

Mapping Text with Phrase Nets

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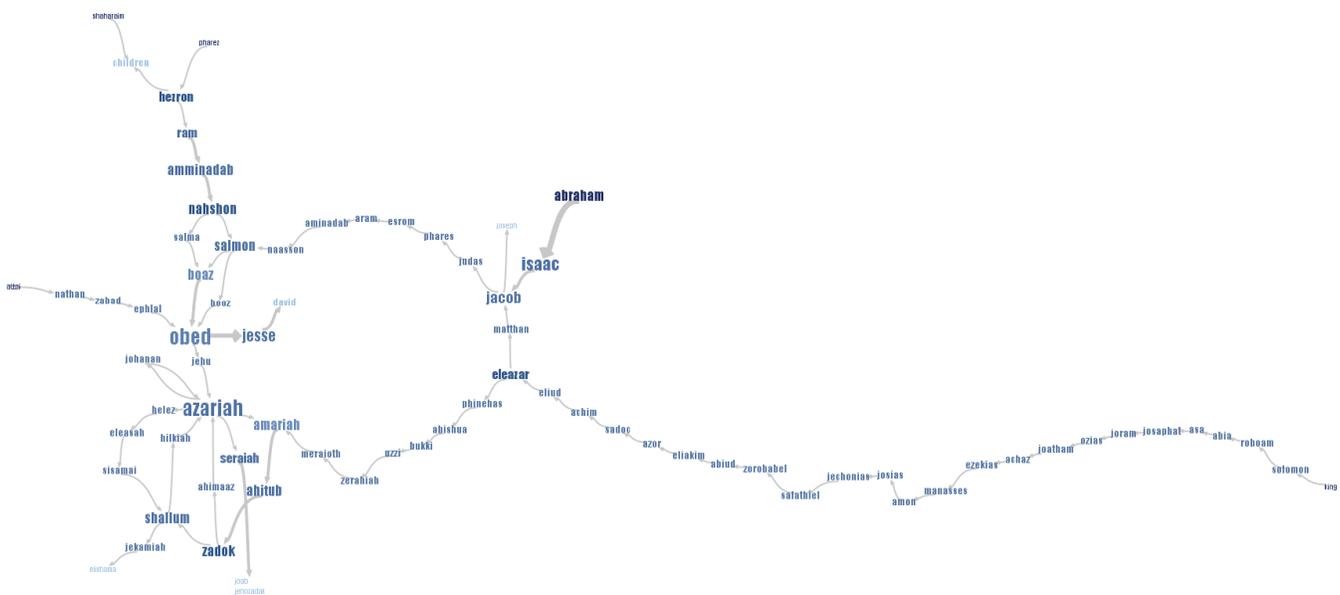


Fig. 1. Scanning the bible for textual matches to the pattern 'X begat Y' reveals a network of family relations.

Abstract— We present a new technique, the *phrase net*, for generating visual overviews of unstructured text. A phrase net displays a graph whose nodes are words and whose edges indicate that two words are linked by a user-specified relation. These relations may be defined either at the syntactic or lexical level; different relations often produce very different perspectives on the same text. Taken together, these perspectives often provide an illuminating visual overview of the key concepts and relations in a document or set of documents.

Index Terms— Text visualization, tag cloud, natural language processing, semantic net.

1 INTRODUCTION

Scholars have long dreamed of turning text—from books to entire libraries—into maps. A visual perspective on a text has many potential uses. A map can serve as a summary and provide a jumping-off point for close reading. Mapping techniques may also be used to compare multiple texts, whether books by different authors or speeches by different politicians.

Unfortunately, anyone who sets out to map a book quickly runs into two problems. The first is purely conceptual: most interesting texts are large (a typical novel has more than 100,000 words) so some kind of analysis and summarization is necessary to make them amenable to visualization. The key issue is to define an effective unit of analysis; such a unit could range from letters to words to general concepts and ideas. Due to the current state of natural language processing, choosing the right unit involves a tradeoff between

reliability and validity. On one end of the scale, computers can reliably pick out the individual words in a book, leaving the task of putting the words together to a human. On the other end, programs that aim to extract high-level meaning from text—say a semantic network of people and their relations—face significant error rates and are easily misunderstood by their users.

