

Tracing Genealogical Data with TimeNets

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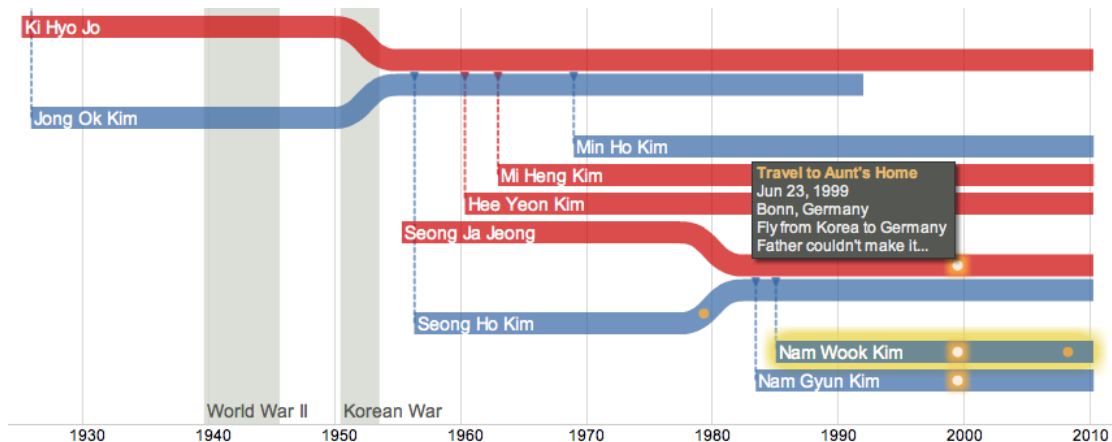


Figure 1: TimeNet visualization of the first author's family. Lifelines represent people, converging lines signify marriage, and drop lines indicate children. Annotations show both historical and personal events.

ABSTRACT

We present TimeNets, a new visualization technique for genealogical data. Most genealogical diagrams prioritize the display of generational relations. To enable analysis of families over time, TimeNets prioritize temporal relationships in addition to family structure. Individuals are represented using timelines that converge and diverge to indicate marriage and divorce; directional edges connect parents and children. This representation both facilitates perception of temporal trends and provides a substrate for communicating non-hierarchical patterns such as divorce, remarriage, and plural marriage. We also apply degree-of-interest techniques to enable scalable, interactive exploration. We present our design decisions, layout algorithm, and a study finding that TimeNets accelerate analysis tasks involving temporal data.

ACM Classification: H.5.2: User Interfaces

Keywords: Visualization, genealogy, timelines, TimeNets

INTRODUCTION

The combination of networking, database technology, visualization, and content analysis algorithms is creating new possibilities for the collective aggregation and interpretation of information. In this paper, we take a specific domain of col-

lective information aggregation—genealogy—and develop an improved visualization that could eventually anchor a social sensemaking system. Genealogy, or the study of families, is a popular activity pursued by millions of people, ranging from hobbyists to professional researchers [17]. The genealogical research process involves determining when and where people lived as well as their biographies and kinship. It often leads to diverse knowledge of religious histories, migration trends, and historical social conditions; tracing ancestry gives us an understanding of our history.

The most common task confronting genealogists is to correctly identify individuals and their familial and temporal relations. To keep track of their findings, people typically use genealogical diagrams, or “family trees,” such as ancestor (pedigree) charts and descendant charts (Figures 2a-b). By aligning people by generation, the charts prioritize the display of kinship relations, facilitating the identification of marriages, parent-child relations, siblings, and cousins.

However, such representations often omit other aspects of genealogical data, particularly time. For instance, genealogists must frequently cope with temporally ambiguous evidence in order to establish kinship [15]. To infer genealogical relations, a researcher may compare estimates of an individual's birth date with the marriage dates of potential parents; misapprehension may lead to an incorrect reconstruction of the family. Most existing genealogical diagrams (e.g., [4, 9, 10, 16]) share a common set of limitations:

1. They do not show family networks well. Families are networks of relationships, not trees. The most popular visualizations are ancestor charts (trees of generations of par-

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ents), descendant charts (trees of generations of children) and hourglass charts (combined ancestor and descendant charts for an individual). This approach assumes a hierarchical structure that does not fit real-world families [16].

