableau. The *Minutes Late* variable was precomputed in Excel using the expression `(Desired Arrival Time - Arrival Time) x 1440`, which converts Excel's day-time difference into minutes. Because Excel stores times as proportions of a 24-hour day, subtracting the two fields produces a fractional value, and multiplying by 1440 converts that into a minutes measure.

In Tableau, the heatmap was constructed by placing `WEEKDAY(Date)` on Columns and `WEEK(Date)` on Rows, producing the familiar calendar layout. The Marks were set to *Square*, with *Minutes Late* assigned to *Color* using a diverging palette set to a range of -30 to +30. The day number was displayed by creating a calculated field called *Day Number* with the expression `MIN(DAY([Date]))` on Label. Minor formatting adjustments were made to reflect a traditional monthly calendar layout.

<u>Design Decisions</u>

1. Week/Weekday Calendar Grid Layout

   The heatmap was arranged in a WEEK-by-WEEKDAY grid to match the structure of a typical calendar. Using this layout makes the visualization quick to understand and supports natural day-to-day comparisons. It would make it easy to detect recurring patterns tied to specific weekdays, such as consistently late Mondays, and it also would highlight weekly clusters where several consecutive days share similar lateness levels. A linear table or a single list of dates would not reveal weekly patterns in the same way. The grid format, combined with color encoding, creates a compact and intuitive view of punctuality over time.

2. Enhanced Tooltip Design for Contextual Insight

   The tooltip was intentionally expanded to provide several pieces of contextual information that are not directly visible on the heatmap. Each day's tooltip includes (1) the *Number of Commutes* recorded for that date and (2) the computed average *Minutes*

Late for that day. The count metric is crucial, because a day with six commutes should not be interpreted the same way as a day with only one. The tooltip allows the daily average to remain visually central while still giving the viewer a clear understanding of how much data contributed to the color. This approach avoids cluttering the square itself with excessive labels, but still delivers essential detail on demand. It supports more informed interpretations without sacrificing visual clarity.

3. Aggregation of Minutes Late at the Daily Level

   A deliberate choice was made to aggregate *Minutes Late* at the day level rather than represent every individual commute directly on the calendar. Averaging the values for each date provides a stable indicator of overall punctuality for that day and situations where a single extreme trip visually dominates the interpretation of that square. It also makes it possible to compare days fairly, even when the number of commutes varies. Without this step, days with many entries would appear disproportionately "important" relative to days with only one or two commutes. By summarizing each date into a single value, the heatmap communicates daily performance in a balanced manner.

