Using visual analytics to explore Community Engaged Learning and Teaching at the University of Otago

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Community Engaged Learning and Teaching (CELT) is an interdisciplinary practice involving students and the wider community. Through CELT, students acquire skills that may not be so readily learned in formal classwork. Practitioners at this university came together to promote CELT to the wider institution, but faced difficulty in clearly defining the boundaries of the practice. To aid the development of a shared understanding of CELT, practitioners engaged in a process of 'visual analytics'. This method involved analysing data on CELT programmes through the collaborative development of interactive visualisations. In the end, the visual analytics approach proved useful for co-constructing a shared understanding of the CELT space.

Keywords: visual analytics, community engagement, information visualisation, higher education

Introduction

In New Zealand, there appears to be a growing need for more effective integration and interconnection between universities, communities and schools (Butin, 2010; Gluckman, 2013). Through Community Engaged Learning and Teaching (CELT), students acquire skills that may not be so readily learned in formal classwork, such as critical thinking, communication skills, and cultural and social understanding (de Koven and Trumbull 2002; O`Connor, Lynch and Owen 2011; Smaill 2010). The University of Otago recently identified community engagement as an important strategic priority in relation to its core values and its wish to enhance student experiences. A special interest group (SIG) of academics and general staff from this institution came together in 2011 to develop this practice-based educational process into a research-led engagement.

One of the goals of the CELT SIG was to collate lists of existing community outreach activities at the university into an overview of the practice. This overview would then be used to promote CELT to a wider audience, including staff, students, community members and policy-makers.

Analysis of available data on CELT programmes, however, revealed that the problem space was 'messier' than originally thought. First, data on known programmes were incomplete and often originally compiled for specific purposes. Information existed as assortments of textual data, such as lists of university and community partners, as well as qualitative accounts of activities and experiences. A lack of common boundaries or categories, coupled with a wide range of embedded personal interests, engendered no user-confidence in the completeness of the lists. As a result, the data did not easily combine. Second, it became apparent that the SIG itself lacked a cohesive model of what defined community engagement. Third, during discussions, members of the SIG also 'discovered' new examples of CELT that were not on existing lists.

To aid in the development of a shared understanding of the boundaries and characteristics of CELT, members of the SIG participated in a visual analytics process (described in the next section). At the end of this process, an interactive, web-based infographic was produced to communicate the findings beyond the group. This short paper details the visual analytics approach taken, and outlines some of the challenges faced. A worked example highlights various features of the process, and demonstrates the effectiveness of visual analytics as a method for developing shared understanding of an interdisciplinary practice.

Visual analytics

Visual analytics is a multi-disciplinary approach that combines aspects of information visualisation and data analysis to address 'messy' problems (Keim et al., 2008). A key feature of a visual analytics approach is the use of interactive visualisations *as part of the analysis process*, as well as for presentation and dissemination. Particularly, visual analytics is useful for developing an overview of a large information space when available data are incomplete. Issues of data quality and uncertainty often mean automated analytic tools are unsuitable for describing these problem spaces; human judgment and expert knowledge is instead required to contextualize the data and fill in the gaps. Visual representation of data, coupled with user interaction, helps elicit this knowledge, which can then be incorporated into the process as new data. (Keim et al., 2008).

The visual analytics method used to guide this project was adapted from Keim et al. (2008). The process is iterative, and features four key steps (Figure 1). First, data are selected and pre-processed. In this step, meaningful data are gathered from available sources, and ‘cleaned’. ‘Cleaning’ the data means: where possible, filling gaps in the information; standardising different ways of describing the same thing; and classifying or categorising attributes. The second step involves visualisation & hypothesis forming. Here, data are visualised to highlight certain attributes or relationships, and hypotheses about the overall system are made. In the third stage, users interact with the visualisation, adding their own contextual knowledge and perceptions to the data analysis. Through their interactions, users confirm or reject the hypotheses made. Finally, in the fourth step, insights are gained from observations of user interaction, and the process is repeated with this new data in a feedback loop.