2. They do not show complex relationships well. Traditional diagrams are unsuited for communicating complex patterns such as divorce, remarriage, out-of-wedlock births, and polygamy. These are part of real family histories and may have different meaning in world cultures.
3. They do not show temporal attributes well. Temporal attributes such as birth, death, marriage and divorce dates are either omitted or depicted only by text labels.
4. They do not scale well. One of the major advances in genealogy in recent years has been the online availability of family data, making it easier to construct larger family relationship networks. Yet, unless heavily edited by hand, automatically generated diagrams are not suited to depict these larger networks. They tend to show perhaps eight generations, sacrificing depth or breadth of relationships.
5. They do not show the relationship between nodes at a distance. It is hard to see the relationship to a famous person or between two people co-mentioned in an historical record if they are not close together in the family network.

To address the limitations of traditional genealogical diagrams we contribute TimeNets, a visualization technique for genealogical data. TimeNets encode both family kinship and timelines of individual life events; interactive degree-of-interest filtering is used to scale to large data sets. TimeNets address complex relationships by laying them out on individual lifespan timelines (Figure 1). These timelines also express temporal attributes, such as birth or marriage date. Scale is handled using focus+context techniques: a degree-of-interest function filters the display based on a user’s indicated interest in some nodes and their relationship to other nodes. The same mechanism also allows for the display of nodes at a distance and the contextual nodes that relate them.

RELATED WORK

To place TimeNets in context, we review existing techniques for both timeline and genealogy visualization.

Genealogy Visualization

In a broad sense, there exist two types of genealogical relations. Parent-child relationships (*consanguine* relations) define a hierarchy in genealogical data. Relationships through marriage (*conjugal* relations) are non-hierarchical and merge family trees. Together these form a network of relationships—complex but simpler than a general graph. The most common genealogical research is ancestral research—tracing ancestry of self—and descendant research—finding descendants of an ancestral couple. They correspond to constructing a tree of ancestors and a tree of descendants. This observation verifies why ancestor (pedigree) and descendant charts (Figure 2) are canonical charting methods for genealogical data.

Other depictions have also been applied. An hourglass chart combines both a pedigree and a descendent chart centered on a specific individual (Figure 2c). Fan charts are ways of drawing these trees without connecting lines and with more

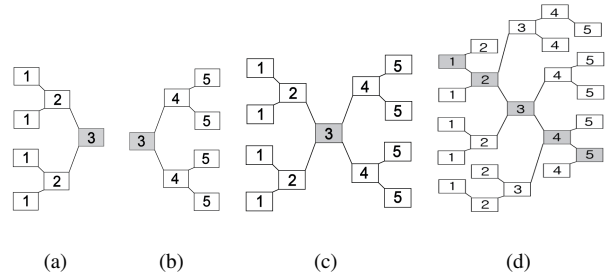


Figure 2: Genealogy diagrams. (a) Ancestor chart. (b) Descendant chart. (c) Hourglass chart. (d) Dual tree.

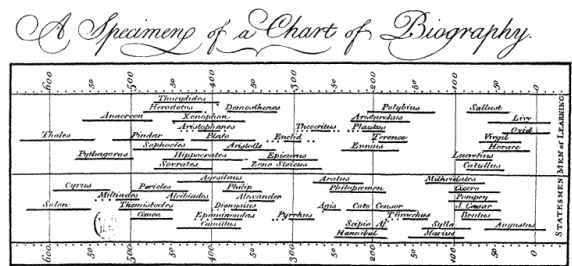


Figure 3: Biographical lifelines by Priestley, 1765 [22].

space available to the leaves of the chart [4]. These charts make it easy to understand the basic hierarchical relationships of direct dependency at the cost of suppressing other relationships. Specialized charts, such as a Table of Consanguinity or a Canon Law Relationship Chart [3] are used to determine the degree of relationship between people who share a common ancestor, such as great aunt or third cousin twice removed. Sometimes these basic genealogical charts are combined with pictorial artwork.

McGuffin and Balakrishnan [16] introduced Dual Trees (Figure 2d). Dual Trees generalize the hourglass chart by offsetting the roots of the trees with respect to each other; multiple roots are connected along the hierarchy and each root has its own hourglass chart. As a result, more information can be shown at a time without introducing edge crossings. To maintain readability, however, only a limited number of nodes are shown on a computer screen. An interaction technique for expanding or collapsing a node is used to explore large data and transition between different dual-tree subsets.

The genealogical techniques described are widely used in published genealogies and software. They are successful in showing a limited number of hierarchical relationships, but have the five limitations we have previously described.