The second problem in the visual display of text involves legibility. In most visualizations, one wants to use spatial position as a meaningful variable. Yet a readable set of words obeys spatial constraints on alignment, grouping, and type size. The conflict between positioning and legibility can lead to displays that are hard to read or where spatial position is essentially random.

In this paper we introduce a new text mapping technique, the *phrase net*, which seeks a balance both in analysis and display. Our unit of analysis is a “phrase,” i.e., a particular relationship between words that can be defined using either simple pattern matching or syntactic analysis. This unit provides a higher level of analysis than individual words, but is easily understood by users and does not require unreliable artificial intelligence. Our visual displays use a standard graph layout engine that has been modified to ensure that text is readable via constraints on alignment and grouping.

In addition to describing the design and implementation of the phrase net, we also provide a series of sample use cases. Some of these were derived from our own exploration. To find others, we deployed a simplified version of the phrase net on the Many Eyes

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site, where any user could create their own visualizations of text. While the period of deployment was too short to draw quantitative conclusions about usage, it resulted in several interesting usage scenarios that had not occurred to us.

2 RELATED WORK

To place the phrase net in context, we review some existing systems that create maps of text. We focus on the two questions mentioned in the introduction: What is the unit of textual analysis? How does the visualization handle legibility concerns?

At the simplest level of analysis, many visualizations focus on individual words. The simplest example is the tag cloud. Conventional tag clouds display up to several hundred words, typically aligning them in rows for readability. This method of alignment, however, means that the only use of the spatial dimension is the order of words (typically alphabetical). More advanced forms of tag clouds, such as Wordle [6] or Word Clouds [2] enhance readability through careful typography—at the expense of a near-random spatial layout.

Not all visualizations that are based on single words dispense with space as a variable, however. The TextArc tool [5] uses a projection that places words in a two-dimensional space based on where they occur in the text. This method adds another layer of information, letting viewers see which words are only used in specific sections, and ensuring that two words that consistently occur in the same passages will be near each other onscreen. The downside, however, is legibility: the number of words shown, coupled with their continuously varying locations, means that letters overlap and there are often no clear groupings.

This legibility problem is shared by other systems that perform some type of multidimensional scaling. In the algorithm of Sarkar *et al.* [17], for example, word co-occurrence relations are analyzed instead of simple word frequency. Based on this co-occurrence data, words are mapped to points in two-dimensional space. As with TextArc, the result may be intriguing, but the resulting display has no clear visual organization and can be hard to read.

Some visualization systems attack the problem by using semantic analysis. ThemeRiver [10], for example, displays the ebb and flow of “themes” over time in a large body of text. The ThemeRiver display typically only tracks a few themes at a time (published examples show at most a few dozen) and therefore can handle label typography in the same way as a standard graph.

The Docuburst technique [3] and Gist Icons [4] use a pre-existing ontology, Wordnet [7], to group words that have related meanings. While this allows for a natural summary, it is not without problems. Words with multiple meanings can only occur in one location. The categories in Wordnet, like most ontologies, are not completely intuitive—e.g., few users will naturally understand the distinction between an “entity” and an “object,” or expect to see “laryngitis” listed as a type of “psychological feature.” Both systems rely on radial-style visualizations that present a typographical challenge. Gist Icons [4] for instance, shows over a hundred word frequencies at once, literally leaving no room for any text. The Docuburst system uses interaction to tackle this problem.

Another common approach—one that we follow as well—is to depict relationships in a text using a network. The analogy is with the idea of a “semantic net” [18], which has often been used to represent relations between concepts. Often these nets are based on co-occurrence relations. For example [14] creates a network of related terms from patent filings. Peter Cho created a network of words from news stories [1] based on information about which words often followed which other words.

These systems can be beautiful and informative, but the approach suffers from two drawbacks. First, when a typical graph layout algorithm is used to arrange words, it can lead to a set of jumbled text, much as in the case of multidimensional scaling. (The Cho example is beautiful, but was adjusted by hand.) Second, simply looking at co-occurrence shows only one generic type of relation. In

any complicated text there are more specific relationships: agents acting on objects, people possessing things, actions taking place at locations. Simply looking at co-occurrence gives no way of focusing on a type of relation.