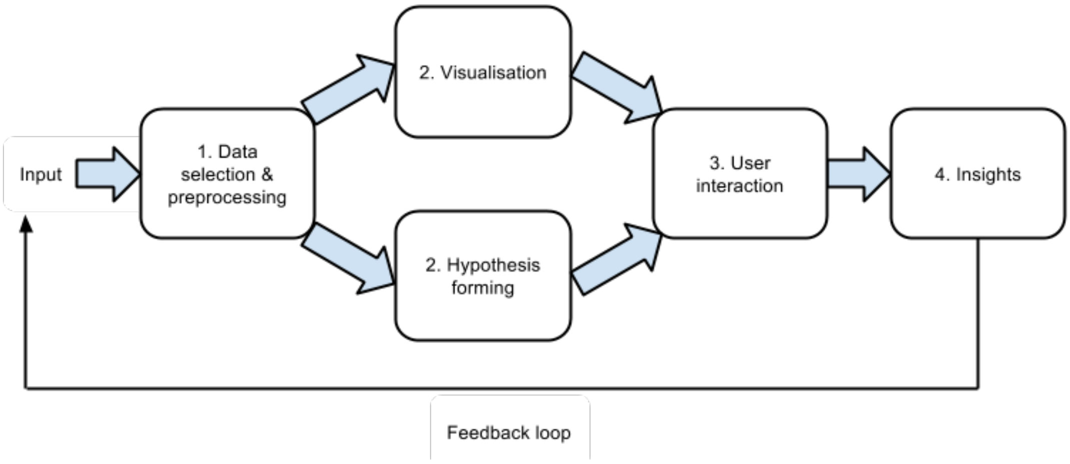

Figure 1. The visual analytics process.

There is no prescribed number of iterations for this method. In this study, researchers repeated the process three times, determined by the project time-line and group consensus.

Before the three iterations are described in detail below, a visual representation is provided in Figure 2. The diagram illustrates the iterations: (1) initial data selection, (2) exploration of attributes and relationships embedded in the data, and (3) to the final presentation of all insights.

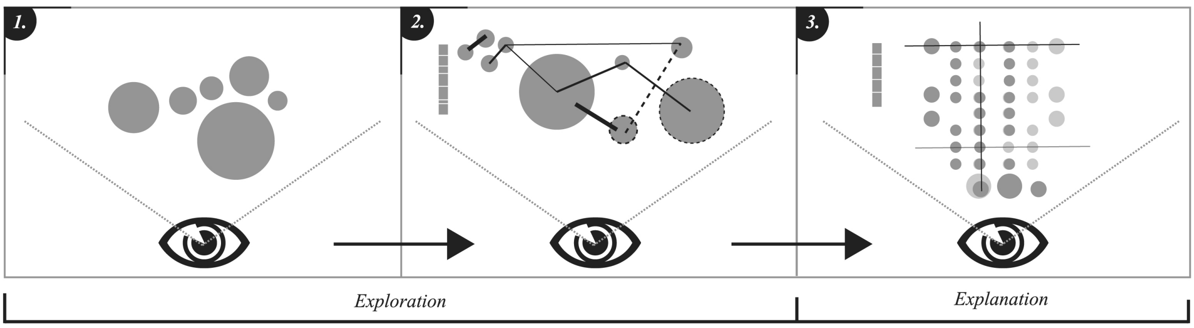

Figure 2. A visual representation of the CELT iterations.

Iteration 1

The initial dataset comprised ‘lists’ of qualitative descriptions of CELT activities. Some quantifiable programme attributes (such as target audience or longevity of programme) were identified in these lists, but these occurred inconsistently across programmes. Further, when present, the way in which these attributes were represented varied considerably (for example, longevity was described in three different programmes as ‘1 year’, ‘far too long’ and ‘unsure’). Due to the inconsistency of these known characteristics, the initial visual concept was illustrated simply as a broad overview of *who* was involved in CELT. This visualisation was intentionally lacking in detail, acting as a ‘conversation starter’ to tease out what information the SIG deemed necessary to include. Members were invited to sketch on paper copies of the diagram their own examples of community engagement, or indicate different ways of organizing the existing groups. This process instigated lively debate.