Timeline Visualization

An inspiration for making genealogical diagrams more expressive has an impressive pedigree itself. In 1765, Joseph Priestley used timelines to depict the lifespans of two thousand famous people from 1200 B.C to 1750 A.D (Figure 3). He also invented using dots to indicate uncertainty in birth and death dates. The horizontal axis is time and people’s vertical position is ordered by “importance.” Kinship is not shown, but Priestley’s diagram makes clear who was a contemporary of whom and who was living during world events.

Timelines have been used to visualize life events in a number of domains, such as medical records and criminal justice.

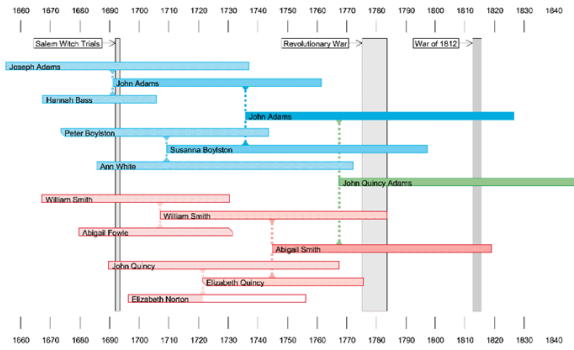


Figure 4: Genelines pedigree chart [9].

One of the best known of these is Lifelines [21] and its successors. Lifelines uses timelines to visualize personal histories based on medical records. Each timeline shows different sections of the record such as diagnosis and medications. Users can drill down into timelines for details-on-demand. Temporal and causal relationships among different sections also can be inferred, but require significant cognitive effort. The Pattern Finder [5] is a descendant of the Lifelines work that visualizes mined temporal patterns in multivariate data.

Randall Munroe of XKCD [18] hand-crafted timelines of interactions among movie characters. Each character is represented using a lifeline differentiated by color. Lines converge and are grouped using a gray background to indicate which characters are together at a given time. A hierarchy is not defined on the data and accordingly not shown.

Timelines have also been applied to the visualization of family networks. Genograms [10] are like family trees, but lines depicting a marriage represent ordinal time. Genograms can depict more complex relationships like divorce and remarriage, but depend on special symbols. Genograms are most useful when the number of people depicted is moderate and they are easiest to use when most relationships are hierarchical. Genelines [9] depict people as timelines (Figure 4) and are good at showing temporal attributes. How they show non-hierarchical patterns such as divorce and remarriage and how they scale to large data are unclear, however.

Degree-of-Interest Techniques

As family networks become larger, they no longer fit on the screen using any of the techniques discussed so far. Degree-of-Interest techniques, introduced by Furnas [7], compute a score for each node in the network based on which nodes are presumed to be of most interest to the user. Nodes below a threshold score are suppressed. Using versions of this technique, Heer and Card [13] were able to display large DOI Trees on the order of a million nodes. Card et al [2] combined DOI Trees with time-varying organizational data to display changes over 50 years of leadership of a medium sized country. van Ham and Perer [23] recently extended DOI techniques to general graphs. DOI techniques might also aid the scaling and filtering of family network diagrams. In this project, we apply it to a neighbor of trees—genealogical lattices. Interest might be assigned based on the relatives of a focal person, the relatives two people might have in common, or search results, such as every relative named “Christopher.”

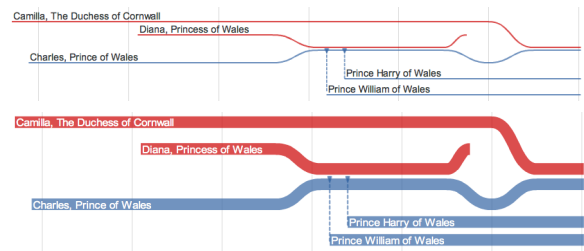


Figure 5: TimeNets with different styles. (a) Thin lines with external labels. (b) Thick lines with internal labels.

TIMENET DESIGN

As the related work suggests, three visualization paradigms have promise for genealogies: hierarchies, timelines, and degree-of-interest techniques. Our challenge is to bring all three of these techniques into correspondence through unified visual encoding and layout algorithms. In this section, we describe the series of visual encoding decisions and associated trade-offs involved in crafting TimeNets. We focus on high-level design goals and defer discussion of implementation and interaction details to the next section.

In designing TimeNets, our goal was to support simultaneous graphical representation of ancestor and descendant relations, complex conjugal relationships, temporal attributes, and data uncertainty—all in a scalable fashion. In addition to generational structure, non-hierarchical relationships can get complicated. Divorce and remarriages are frequent in modern family settings. Furthermore, in non-traditional family arrangements, one might have more than one spouse at a time. A timeline is a natural way to visualize these relationships as well as other important temporal attributes such as marriage dates. Taken together, both hierarchical and temporal information will enable effective understanding of relationship dynamics and story telling of family history.