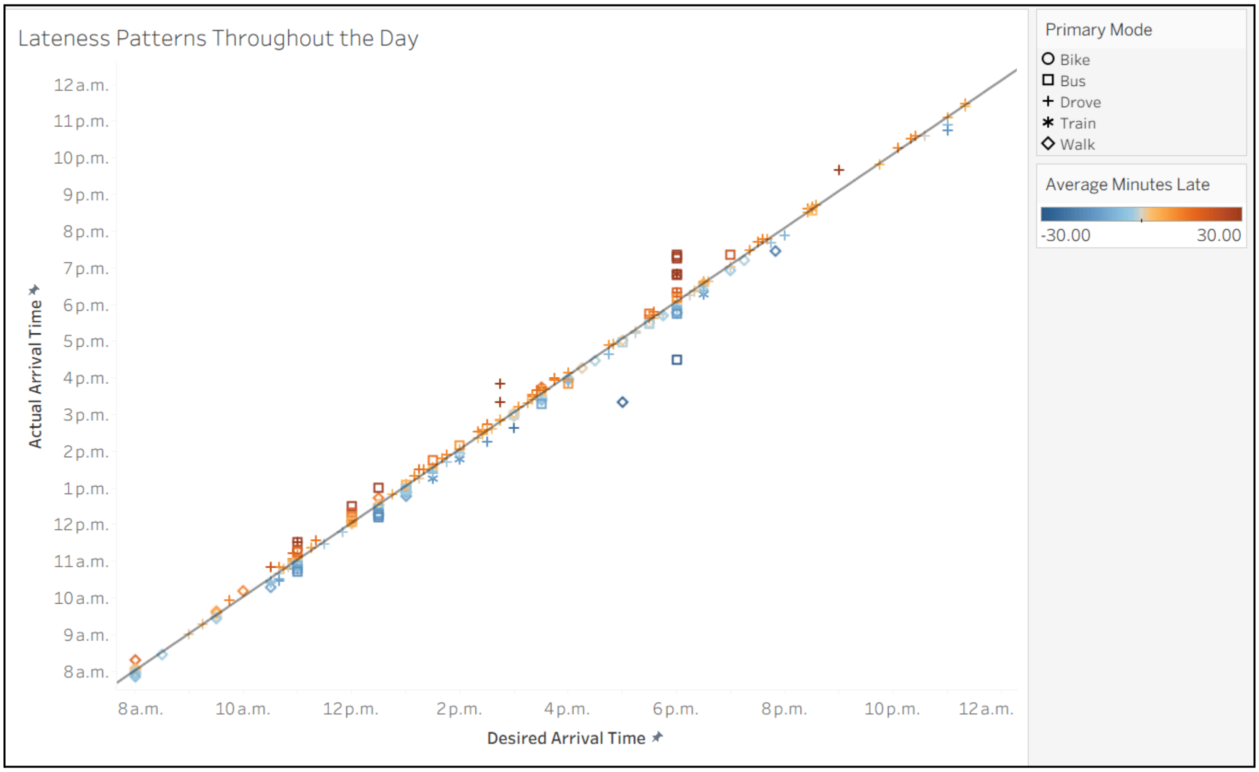
<u>Reflection</u>

The calendar heatmap provided a clear month-level summary of punctuality across the dataset. It highlights stretches of consistently early or late arrivals, exposes differences between weekdays and weekends, and makes it easy to compare how punctuality shifted from week to week. Although this was the goal of the visualization, we actually discovered that the day of the week was not a major contributor to the overall timeliness, but still had value to show. At the same time, the heatmap has natural limitations. It does not display individual trip-level behaviour, differences across transport modes, or the timing precision captured in the scatterplot. The visualization is best suited for broader trends and relies on complementary views for detailed explanations.

During development, weather was evaluated as a potential attribute. If the dataset had contained extreme fluctuations such as temperature swings, snowstorms, or weather-related transit disruptions, the calendar would have been an appropriate place to show how external conditions influenced punctuality. However, the weather values collected did not exhibit strong variation or clear relationships with lateness, and as such, were excluded from the final design.

Although the heatmap focuses on broader daily patterns, it becomes more informative when paired with the scatterplot. The dashboard filter connecting the two views allows each calendar square to reveal its underlying commutes, including transport mode and exact timing. This linkage ties the month-level summary to the individual events that shaped it. Overall, the heatmap emphasized the importance of choosing visual encodings that match the questions the data can support. It works well for highlighting daily trends, while the linked scatterplot provides the detail needed to interpret those trends more precisely.

<u>Visual 2: Arrival Time Proximity Graph (Time of Day)</u>



<u>Questions</u>

The graph was designed to explore precise, event-level questions

1. To what extent do actual arrival times deviate from desired arrival times?
2. Are patterns evident across different times of day?
3. Do different transport modes show visible patterns or clusters when mapped against the ideal arrival time?

Description

The scatterplot visualizes each commute as a point positioned by *Desired Arrival Time* (x-axis) and *Actual Arrival Time* (y-axis). Both axes use AM/PM time encodings. A reference diagonal line indicates the "on-time" arrival scenario. Points above the line represent late arrivals, while points below the line represent early arrivals.

A diverging blue-to-orange palette encodes *Minutes Late*, matching the calendar heatmap's color scheme. Transportation mode is encoded through point shape, enabling categorical distinction without conflicting with the lateness color encoding. Tooltips provide trip-specific details including Primary and Secondary modes of transportation, Date, and Minutes Late.

