FineDyne: An Interactive Comparison Tool for Effective Dining Decision Making

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Introduction

The simple act of deciding where to eat can be surprisingly complicated despite the wealth of information available. Yelp is one notable service that provides a huge database of restaurants with pertinent information such as user reviews, rating scores, price ranges, and cuisine types to assist in this process.

However, despite having a great deal of information, Yelp does not present all of this information in the best manner especially when users who want to use this information to compare restaurants. The presentation of information is specifically tailored towards more common acts in restaurant decision making. But more advanced decisions considering multiple factors is currently limited. For example, Yelp not does currently allow viewing a holistic overview of available restaurants based on a combination of user criteria (eg. cuisine type, price range, etc). Nor does it allow for easy comparison of possible candidate restaurants directly.

In other words, Yelp is currently useful for simple browsing of options based on loose criteria *eg. In Granville show me the general list of highly ranked restaurants*. But it is not good for a more complex task that power users might want to accomplish: *eg. In Granville, show me just the Japanese and Italian restaurants with an average price of $20.*

We propose to improve upon Yelp, by implementing features and their appropriate visualizations that are helpful for more informed restaurant decision making that better leverages the rich data of the service.

In particular, we wish to create a visualization tool that assists users in easily assessing possible candidate restaurants and comparing information between them. By doing this, we hope that everyday users of Yelp will be able to make more informed dining decisions in a straightforward manner rather than relying on external/alternative methods which we have observed to be by opening multiple browser tabs and keeping track of candidates which results in cognitive overload.

Dataset Details

Yelp provides a dataset [1] that is quite massive in its scope. The following provides an overview of the dataset:

- Information about 85,901 businesses across 11 cities in 4 different countries
    - UK: Edinburgh
    - Germany: Karlsruhe
    - Canada: Montreal and Waterloo

    - US: PIttsburgh, Charlotte, Urbana-Champaign, Phoenix, Las Vegas, Madison, Cleveland
- Reviews (4.1 million), business attributes (eg. hours, ambience, parking information, etc)
- Geographic data is included (eg. latitude and longitude)
- Photo data

Past example usages of this dataset have involved discovering cultural trends (*eg. do Americans tend to eat out later than Germans*), location mining and urban planning (*eg. Does a restaurant's popularity really have to do with their location?*), and inferred restaurant categories (*eg. Is a Chinese restaurant also really Szechuan or Hunan style?*).

Task

To set up our abstracted tasks, we'll use a common domain task of comparing different restaurants of varying cuisine types (*eg. Japanese vs. Italian*) based on a certain geographic constraint (*eg. Granville street in downtown Vancouver*) in order to make a restaurant decision.

In reflecting upon our own typical restaurant decision making process, as we are also everyday users of Yelp, we've found that the process is constrained by several criteria. There is an initial constraint that will form the first search term. Subsequently, other criteria will then "stack", acting as filtering constraints to narrow down the decision.

Put into abstract task terms, users will commonly first explore a larger dataset, then use filtering to see a smaller set of choices that will make decision making simpler, until they are satisfied.

For example, users will likely have an initial constraint that will serve as the first query of a restaurant database, such as knowing the cuisine type they would like to eat (*C1 in Figure 1*). An alternative first query could be the general dining neighborhood. The result of this initial query is a large set of restaurant options based on the sole criteria so far *eg. all Japanese restaurants in Vancouver.*

From here, the usage of additional criteria will reduce this large set of restaurants to something more manageable for a later comparison task. For example, users may filter their initial results based on other criteria such as certain price/review ranges, locations, etc (*C2 in Figure 1*). The results of this step should be a much smaller but more specific set of restaurant choices that is much closer to the final decision *eg. Japanese restaurants in Granville with a medium price tag but high review scores.*

With this smaller subset of specific restaurants, users will now enter a final phase of picking candidate restaurants through a final comparison. Ideally, it should be straightforward to assess the merits of each candidate in a holistic manne*r eg. Japanese restaurant A has an open bar,* *but Japanese restaurant B is open longer (C3 in Figure 1)*. After comparing, users will now hopefully be able to make a final informed dining decision. Figure 1 displays the workflow of this process below.