People as Individual Lifelines

To make temporal attributes salient, we started with the common convention of a linear timeline. A TimeNet’s horizontal axis represents time progressing from left to right. The examples in this paper use metric timelines; ordinal timelines are possible with minor modifications. Similar to prior genealogical timelines [9, 18, 22], we represent a person as an individual lifeline (Figure 5). The left end of the lifeline represents a person’s birth and the right end represents their death; thus the horizontal extent of the line depicts a person’s lifespan. By default we use line color to depict sex (blue for male, red for female). Lifelines include text labels consisting of a person’s name and potentially other data. Line width is left as an aesthetic design parameter; if the lifeline is thick enough, we place the label within it (Figure 5b).

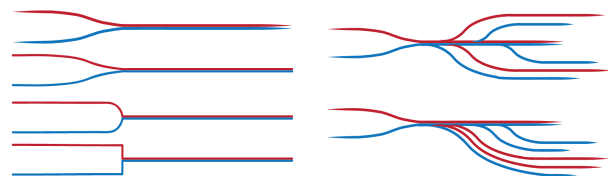


Figure 6: Early design prototypes. (a) Lifeline interpolation techniques. (b) Different children layouts.

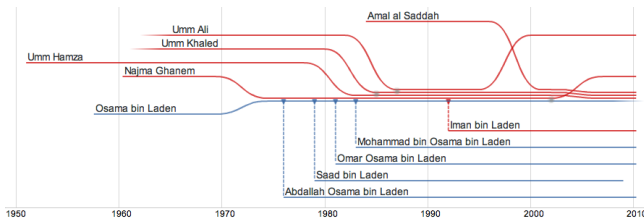


Figure 7: The marriages of Osama bin Laden. Gradients indicate uncertainty of birth or marriage dates.

Marriage/Divorce as Converging/Diverging Lifelines

With the horizontal axis devoted to time, the vertical axis is free to represent relationships. We use vertical proximity to encode conjugal relations: two or more lifelines converge into a bundle of adjacent lines to denote a marriage (Figures 5–7). The point at which the lines meet represents the marriage date. Conversely, lines diverge to indicate divorce. This representation naturally encodes a variety of marriage patterns, as sequences of marriage, divorce, and remarriage are depicted by the convergence and divergence of lifelines. Plural marriage (polygamy) is represented by more than two lines converging into a shared marriage bundle (Figure 7).

In the case of multiple marriages, the question arises of how to order spouses. Our default approach is to vertically order spouses by their first marriage date; hence a vertical scan visits spouses in chronological order. A different approach is to alternatively place spouses above and below a focal person (Figure 9). An alternating placement reduces line crossings, but makes it more difficult to determine spouse ordering. In either case, when a person divorces we return their lifeline to its original position, facilitating consistent placement and enabling a horizontal scan to determine if a divorce occurs.

We have also explored a variety of lifeline interpolation strategies (Figure 6a). Orthogonal lines and circular arcs clearly depict the dates of marriage and divorce, however, splines with continuous curvature are easier to follow (particularly for line crossings) and elicit higher user preference ratings. We default to using cubic Bézier curves, but users can change the interpolation settings if desired.

Unfortunately, line crossings due to multiple marriages are sometimes unavoidable. To alleviate this problem, we use the aforementioned spline interpolation and can apply alpha blending to facilitate line-following. In some cases, a divorce and subsequent remarriage may be in close temporal proximity, resulting in nearly vertical line crossings. In such cases, we slightly exaggerate the time period to enable better perception of the crossing (Figure 8).

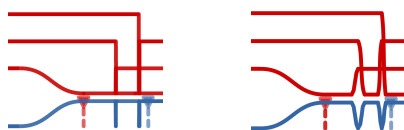


Figure 8: Divorce and remarriage in close proximity. (a) No perturbation. (b) Perturbed event points.