The technique presented in this paper attempts to address these shortcomings. We analyze text at the level of relations between words, rather than individual words, and allow users to specify those relations in a variety of ways. We also tune a standard graph layout to create a more legible arrangement of words.

3 HOW THE PHRASE NET WORKS

The phrase net extracts and then visualizes networks of terms from bodies of text. In this section we give a basic description of these two steps and the ideas behind them. We do this by conceptually separating the visualization into different stages that map directly to the two main questions defined in the introduction. In the *text analysis* stage we define the unit of analysis and extract a network of terms from the raw text. Subsequently, in the *network abstraction* and *visual representation* stages we deal with the problem of rendering this network effectively. This section discusses each of these stages separately.

3.1 Text analysis

To convert a text into a network we define the nodes to be a subset of words occurring in the text, and edges to represent certain relations between these words. There are many ways to choose these node and edge sets. For example, one straightforward method is to take the nodes to be all words, and link two terms if they appear in immediate succession in the text without punctuation between them. We now discuss two finer-grained methods, each based of which uses a certain kind of template to define connections between words. The first method uses syntactic patterns to define word relations, while the second relies on orthographic pattern matching.

3.1.1 Syntactic linking

A natural thought is to use patterns based on the syntactic structure of English sentences. To explore this idea, we used the open-source Stanford Parser [13]. Conveniently, one of the output formats of this system is a “typed dependency parse,” which breaks a sentence into pairs of words connected by relations. The relations can be any of several dozen types, ranging from common types like “conjunct” (as in “A and B”) to very specific, such as “element of compound number.”

Given a text that has been parsed in this way, our software allows the user to specify one or more of these relations and then creates a graph where nodes correspond to words, and edges indicate pairs of words that are connected by the specified relations. There are two advantages of using these dependencies rather than relying on a simple method such as word adjacency. First, it gives far more fine-grained control over the network, allowing the user to spotlight only certain types of relationships in the text. Second, it avoids obvious problems inherent in simple word-order approaches: in a sentence like “the keys were found,” a typed-dependency parse will know that “keys” and “found” are related.

Unfortunately, this increased sophistication comes at the price of an unwieldy amount of processing power. For example, running the parser on the novel *Pride and Prejudice* (about 1 MB of text, and slightly under 6,000 sentences) requires more than 24 hours of CPU time on a Windows Thinkpad T60 with 2GB of RAM. This is more time than it would take an average human to read the whole book. Such a lengthy processing time significantly increases the upfront cost [21] of the visualization, and makes interactive exploration of different corpora a challenge.