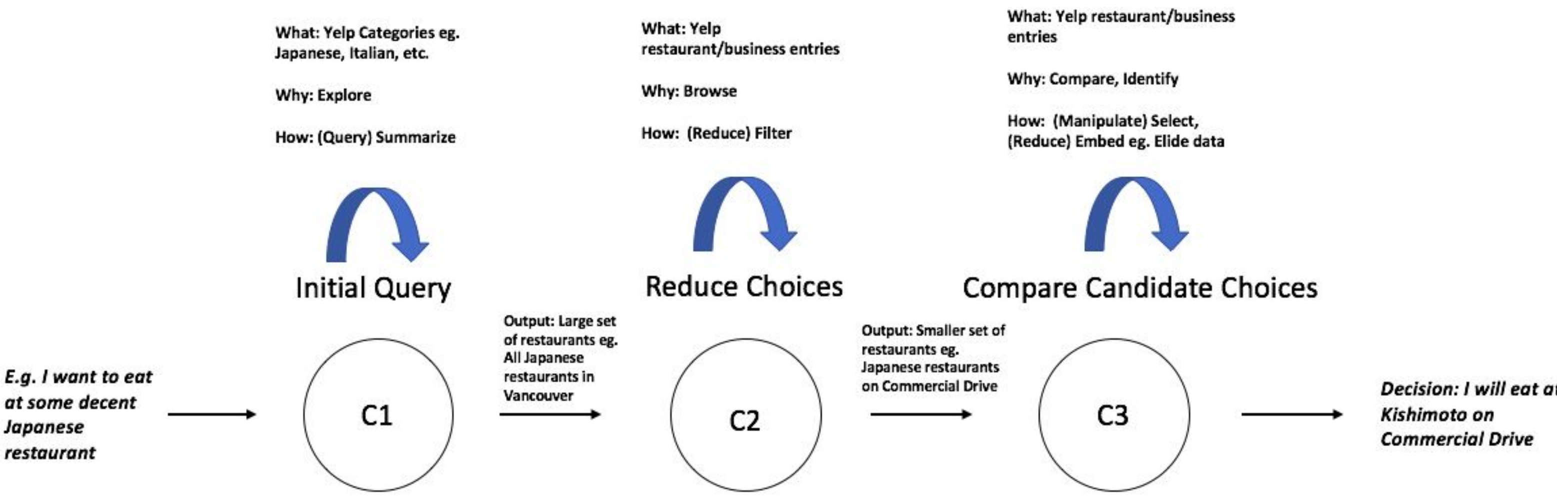


Figure 1. General restaurant decision process. Looping arrows indicate possible iteration at particular step of process eg. May change initial query (C1), or use different filters for categories (C2). Each step produces an output for next abstract task in process.

Personal Expertise

We have both used Yelp on several occasions for finding places to eat. A huge motivation for us was to greatly improve upon the current Yelp interface, using the visualization techniques learned in this course. We want to end up with a tool that is more informative yet sensible in its presentation of desired information such that anyone can benefit from the tool. Who hasn't been frustrated with restaurant decision making in their lives?

Previous Work

Flamenco [2] is a faceted search interface for images, that utilized multiple label querying to search for a specific subset of the larger facet space. For example, a facet may be food ingredients which could have the labels vegetables, breads, etc. Besides used as a querying method, Flamenco also had the notion of a "query breadcrumb" to help anchor users to their initial search criteria. This could especially be helpful in situations where many types of search queries may be employed, which could be useful for our design later.