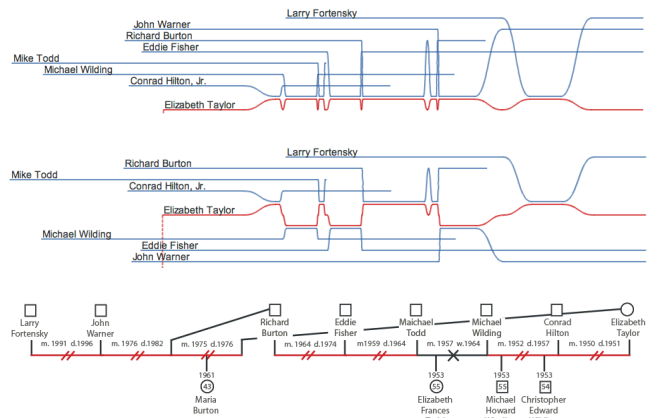


Figure 9: Marriages of Elizabeth Taylor. (a) Spouses ordered chronologically. (b) Alternating spouse layout. (c) Genogram representation [10].

Parent-Child Relationships as Drop Lines

To represent consanguine relations, we depict children as lifelines emanating from their parents. Our first design iteration initiated a child’s lifeline directly on the parents’ marriage line; the child line then diverged into its own space (Figures 6b, 10c). Informal user testing revealed that this representation is confusing, as it is often ambiguous which line corresponds to a child and which to a divorced spouse. Furthermore, this representation can result in lifelines with very long vertical stretches that both add visual noise and complicate perception of temporal patterns (Figure 10c).

Instead, we adopt a strategy similar to Genelines [9]: we depict parent-child relations using a directional edge (or “drop line”) that connects the parents to the start of the child’s lifeline. To make lines perceptible but not distracting we render parent-child edges using faded dashed lines. Parent lines are annotated with a visual marker indicating the directionality of the edge. One disadvantage of this approach is that tracing from parent to child requires more complex line-following. However, there are a number of compensating advantages: drop lines enable more accurate perception of temporal attributes (e.g., birth date and lifespan) and reduce the saliency of edge crossings when child lines are positioned far from their parent lines (compare Figures 10b and 10c). Moreover, drop lines easily accommodate children born out of wedlock: we simply place markers on each parent’s lifeline and connect them with the drop line (Figure 10a).

By default, we vertically sort children by birth date. We place younger children closer to their parents, as this arrangement helps minimize line crossings. We can also alternate child placement above and below parents (Figure 6b), but such alternation impedes quick apprehension of birth order.

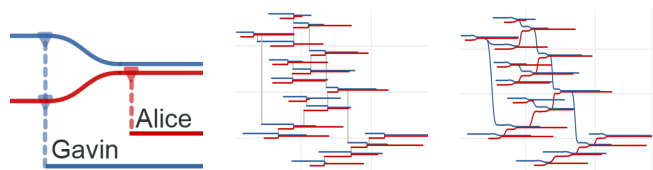


Figure 10: Child layouts. (a) Children born out of and in wedlock. (b) With drop lines. (c) Without drop lines.

Uncertainty

Genealogical data regularly suffer from missing or approximate values. Without indications of uncertainty, visual analysis may lead to inaccurate conclusions. Missing temporal attributes such as birth and death dates can be particularly problematic for our time-based layout. As described in the next section, we first estimate missing attributes to derive potential birth, death, and marriage dates. We then include visual markers to convey missing and uncertain values to viewers (Figure 7). By making uncertain data values more apparent, we hope to assist users as they clean and curate their data. For uncertain birth and death dates, we fade lifelines using a gradient; the lifeline takes on full saturation at the estimated date of birth or death. For uncertain marriage and divorce dates, we draw an underlying marriage marker and again use a gradient to indicate uncertainty. By clicking an uncertain value a user can then enter a revised date.

Other Patterns and Attributes

While TimeNets directly show marriage, ancestry, and temporal patterns, they can also be used as a substrate for conveying additional data. For example, the color encoding of lifelines can be changed to communicate attributes other than gender. A variable color encoding scheme may show changes in geographic location (e.g., continent or country) over time, or the occurrence of different diseases. TimeNets can also highlight structural patterns: one might highlight an ancestral path or view the output of a graph analysis routine. We can also add annotations for historical or personal events of interest (Figure 1), allowing one to tell a family story.

Focus + Context Techniques

To navigate large genealogies, we use degree-of-interest (DOI) estimation to determine the most salient aspects of the data and then filter the elements deemed less interesting. TimeNets visually communicate the existence of elided elements in two ways. First, when a person has a DOI value beneath the visibility threshold but is married to someone with above-threshold DOI, a segment of their lifeline is shown to indicate the duration of their marriage (Figure 11). Second, to handle low-interest descendants, drop lines are still used, but are faded out (c.f., [23]). These marks provide an indication of the elided context, and thus serve as “information scent” [19] for further exploration.