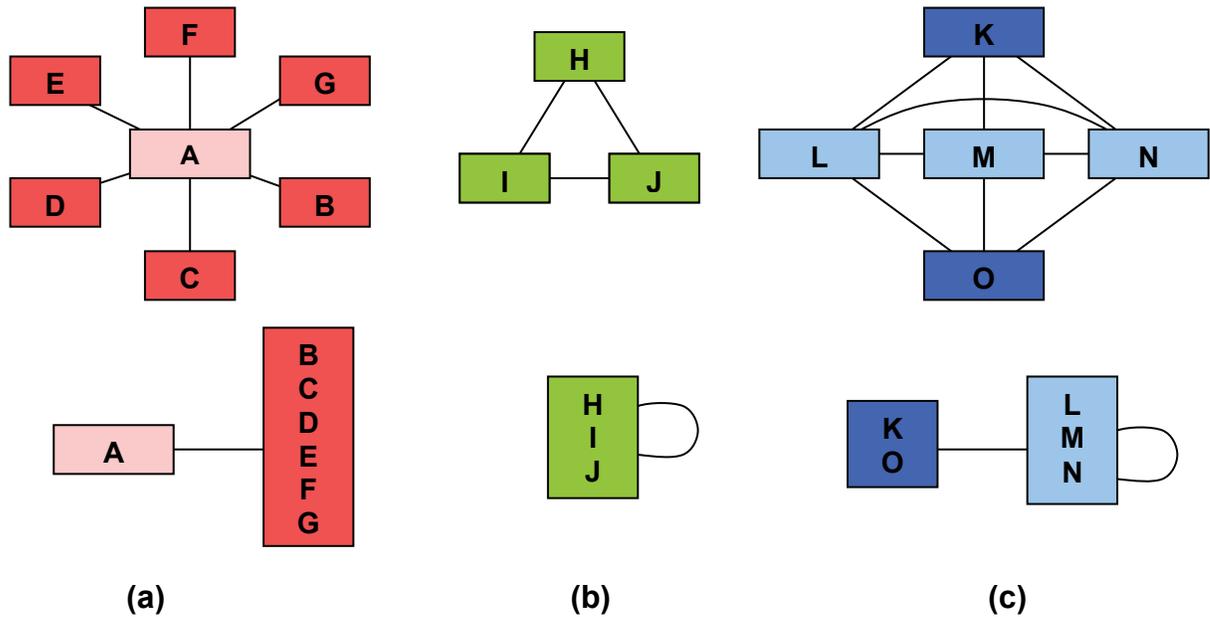


Fig 1. **Edge compression**: Collapsing networks based on identical network neighborhoods. The darker nodes in (a) all have identical neighbor sets $\{a\}$ and can be collapsed into a single clustered node. Although the nodes in (b) are all structurally interchangeable they have different neighbor sets $\{i,j\}$, $\{h,i\}$ and $\{h,i\}$ respectively; we can still merge them if we consider N_{self} set $\{h,i,j\}$ instead. The graph in (c) has neighbor sets $\{l,m,n\}$ for both K and O (dark blue) and N_{self} set $\{k,l,m,n,o\}$ (light blue) for L, M and N.

3.1.2 Orthographic linking

To allow more rapid exploration, we investigated a second method: simple text-based pattern matching. For example, instead of using a parser to look for possessive relations between nouns, we can define an edge (X,Y) for each literal occurrence of "... X's Y..." which allows us to extract basic genitive relationships from the text. Similarly we can look at occurrences of "... X at Y ..." which might hint at relationships between objects and places.

Using regular expressions we can define a wide variety of potentially interesting patterns. For example, we might require that both X and Y start with a capital letter, that either one is a number, or define complex patterns such as "... because X (is|are|was|were) Y ...". Matching regular expressions can be done at interactive speeds (a few seconds for a text of a million words).

We often found these simple pattern matching techniques as useful as full parse-based methods when applied to sufficiently large bodies of text. The basic idea is reminiscent of Hearst patterns [11] for extracting hypernym relations—with enough data, seemingly "superficial" methods produce useful results. A bonus is that simple pattern matching can be explained to users without resorting to technical linguistics terminology.

Figure 2 shows a comparison of two networks generated by these two different methods (with filtering as described below). Although the main terms are very similar, the syntactical parser also picks up occurrences such as "looked at the time". The orthographical parser ignores the "looked at the" match, since "the" is classified as a stop word.

3.2 Network filtering

After parsing the text, we are left with a graph where nodes represent words in the source text and edges represent a particular connection between those words. The edges are directed—representing the order the words occurred in the slots in the pattern—and weighted according to the number of times the pattern was matched. This graph is potentially too large to render legibly on screen, so we include a filtering phase to reduce its size. As a first

step, we provide the user the option of removing nodes representing commonly occurring words in the English language. These "stopwords" often do not add useful information content and greatly increase the density of the graph as they occur in combinations with many other words.

The next step is to rank words by relevance. There are several simple possible relevance measures. One is degree in the network; another is overall frequency in the text. In our prototype we found that overall frequency was a good relevance measure, with the additional benefit that the resulting display was directly analogous to a word cloud view. Given a relevance rating, we allow the user to set a maximum number N of nodes to display. Our software then looks at the induced subgraph for the N most relevant nodes, discards any degree-zero nodes, and displays the resulting graph. Both this step and the stopword filtering can be executed efficiently; stopword filtering is easily integrated with the pattern matching stage, while the second step involves a single sort of the terms and a linear time filtering operation.

3.3 Edge compression

Despite the simplification induced by node filtering, standard graph layouts often produced busy and confusing graphs. One common problem involved a node with many degree-one neighbors. Most graph layouts, when applied to such a node, will produce a "starburst" of edges evenly spread across different angles and distances. This can be effective when nodes are drawn as points or circles, but creates an unreadable mass of overlapping text when the nodes are words.