A dashboard filter action creates interactivity by linking the scatterplot to the calendar heatmap, where selecting a date filters the scatterplot to only the commutes that occurred that day.

By fitting all modes into the same coordinate space, the chart reveals whether lateness or earliness trends to cluster around specific time windows (like noon peaks or late evening delays), and whether certain transport modes visibly drift farther from the ideal arrival line than others.

Implementation

The scatterplot was created in Tableau. Because the original *Desired Arrival Time* and *Arrival Time* fields were stored as time-of-day values, Tableau automatically assigned a default date (1899-12-30) to them. To prevent this from affecting the visualization and to ensure both axes represented only the time-of-day, new time-only calculated fields were created using Tableau's

`MAKETIME` function. These calculations extracted the hour and minute components and recombined them into standardized time values. The prior *Minutes Late* formula was used for the scatterplot.

In Tableau, the scatterplot was constructed by placing *Desired Arrival Time* on the x-axis and the *Actual Arrival* Time on the y-axis, both set to continuous scales. The same diverging color palette (-30 to +30) encoded *Minutes Late*, while transportation type was mapped to point shape.

<u>Design Decisions</u>

1. Encoding Transportation Mode Through Shape

   Color was dedicated solely to *Minutes Late*, so *Transport Mode* classification was assigned to shape. This prevented visual interference between lateness and mode, while ensuring that mode distinctions remained legible even when points shared similar lateness values. The separation kept the interpretive load low and reinforced the clarity of the lateness palette.

2. Inclusion of an On-Time Reference Line

   Adding a diagonal benchmark line made deviations immediately visible. Instead of mentally comparing x-and-y values, viewers can assess punctuality at a glance. The reference line acts as a visual anchor and is essential for interpreting how far and in what direction each commute shifts from ideal timing.

3. Custom Tooltips for Precise Trip-Level Context

Custom tooltips were introduced to supplement the visual encodings with contextual details such as *Primary* and *Secondary* Transport Modes, *Date*, and *Minutes Late*. Since many points cluster closely together on the chart, replying on position alone would not effectively communicate all the nuance with the data. Tooltips provide an on-demand view without increasing visual clutter. This design keeps the scatterplot clean while still giving viewers immediate access to critical information needed for interpretation.