ICLIC [3] is a method upon which subsets of large image collections could be viewed based on particular metadata attributes. Key to this was a histogram view of a distribution of images that would fall under a specific attribute, that would be used to inform future filtering steps *eg. see photos of sports and competitions since both had interesting distribution breakdowns*. In terms of design implications, the notion of using a multiple step process to filter out certain categories of data could provide to be very useful. The method of distribution visualization in histograms could also be used. However, the authors did note an issue with display areas being compromised depending on the scale of the data.

Product Plots [4] is a method for visualizing joint distributions of some interesting conditional proportions *eg. proportion of those who are happy, male/female, and are married*. The method could be used with various types of plots (barcharts, treemaps, etc), but an emphasis was placed on using hsplines and vsplines to demonstrate proportions of conditioned categories of data. In terms of our potential design, this method could serve as one way to display conditioned data from Yelp *eg. show me the proportion of restaurants that are Chinese, medium price range $$, and good review quality of 3 stars*.

Direct manipulation through control panels, filters, or other widgets is a common interaction paradigm used to interact with exploration visualizations. In VisExemplar, the user and the system collaborate incrementally “until the most effective possible visualization is created.“ We also propose to use a control panel with filters to filter data until the user is satisfied. [5] [6]

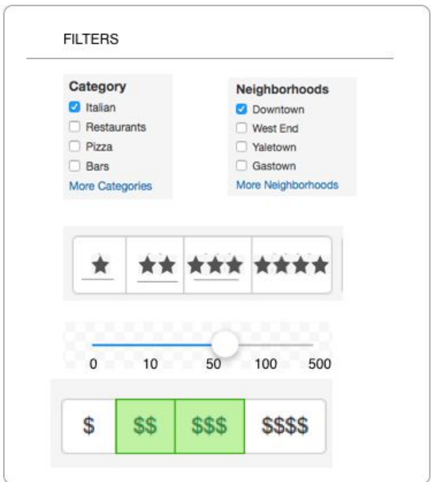
Proposed Solution

Based on our defined abstracted tasks, and previous experience with the current Yelp interface, our proposed solution consists of maintaining the map metaphor used by Yelp, but augmenting its utility through various selectable and stackable filtering options that supports an iterative decision making process.

Most notably, the current Yelp interface faces a major issue in not being able to display more than 1 category to filter the information shown. This greatly limits decisions that involve more than 1 category *eg. various cuisine types, locations, etc.*

Another important pain point identified through cognitive walkthroughs with the current Yelp interface was that once people decided to focus in on a certain area in the map, they could zoom into the map but the list view on the left of the map would not reflect these choices as filters. This meant that users needed to keep their filtered choices in mind, which could potentially result in cognitive overload.

FineDyne



FILTERS
Category
Italian
Restaurants
Pizza
Bars
More Categories
Neighborhoods
Downtown
West End
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Gastown
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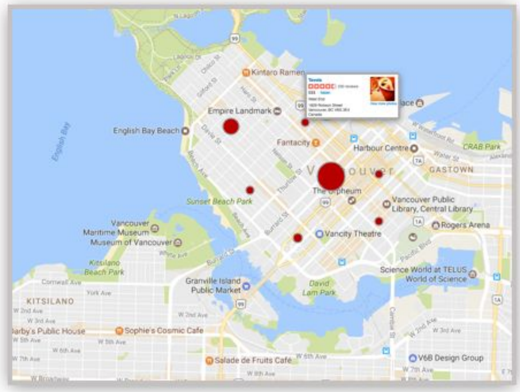