To address this problem and draw the graph in a "text friendly" manner, we perform a step we call *edge compression*. To motivate this step, note that all the degree-one nodes in a starburst are *topologically equivalent*, in the sense that permuting two of them will result in an isomorphic graph. Since they are equivalent in this sense, we collapse them to a single large node, and draw them in a nicely flush-left vertical column, with a single edge drawn between this column and the central node of the starburst (Fig. 1a). While information is lost about the specific edge weights, all the original topological information remains available.

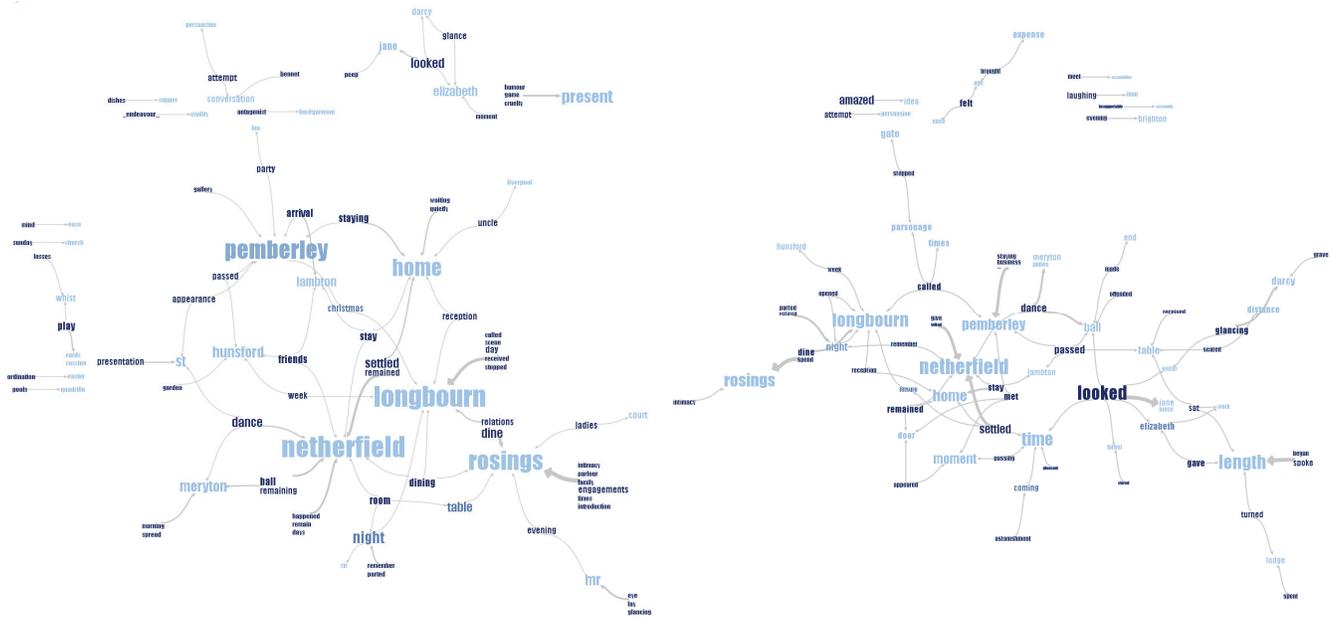


Fig 2. Comparing phrase nets of *Pride and Prejudice*. The left network was generated by an orthographical parser matching ‘X at Y’, while the right network was generated by a syntactical parser looking for the preposition ‘at’. Both manage to identify major locations in the novel., yet the orthographical parser finished in under a second, whereas the syntactical parser took over 24 hours.

This method generalizes naturally: whenever we have a set of nodes that are topologically equivalent, we can collapse them into a single supernode. These sets form equivalence classes, so the supernodes are well-defined. Furthermore, it is immediate that sets of equivalent nodes must either be completely disconnected from each other, or must form a clique. We indicate the difference by drawing a small self-loop for cliques as in Fig 1b. Edge-compression saves time in the layout procedure, improves the quality of the resulting layout, and creates a cleaner visual representation. Fortunately, it is also straightforward to perform this calculation efficiently. For each node x , with neighbor set $N(x)$, define $N_{\text{self}}(x) := N(x) + \{x\}$. Nodes x and y are topologically equivalent if $N(x) = N(y)$ or $N_{\text{self}}(x) = N_{\text{self}}(y)$. Note that this computation can be applied to both directed and undirected graphs. For undirected graphs we can directly compare the set of neighbors, while for directed graphs we need to compare neighbors connected by an in-edge and neighbors connected by an out-edge separately. In our particular case direction is relevant, so we perform directed edge compression.