It became clear that there were a number of competing views about how CELT should be represented within the group, dependent on each individual's subjective experiences and specific areas of focus. The diagram was critiqued as not representing enough attributes to get a sense of what CELT actually was.

From this insight, it was decided to re-visualise CELT with a different focus; the next iteration would concentrate on exploring common attributes of a subset of CELT initiatives, rather than attempting to capture the maximum range of activities at Otago University.

Iteration 2

Researchers selected a subset of CELT programmes that exhibited some shared characteristics (specifically, from a collection of Science Outreach programmes) as the dataset for the next exploratory visualisation. These shared attributes included longevity of programme, whether the programme involved paid or volunteer students, and where the outreach primarily took place. The visualisation step was semi-automated by feeding data into a social network analysis software application (in this instance, Gephi, although this was due to it being freely available, rather than any specific functionality). This produced a series of network graphs that highlighted some characteristics and relationships of the CELT programmes that were not immediately observable in the data. For example, one graph featured different coloured circle nodes to represent the length of time a programme had been running (red nodes were well-established programmes, whereas green nodes were relatively newer). The social network analysis software also allowed for more user interaction from the SIG; members were encouraged to manipulate the graphs by changing node colours, sizes and the position of nodes to foreground characteristics of interest. Consequently, this meant that the SIG could quickly and easily recognise patterns in the data.

Through discussion and shared visual analysis of the graphs, a more comprehensive list of important characteristics was developed. This list was distilled into a data collection form, and circulated around the SIG for further input. The result was a list of shared attributes of CELT that most thought useful and necessary, which would inform the development of the final infographic. The key attributes to be included were: longevity of the programme; whether university teachers, students or community members were the primary teachers in the arrangement; the target 'audience', or learners; the primary location of the activity; the University division responsible.

With final consensus on which attributes should be represented, it was time to repeat the process again for the final iteration.

Iteration 3

In the final iteration, the focus shifted from producing *exploratory* visualisations (where visualisation is used to identify features such as trends and outliers) to producing an *explanatory* visualisation (presentation and communication of insights) (Iliinsky & Steele, 2011). The aim was to communicate what CELT at Otago looked like to a wider audience (the live infographic can be viewed at tiny.cc/cc8mlx). This would prove to be the final 'insight' in the visual analytics process.

To present the multi-dimensional data in a comprehensible way, researchers adopted the common mantra of 'Information Visualisation': "overview first, zoom and filter, then details-on-demand" (Shneiderman, 1996). Simply put, the visualisation would provide an overview of the entire information space, but also allow users to filter out details they deemed unnecessary, and allow them to highlight meaningful details to deepen their understanding. In terms of the visual analytics process (Figure 1) users would be able to repeat steps 3 (interaction) and 4 (insight) as required.

Discussion

Adopting a visual analytics approach to the problem of conceptualising CELT proved useful for the researchers in this case study. Visualisation aided the analysis of incomplete datasets, allowed the SIG to more deeply explore the attributes of their programmes, and helped facilitate the identification of common characteristics. Visual analytics was also a useful method for the SIG as an inter-disciplinary entity: sporadic meetings, as well as the divergent concerns held by its members, meant efficiency became an important consideration for the group. As Thomas and Cook note, "Visual representations make it easy for users to perceive salient aspects of their data quickly. Augmenting the cognitive reasoning process with perceptual reasoning through visual representations permits the analytical reasoning process to become faster and more focused." (Thomas & Cook, 2005, p. 69).

A number of technical issues were identified throughout the process. Issues of data quality and uncertainty at the outset meant a much more laborious process than initially envisioned, mainly due to the extra emphasis on creating forms and cleaning data. Also, visual analytics typically makes use of automated data selection tools to expedite the selection process, and to uncover hidden patterns in the data (Keim et al., 2008). The datasets in this project, though, were too small to make effective use of automated tools. This, in turn, affected the visual exploration of the data.