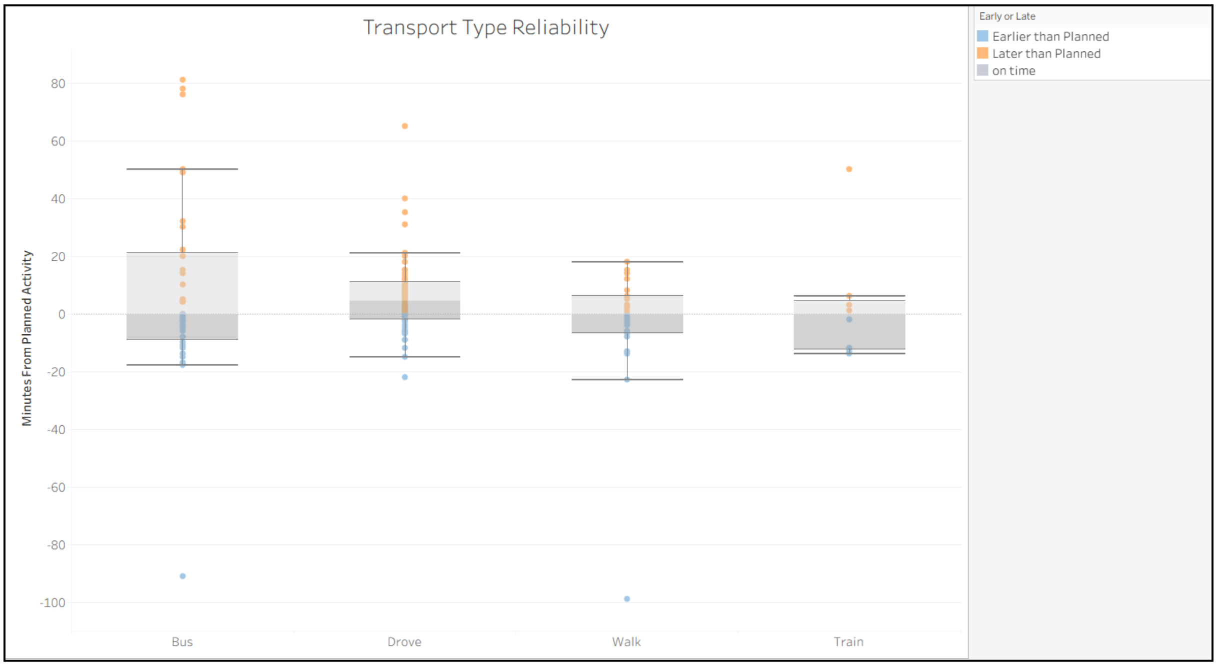
<u>Reflection</u>

The scatterplot provides a detailed view of punctuality variation, making it possible to examine how arrival behaviour shifts across different times of day and transportation modes. Its connection to the calendar heatmap through dashboard filtering strengthens the overall analysis by linking day-level summaries to individual commutes that produced them. This combination makes it easy to move from an overall view of the month to the specific commutes that shaped each day's result.

However, the scatterplot is limited in what it can reveal about differences between individuals or activity types beyond their timing. It cannot show whether academic related commutes behave differently than social trips, nor can it communicate how far each person traveled or how consistent someone was across days. Because the visualization focuses entirely on timing relationships, any question involving motivation, distance, or context beyond transport mode must be answered through other views or additional data fields.

If the scatterplot were redesigned from the beginning, different combinations of shape, such as icons, and color encodings would be tested earlier to confirm which visual choices worked best. Trying these alternatives sooner would have helped confirm the most effective encoding choices.

Visual 3: Transport Type Boxplot



Questions

The design of this visualization was driven by the following questions:

1. How reliable are different primary transport modes with respect to our planned arrival times?
2. Do some modes tend to make us consistently early or consistently late?
3. Which modes produce the largest variability and most extreme cases of lateness or earliness?

Description

This visualization utilizes a box-and-whisker format to compare the reliability of different *Primary Transport Mode*s. Negative values to the left (blue) represent arriving early, while positive values to the right (orange) represent arriving late. For each mode of transport, the grey box summarizes the interquartile range, where the horizontal line in the middle marks the median, the upper and lower hinges represent the first and third quartiles respectively, and the whiskers extend to show the calculated range of the data excluding outliers.

This allows a viewer to quickly interpret the typical reliability of these modes through the summarized view of the distribution and included outliers. For example, bus trips show a wider spread in their quartile ranges and individual entries, while trips completed by driving, taking the train, and walking have tighter ranges with the presence of fewer extreme arrival times.

Implementation

This visualization was implemented in Tableau using the base box-and-whisker format, with the same cleaned dataset as utilized in all other visuals. The *Minutes Late* attribute is included as a calculated field, defined as: `[Actual Arrival Time - Desired Arrival Time]`, measured in minutes to produce a signed value. A horizontal reference line is added at zero minutes to show the on-time target. A final calculated field is used to determine whether the entry is considered early or late, and is used to determine point colour.

Design Decisions

1. Box Plots and Overlaid Points versus Averages:

   A simple bar chart of average lateness by transport mode was considered and included in early conceptual designs, and could have communicated a similar trend. While this may have been slightly more intuitive to read, we ran the risk of misrepresenting the data, since the distribution of entries within each category contained a number of outliers and was not necessarily normally distributed. Using a boxplot communicates the overall variability more descriptively, while the size of the interquartile range lends itself better to display the overall reliability of different modes.