For simple (i.e. no self loops, no multi-edges) unweighted graphs, the edge-compressed representation is lossless, meaning that all basic information can still be extracted from the resulting diagram (Fig. 1c). The actual reduction in the number of edges depends on the structure and density of the graph, but we the low complexity and often lossless compression of the network representation potentially makes this algorithm valuable to other graph drawing cases.

3.4 Visual Representation

After data extraction and network filtering we are left with a network containing several clusters, some composed of a single node and others made up of a collection of topologically equivalent nodes. The clusters are connected by edges where the weight of an edge depends on the number times a matching pattern was found between the term or terms in the two clusters.

3.4.1 Layout

We render each connected component in this network using a node-link diagram, where individual nodes are replaced with a rendered version of the term(s) they represent. Each term is scaled proportionally to the total number of occurrences in the text, as in a tag cloud. For clusters containing multiple terms, we render all the

terms in a vertical list, scaling each of them individually based on frequency of occurrence. Layouts are computed using a stress majorization algorithm [8]. A post-processing step removes any remaining overlaps using an algorithm based on the Force-Transfer approach [12], and enforces a minimum distance between words. Individual connected components in the network are laid out using an incremental approach that tries to minimize the total area of the layout, while avoiding overlap. In a final step, node coordinates in the layout are scaled so that the resulting layout matches the aspect ratio of the screen.

3.4.2 Encoding

Since connections between clusters are typically directional (i.e. there is a match for ‘cold and strange’ in Fig. 3, but ‘strange and cold’ never occurs in the text) we indicate them with arrows, where the thickness of an arrow is proportional to the weight of an edge. Every term is rendered in a heavy font with compressed spacing, for a compact and coherent visual representation. As an additional encoding, we decided to encode the ratio of out-degree to in-degree for a node and render terms with a high ratio (i.e. more out-edges than in-edges) in a darker color. This allows the user to quickly spot terms that only occur in the first or last part of the matching pattern. The colors follow a sequential palette running from light to dark blue; an early version of the system used a diverging color scheme that seemed to lead to a cluttered display. Basic zoom and pan controls allow the user modify the viewport, while popover hints provide more contextual information on demand, such as the actual textual matches for a relationship.

3.5 User Interface and Many Eyes deployment

We developed several versions of the phrase net. The first two were aimed at experts, and allowed users either to type in regular expressions as matching templates or—if a parsed text had been loaded—to choose syntactic relationships from a menu. While these simple interfaces were effective for our own experimentation, we discovered they were confusing for users who were unfamiliar with the software.

To better understand how people might spontaneously use phrase nets, we deployed a version on the Many Eyes [19] web site. Because of the long time required to perform syntactic parsing, this