Finally, the opportunity to introduce members of the SIG to a visual analytic process was regarded by researchers as an important output in itself. As these emerging processes for handling complex data become more commonplace in higher education, it is crucial that staff understand how, when and why to use them. In a recent blog post, data artist Jer Thorp (2013) addressed the proclivity for people to refer to 'visualisation' as a product, rather than a process. Shifting this perception is important for anyone involved in data analysis. "If we set out to visualise, instead of making a visualisation, we can end up with any number of outcomes. In fact, many of those outcomes may not even be visualisations, but rather solutions, new ideas, and better questions" (Thorp, 2013). In this case study, researchers deemed the knowledge gained throughout the process as more valuable than the final output.

Conclusion

Community engagement as a field of inquiry is still developing. Conceptually, the benefits of students engaging with the community are well-recognised; practically, the boundaries of the practice are ill-defined. For institutions identifying CELT as a strategic imperative, delineating clear boundaries will prove necessary for effective implementation and promotion. Determining these boundaries may prove problematic, however, if there is not clear understanding of what constitutes CELT amongst practitioners. In this case study, the consensus of group members over what should be depicted in the final infographic, opposed to the debate in the early stages of the project, suggests that visual analytics can be a useful tool for fostering this shared understanding.

Future work will entail inviting other practitioners into the visual analytics process, in the hope that many eyes will form a more holistic vision of CELT. Additionally, we are interested in seeing how expanding the dataset could affect steps 1 and 3 of the visual analytics process (Figure 1). Specifically, (1) will a larger dataset present greater opportunities to employ automated data analysis techniques, and (2) how might this inform the final infographic?

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References

Butin D.W.. (2010) *Service-Learning in Theory and Practice: The Future of Community Engagement in Higher Education*. Basingstoke: Palgrave Macmillan.

deKoven, A., and D.J. Trumbull. (2002). Science graduates doing science outreach: Participation effects and perceived barriers to participation. *Electronic Journal of Science Education*, *7*(1) Retrieved from http://ejse.southwestern.edu/issue/view/732.

Gephi (v0.8.2 beta) [Software]. (2012). Retrieved from https://gephi.org

Gluckman, P. (2013). *Interpreting science – implications for public understanding, advocacy and policy formation.* A discussion paper. Office of the Prime Minister's Science Advisory Committee. Auckland, NZ

Iliinsky, N., & Steele, J. (2011). *Designing Data Visualizations: Representing Informational Relationships.* O'Reilly Media, Inc..

Keim, D., Andrienko, G., Fekete, J. D., Görg, C., Kohlhammer, J., & Melançon, G. (2008). *Visual analytics: Definition, process, and challenges* (pp. 154-175). Springer Berlin Heidelberg.

O'Connor, K, M., K. Lynch, & D. Owen. (2011). Student-community engagement and the development of graduate attributes. *Education & Training, 53*(2), 100-115. doi: 10.1108/00400911111115654

Shneiderman, B. (1996, September). The eyes have it: A task by data type taxonomy for information visualizations. In *Visual Languages, 1996. Proceedings., IEEE Symposium on* (pp. 336-343). IEEE.

Siemens, G., & d Baker, R. S. (2012, April). Learning analytics and educational data mining: towards communication and collaboration. In *Proceedings of the 2nd international conference on learning analytics and knowledge* (pp. 252-254). ACM. https://doi.org/10.1145/2330601.2330661

Smaill, C. R. (2010). "The implementation and evaluation of a university-based outreach laboratory program in electrical engineering." *IEEE Transactions on Education* 53(1): 12-17.

Thomas, J. J., & Cook, K. A. (Eds.). (2005). *Illuminating the path: The research and development agenda for visual analytics*. IEEE Computer Society Press.

Thorp, J. (2013). *Visualization as process, not output.* Retrieved from http://blogs.hbr.org/2013/04/visualization-as-process/

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