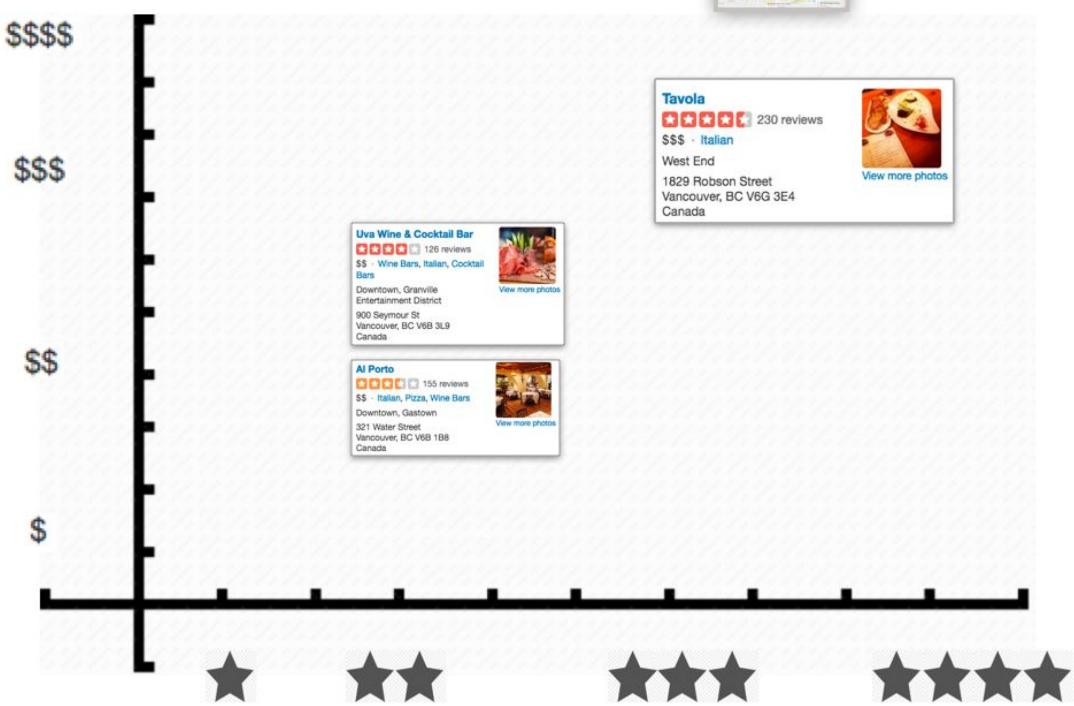

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Tavola
230 reviews
\$\$\$ · Italian
West End
1829 Robson Street
Vancouver, BC V6G 3E4
Canada
View more photos
Uva Wine & Cocktail Bar
126 reviews
\$\$ · Wine Bars, Italian, Cocktail Bars
Downtown, Granville Entertainment District
900 Seymour St
Vancouver, BC V6B 3L9
Canada
View more photos
Al Porto
155 reviews
\$\$ · Italian, Pizza, Wine Bars
Downtown, Gastown
321 Water Street
Vancouver, BC V6B 1B8
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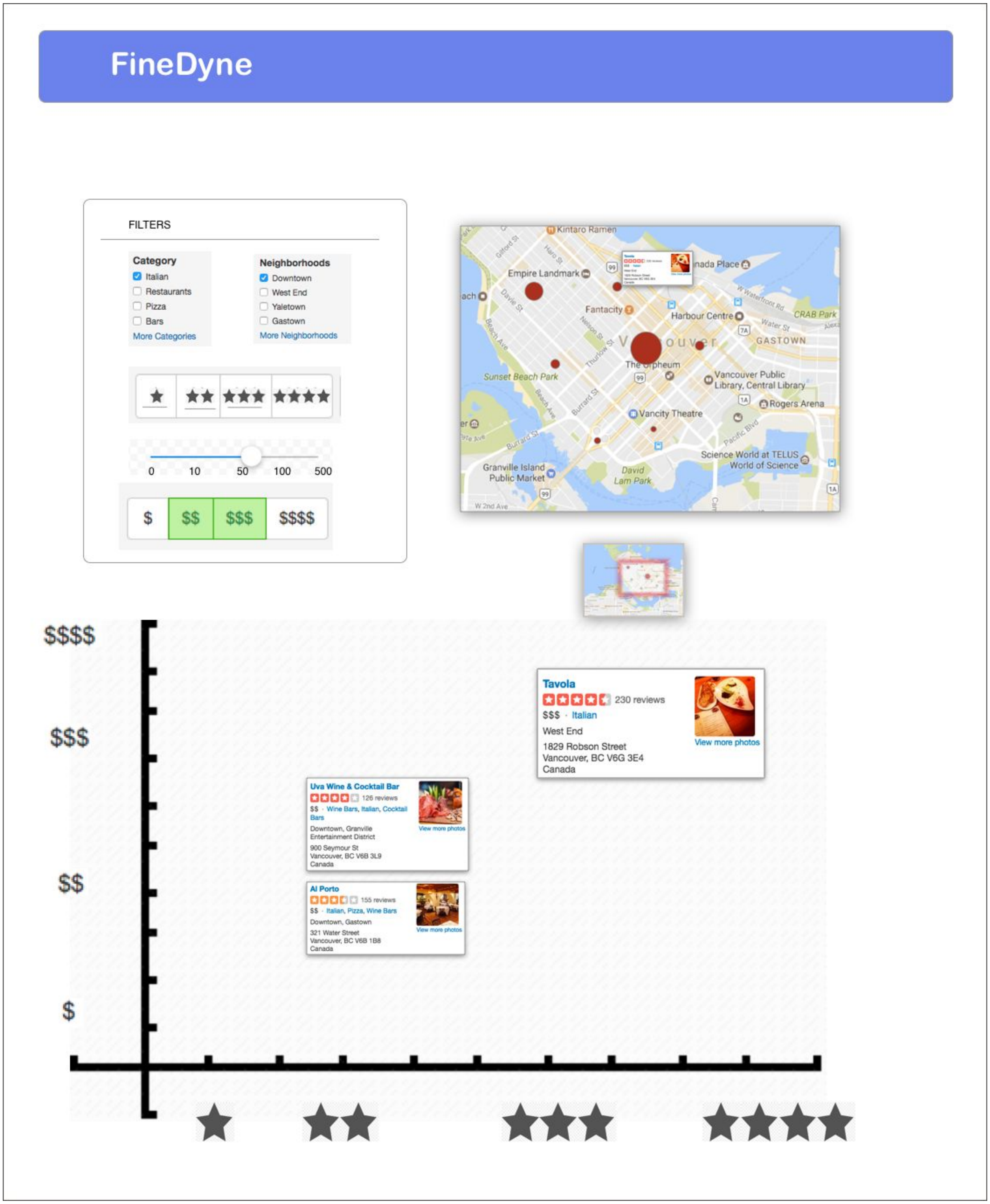

Figure 2. Top displays our proposed solution based on a zoomed out geographic region perspective. Users can select a region of interest and zoom in the desired area to see more specific restaurant marks (Bottom).

As seen in Figure 2, the map view and its associated restaurant icons are controlled by category filter checkboxes that can be toggled, or stacked on the left hand side of the interface. Clicking one filter will populate the map with the filter's corresponding restaurants, while subsequent filters will act as an additive filter, providing breadcrumbs on the side. These checkboxes act as the main ways to initially query, and adding filters will create a smaller subset of restaurants to work upon.

The map's icon sizes will denote the number of restaurants in a given area of the map that matches the current criteria. Thus, zooming in on the area will display more detailed smaller icons that represents the specific locations of these restaurants.

The main map view is intended to display a particular neighborhood category filter (eg. Downtown). There is a complimentary mini-map view below this, in order to maintain the zoom level of the chosen location at the highest level, in the case users wish to zoom in on a specific location's neighborhood (eg. Granville and Robson) to investigate restaurant options there. The mini-map will maintain all relevant filters entered such that users can perform a comparison later. If no location filter is applied, both map views will default to a high level overview of the city, although filtering is encouraged to truly get the most of the dining decision process.

Furthermore, sliders below the filter checkboxes provide options to further narrow down the initial filters above. We decided to base the sliders on the most likely secondary filtering options of our abstracted tasks, that is seeing restaurants of a specific price and review score rating to set limits of matching restaurants. We also incorporated an option to filter by number of reviews, in the case that more trust in the quality of a restaurant comes from a larger crowd. The result of using these sliders will further create a smaller subset of restaurants on the main map view.