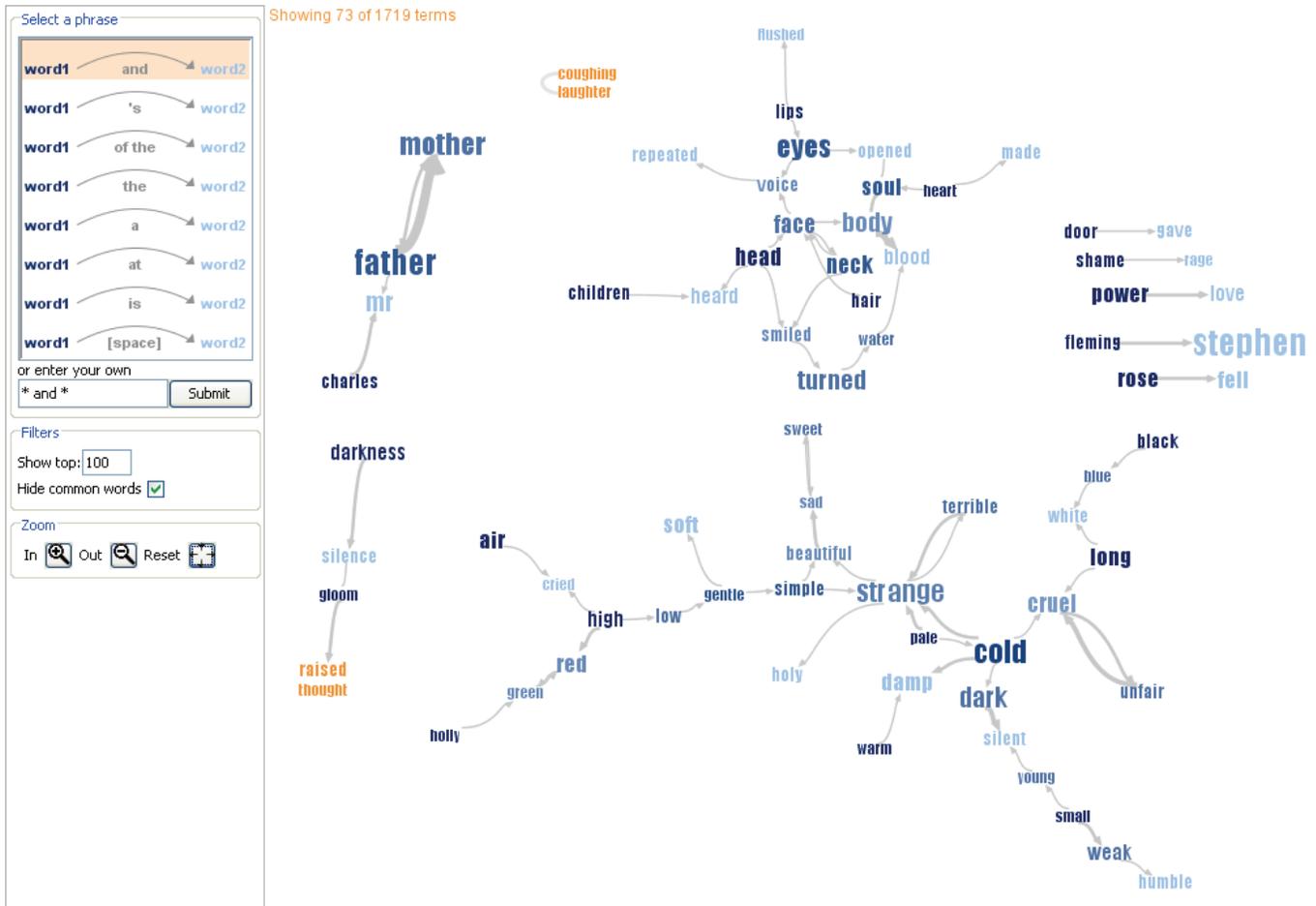


Fig 3. The Phrase Net user interface applied to James Joyce's Portrait of the Artist as a Young Man. The user can select a predefined pattern from the list of patterns on the left or define a custom pattern in the box below. This list of patterns simultaneously serves as a legend, a list of presets and an interactive training mechanism for regular expressions. Here the user has selected "...X and Y...", revealing two main clusters, one almost exclusively consisting of adjectives, the other of verbs and nouns. The highlighted clusters of terms have been aggregated by our edge compression algorithm.

version used regular expression templates as a matching device. Of course, it would be unreasonable to expect novice users to master standard notations for regular expressions. This posed an interface challenge: how to combine maximum flexibility with an accessible user experience. To that end, we iterated over several UI options, testing them informally with users in our lab.

We settled on using a simplified version of the basic regular expression syntax: instead of the cryptic $(w+)$ notation to match an arbitrary word, we used a single asterisk. For instance, if a user wants to define a pattern that looks for two words connected by "and", she would type in: "* and *". Users may either enter matching patterns in this simplified form or enter them in full regular expression syntax.