2. Colour Palette and Reference Lines:

   The orange and blue colour palette was chosen to match the theme of the rest of the dashboard, where orange points signify late entries and blue points signify early entries. This avoids the moralizing of the red-green framing that might imply that lateness is “bad” and earliness is “good”, while still giving viewers a sense of direction. The reference line at zero minutes anchors the colour coding and gives additional perspective, where a consistent vertical scale in either direction ensures that patterns and extremes are easy to interpret.

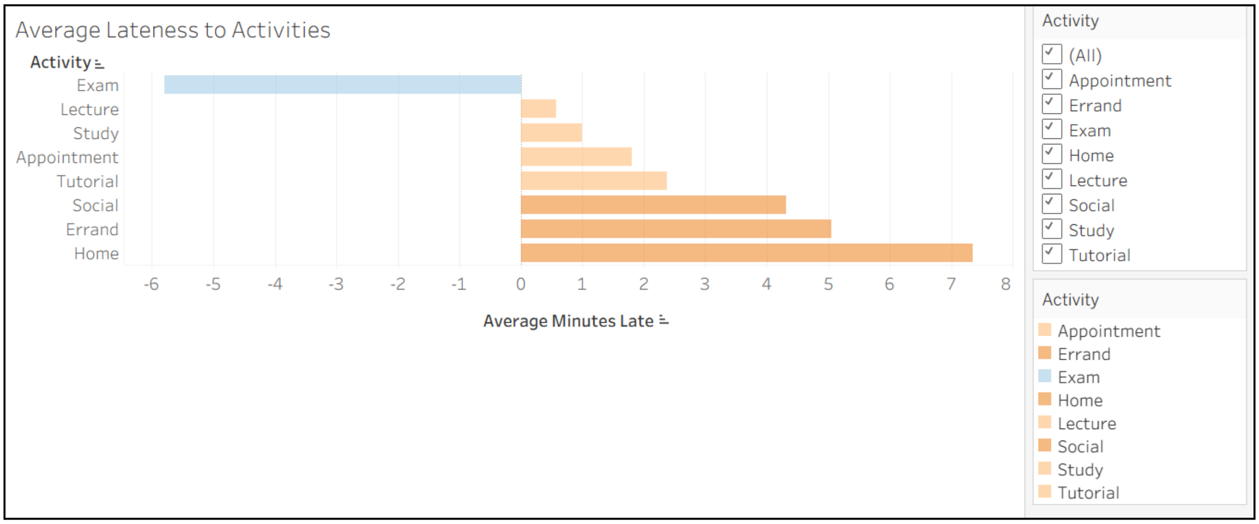
3. Derived *Minutes Late* Metric:

   We chose to encode reliability in this fashion rather than using raw total arrival times or binary (early/late) encodings because these alternatives would hide how early or late each entry actually was (magnitude). By converting each commute into a derived difference using actual vs planned times, the final encoding places all entries on a common scale for easier interpretation, where the direction and magnitude of each individual entry is easily apparent, and matters in determining practical reliability.

<u>Reflection</u>

Overall, this visualization helped to define reliability a bit more comfortably, in representing it with a distribution rather than a simple average. Tighter box plots effectively display more reliable modes (Train, Drove) while less reliable modes (Bus) have a wider quartile range. One limitation of this visual is that it can't explain why individual trips were off, as there are always additional factors to consider (activity type or participant habits). If we were to redo it, we might add additional tooltips on hover to give some context to outliers and extreme values within the visual itself, as well as a description of the sample size of each mode, so viewers can have more confidence in each distribution.

<u>Visual 4: Activity Type Bar Chart</u>



<u>Questions</u>

The design of this visualization was driven by the following questions:

1. For which activity types is lateness more socially acceptable or common?
2. Are there activities where we consistently arrive early (i.e., exams) versus those where we regularly cut it close or show up late (i.e., social events and going home)?

<u>Description</u>

Here, we use a horizontal bar chart to compare *Average Minutes Late* across activity types. The x-axis encodes *Average Minutes Late*, where negative values to the left (blue) represent arriving early, while positive values to the right (orange) represent arriving late. Activity Types (Exam, Lecture, Study, Appointment, Tutorial, Social, Errand, Home) are listed on the y-axis. The three bottom activities are colored in a darker orange to indicate that they are more self-scheduled and less strict, therefore having larger, more late, averages.