Once an acceptable amount of restaurant options has appeared on the map, users can begin to hover over the icons to get a pop-up summary of information *eg. name, main photo, review blurb.* When an interesting restaurant is found, a "pin" option will be available. Pinned restaurants will appear on the bottom of the map view on a scatterplot inspired view. The axes of the scatterplot corresponds to the price ranges and review star rating categories of Yelp. Pinned restaurants will appear as summary cards that will lie along this distribution such that users can immediately compare where a restaurant's specific price/quality lies to make their final dining decision.

With these solutions, users can also make sure they plan the whole event rather than making a restaurant choice. For example, if the user wanted both dinner and dessert at separate locations that are close in walking distance, they could first pin specific restaurants then subsequently update the map for dessert places, all while being able to view the pinned restaurants for assessing walking distance. This approach would assist users in comparing locations of different "searches" in the same view to make more complex decisions simpler.

Example Use Case

Katie wants to plan her best friend's birthday with other friends invited. She knows for sure that her best friend is a huge Japanese fan but her other friends are more keen on Mexican. While these are important, it would be great to find a place that has great after party options nearby, such as a bar. Given that this is a special occasion, Katie is willing to spend more, upwards of a $45 dollar budget per person given that it is a higher quality restaurant.

She opens the new FineDyne website. The app figures out her current location and renders a map of her city. It presents her with filtering choices such as food categories, neighbourhoods, number of stars and ratings a restaurant has, and the price ranges for the venues as selectable checkboxes.

She then selects Downtown as she wants to have the party downtown, and selects Japanese and Mexican as the two food options. This populates the map with many icons that meet these options. She also selects $$ and $$$ price ranges which really is a range of $20 to $60 in Yelp terms. Subsequently, this again adjusts the map's icons, this time causing a reduction in icons that further meets the price/rating criteria along with the previous ones.

She hovers over some of them that she finds to have good quality for the price, and if she likes what she sees in the pop-up based on the photo, and review abstract, she clicks to "pin" it. After she starts pinning them, the restaurant's' details appear on a scatterplot that falls under a distribution of number of stars vs. price of restaurant. She ends up with 7 restaurants that can be seen in their distribution in terms of overall quality and price.

She then changes the category from Japanese and Mexican, to bars and nightclubs. The pinned restaurants from before remain on the map, so she looks at bars that are close to the restaurants she had liked from before. She goes through the same iterative filtering process, hovers on the bar icons she likes, and pins the ones that are her favorites. The pinned bars also appear on the scatterplot below where the pinned restaurants were. From the scatterplot, she considers the tradeoffs. She decides on a bar and restaurant that is close to one another as she can see them highlighted on the map when she hovers over the item in the plot. She picks a restaurant and bar that are both $$ and has 4 star ratings.

Implementation Approach

Early prototyping with low fidelity prototypes will use pen and paper sketches to further explore and refine our design approach, we will then use SketchApp to make prototypes to get feedback on our designs from our peers. For the sake of flexibility, d3.js and Javascript will be the main tool of choice for development.

Milestone Schedule

Based on our overall time constraints, tool usage learning, and general refinement of ideas needed, we propose the following schedule with expected milestones.

- March 21 peer review 1: low fidelity sketches done for peer review
- March 31 Interim Report: background lit review, review design idiom, near final. Pretty solid design choices.
- April 4 peer review 2: if d3.js experience is far along, present rough prototype with d3.js otherwise use sketch App to show a prototype of the interactive vis.
- April 6: Finalize, solidify design and focus on d3.js Development.
- April 25: Final presentation: code freeze
- April 28: Paper due

Note, that some of the work required for these milestones will likely have to occur in parallel, such as learning the appropriate d3.js skills and finalization of idiom design.

References

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