In addition to this text-based input method, we also included a "beginner's menu" with a number of preset patterns. This menu not only lists a series of simple regular expressions to get the user started, it also serves as a visual guide for how phrase net patterns work (Figure 3). On this list, each pattern appears as a pairing of words with a curved arrow between them, labeled with that pattern's connector. The first word of the pair appears in dark blue and the second in light blue. This distinction echoes the phrase net color coding. Users' choice of a preset pattern is reflected on the more advanced free-text input field so that novices may learn how the simplified regular expression syntax works. Finally, users may also

change the maximum number of words on the graph and choose whether to include stop words in the network.

4 EXAMPLE USE CASES

The examples in this section illustrate how phrase nets have been utilized so far and the kinds of insight that have been generated by these graphs. We discuss graphs that have been created by the authors as well as those generated by Many Eyes users.

4.1 Styles of exploration

Because of its querying capability, a phrase net provides viewers with great flexibility when exploring a piece of text. Yet there are two main exploratory processes that seem natural when working with phrase nets: using the same regular expression to compare different texts and using different regular expressions to explore the same text.

One example of applying the same regular expression to different texts comes from a Many Eyes user who utilized a phrase net to examine different books in the Bible (see Fig. 4). The pattern "X of Y" reveals stark differences between the Old and New Testaments. While the Old Testament clearly shows the centrality of "Israel"—phrases such as "Children of Israel," "King of Israel," and "Land of Israel" loom large—the New Testament shifts in emphasis to "Son of God" and "Kingdom of God."

I spend a lot of my time reading endless pamphlet and newspaper wars, trying to figure out who the sides are in the railway debates and what they care about. While I don't think that I'll ever be freed from reading, algorithms like these promise to give me some of the keywords that can offer me a short cut direct to some of the major controversies in question. The paragraphs on railroads that accuses others of "interest" reference which place-names, for instance? [...]

A machine that can predict who the controversialists were and where the places they argued about were located would save the historical researcher untold time.

Although we cannot draw any definitive conclusions from this single case, it illustrates some of the needs of and challenges confronting modern day humanities scholars. Although many of their databases are in digital form, they do not have the tools to quickly explore this data at a higher level of abstraction. Any tool that can create a projection of the text that highlights one particular aspect can be an invaluable asset.

5 CONCLUSION

We have introduced the phrase net, a new technique for mapping unstructured text. The phrase net technique consists of two steps. First is a pattern matching phase, in which linkages are defined between words based on user-defined templates. The second phase involves laying out and rendering the graph. The layout phase includes a new, general clustering procedure that reduces the complexity of the graph while retaining its information content. Finally, we provided examples of spontaneous usage on the public Many Eyes site, along with some of our own scenarios, in which the phrase net provides a lens onto interesting aspects of a text.

There are several natural avenues for future work. First, one might plug many other possible matching template methods into the basic phrase net technique. One might also allow the user to filter words in ways other than by simple word frequency, combining semantic and syntactic information. It is easy to imagine scenarios where a user might want a net consisting only of people, or only of nouns that are related to emotions. Similarly, one might match only patterns that occurred in particular sentences, such as those spoken by a particular character in a novel. It might also be possible to plug in semantic classification services such as openCalais [16] to identify central actors in our document. Finally, applying phrase nets to languages other than English may lead to new challenges.

Many additional possibilities for interaction remain. One might combine the phrase net with other visualization techniques. Often users wish to drill down into a text, and one could imagine selecting a given edge of the graph to bring up a word tree showing all the following or preceding passages to the template match. A last, promising area for future research would be to allow users to easily compare different texts using a phrase net. For example, one might ask if different novelistic genres have distinctive networks, either in word usage or overall topology. Or one might wish to see how document collections change over time, e.g., comparing phrase nets of news stories from day to day.

In addition to the contribution of the technique itself, we believe the design of the tool itself provides useful principles for text visualizations. One is the notion of multiple viewpoints. A novel is much like a high-dimensional numeric data set: there is unlikely to be a single perfect view. Instead, as with high-dimensional data, the best way to visualize it may be to use multiple views. Instead of choosing different projections one may want to choose different types of relationships in the text to highlight. The phrase net provides this control by allowing the user to specify the matching templates. A second theme in the design of the phrase net is the careful tuning of the display to allow for legibility of the text: In addition to careful typographic choices, we have modified the graph layout method to maximize readability. We believe both these themes—multiple

viewpoints, and special tuning of existing geometric techniques—are likely to continue in future text visualization work.

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