Implementation

This visualization was implemented in Tableau using a bar graph format, using the same cleaned dataset as other components. The key measure is the calculated field *Minutes Late* `(Actual Arrival Time - Desired Arrival Time)` in minutes. This measure is aggregated as *AVG(Minutes Late)* for each activity category. Activities were sorted by their average lateness so that more punctual activities appear at the top.

Design Decisions

1. Change to Single Attribute Focus

   The initial conceptual version of this visualization was a categorical scatter plot that showed individual lateness entries for both mood and activity. While it captured more detail, it was visually dense and made it harder to answer simpler questions in interpretation, such as: “On average, how late are we for activity type X?” Switching to removing the mood attribute from this visual simplified the encoding and allowed us to focus on a single attribute at a time.

2. Aggregated Bars vs Categorical Scatter:

   We also chose to aggregate lateness and represent each activity as a single horizontal bar rather than a cloud of individual points. The scatter made it difficult to see overall trends, especially when the disparity of values was larger; by contrast, the bar chart gives a clear ranking of activities from earliest to latest. The trade-off is that we lose some information about variability within our data, but we gain a much more readable summary that can be interpreted at a glance.

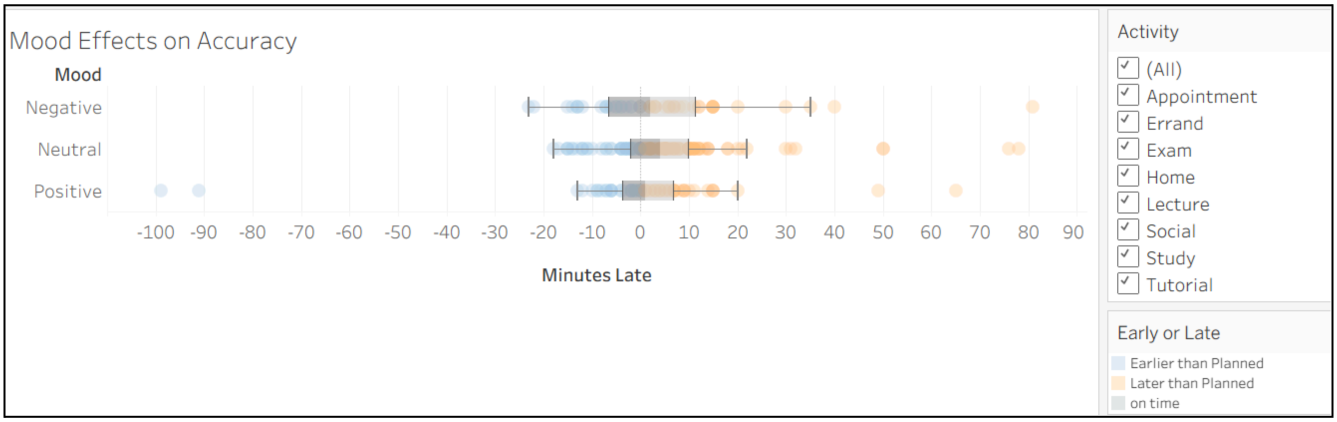
3. Diverging Scale, Colour, and Sorted Ordering:

   The x-axis is centered around zero to allow bars to extend left for early arrivals and right for late arrivals. Activities are sorted based on average minutes late. This allows more time-sensitive activities to appear near the top and more flexible activities to sit at the bottom. Home, Errand, and Social activities were intentionally coloured a darker orange to indicate that they are self-scheduled and have more flexibility. Together, these choices turn the chart into a clearer expectation ladder to measure how strict we are in each type of commitment.

<u>Reflection</u>

This visualization was useful in shifting focus from individual commutes to the social norms surrounding punctuality for different activity types. By aggregating to average minutes and presenting a diverging, sorted chart, it became clear that we treat exams much more strictly than social events, for example. However, this design also has a few limitations. By using raw averages, we hide any variability within each activity type, where overall distributions might give us deeper insight into the data. This chart also might be less effective in that each category has a different number of total observations. Some activities, like exams, have significantly fewer entries and may be less reliable due to sample size, which is not easily apparent. It is important to distinguish that this visual should be used as a high-level summary rather than a complete picture of punctuality behavior.

<u>Visual 5: Mood Scatter Plot</u>



<u>Questions</u>

The design of this visualization was driven by the following question:

1. Does our general mood before our commute affect our timeliness?
2. Are we more punctual when we start a commute feeling positive, or does mood have little to no impact?
3. Does a certain mood correspond to more extreme arrival time deviations (very early or very late)?

<u>Description</u>

Here, we explored the accuracy of our arrival times by plotting each commute in terms of *Minutes Late*, separated into their respective *Mood* categories. A box plot reference line is used to exemplify the difference in spread between negative commutes and positive ones. While all of the commutes have early and late entries, the entries with the "Positive" mood attribute are clustered much closer to 0 minutes late compared to the “Negative” mood entries. An activity filter is provided with this visualization to allow the user to explore this phenomenon with context for the “Average Lateness to Activities” visualization.

Implementation

Minutes Late was calculated as `[Arrival in Minutes]-[Desired in Minutes]`, where *Arrival in Minutes* and *Desired in Minutes* are the attributes *Arrival Time* and *Desired Arrival Time* converted to minutes, respectively. These were individually plotted by adding *Date*, *Arrival Time,* and *Desired Arrival Time* as details, which were removed from the tooltips for simplicity. *Mood* was used as the row attribute.

Design Decisions

1. Box Plots versus Averages of Absolute Values

   In the early concepts of this graph, late plots were overlaid with the early plots (by using the absolute value of minutes late), and the visualization would have only shown average marks to express how offset the *Actual Arrival Time* was from the *Desired Arrival Time*. This early version was extremely muddy, overplotted, and crowded with the “Average” label, making the graph hard to read. Simply taking the average of all the points also made it unclear if the entries trended earlier or later. Using box plots and separating the early and late points solved all of these major issues, as the points became more distinguishable and the box plot gave a comprehensive range and median to those points.

2. Tooltip Inclusions

   The tooltips for this visualization only include *Minutes Late*, *Early or Late*, and *Mood* to ensure that the focus of this visual was mood-related. This keeps the visual decluttered and lets the other visualizations explore the other factors on their own. Originally, the tooltips included the datetimes, activities, and transport types, which only served to water down the visualization's specialty in the dashboard.

3. Colors, Opacity, and Box Plots

   This graph uses categorical color rather than a color scale, which allows the use of opacity to help express density. The boxplots obscure a lot of the actual points, but communicates the density better than opacity alone. A lighter opacity also draws less attention to the outliers.

<u>Reflection</u>

This visualization does a really good job of showing the impact *Mood* has. This would not be an accurate visualization outside of the dashboard, as the design decisions obscure all of the other attributes that impact the commute, but I think it does a really good job in collaboration with the rest of the visuals. Stripping down the visualizations in this way lets the viewer interpret the different factors one at a time, and independently conclude how important each attribute is.

Integration

We wanted to make sure our dashboard was digestible and easily viewed by anyone with no additional context. To accomplish this, we leaned into the magazine genre of visualization, taking advantage of introductory text, headlines, and summaries between our visualization groupings. For navigation, we chose a taller format to reduce clutter and allow the user to scroll through the data at their own pace. This style also helped create a clear narrative for the viewer, starting with weakly correlated factors that we anticipated to be major factors, then actual major factors of arrival accuracy, and finally showing the user a way to calibrate their expectations based on activity type. We decided to use a blue-orange color scheme, which reduces any possible confusion for colour-blind viewers, and it avoids creating some 'objective' negative connotation towards lateness that would have occurred with a green-red color scheme.