IMPLEMENTATION

TimeNets are constructed in a two-stage process: data processing and visual encoding. In the data processing stage, we ingest genealogical data and apply a series of data transformations, including estimation of missing temporal attributes. In the visual encoding stage, we calculate degree-of-interest values and use them to layout the graph and label visible elements. In this section, we detail each of these steps.

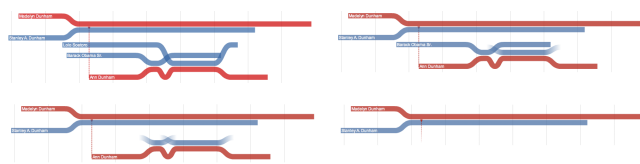


Figure 11: Progressive elision by DOI (left-to-right).

Data Model

Although a variety of genealogical data formats exist, the de facto standard within the genealogical community is GEDCOM [8]. Accordingly, we parse GEDCOM files as one data source for TimeNets. Unfortunately, the GEDCOM specification can not represent many types of interpersonal relationships, including same-sex marriage, polygamy, and incest. In response, we developed our own data model for genealogical data. The first step in our pipeline is thus to ingest data from an external source—such as a GEDCOM file or web repository such as Freebase [6]—and map it to our data model.

We use a basic relational data model. At its simplest, the model consists of two relational tables: a list of individual people and a table of relationships. For individuals, we assume the presence of at least five attributes:

```
<id, name, sex, date_of_birth, date_of_death >
```

We encode relationships using foreign keys for two people and require relationship type and temporal attributes:

```
<person1_id, person2_id, relationship_type,  
relationship_start_date, relationship_end_date >
```

Here *person1_id* and *person2_id* refer to individual records in the person table. Relationships involving multiple people are represented by multiple entries (rows). The primary *relationship_type* values are *Child-of* and *Spouse-of*, though these types are extensible. The data model can be extended by introducing additional columns (e.g., geographic data) or by introducing additional tables (e.g., historical events).

Missing Data Estimation

TimeNets rely on temporal attributes such as birth date and death date in order to compute a layout. However, it is common for genealogical data to have missing or incomplete temporal values, e.g., a data set may have birth and death dates but lack marriage dates. To address this issue, we estimate missing data values as part of our data processing stage.

We use a rule-based method to estimate missing dates. The basic idea is to take advantage of the regularities among temporal attributes. We define an ordered chain of rules for each attribute, and use the first applicable rule in the chain:

- **birth** ← parents’ marriage; mean sibling birth; mean spouse birth; ...
- **death** ← mean sibling death; mean spouse death; ...
- **marriage** ← oldest child’s birth; ...
- **divorce** ← assume no divorce

We use default estimates if no applicable rule exists. For instance, we offset a person’s birth date (e.g., by 20 years) to estimate a missing marriage date and assume a the person is alive if their lifespan is under a threshold (e.g., 85 years).

The main goal of our estimation rules is to ensure that we have at least reasonable values for missing attributes for subsequent visualization. However, our current solution is only a stopgap method. While we have attempted to select suitable defaults, analysts can modify the estimation rules or add new ones; in the future we plan to improve the estimation process using machine learning techniques. As discussed previously, TimeNets also visualize the uncertainty of estimated dates so that analysts can identify and repair missing values if desired.

Degree-of-Interest Calculation

Once the data has been suitably transformed, we calculate degree-of-interest (DOI) estimates. These DOI values provide a rank-ordering of the “interestingness” of people within the genealogical graph based on a current set of focal nodes (e.g., clicked elements or search result hits). These values are in turn used to subsequently filter and layout the graph; after the DOI values are computed, only the nodes whose DOI values are above a chosen threshold are visualized. Our approach is based on previous models [1, 2, 13], with modifications to support non-hierarchical marriage relationships.

Our default DOI function is as follows. Starting with a set of maximally interesting focus nodes, we traverse the genealogical graph and assign lower DOI values with increasing distance. If a root element (e.g., central matriarch) is defined, maximal DOI values are assigned both to focus nodes and their relatives along the path to the root. Otherwise, DOI values decrease linearly across consanguine relations. Across conjugal relations, DOI values decrease more slowly using fractional DOI increments. Thus for a given focal node, spouses will be given higher interest than either parents or children. For both spouses and children, additional fractional DOI increments are assigned based on date order; for example, first spouses have slightly higher DOI than later spouses.

Of course, other DOI functions are possible. For instance, one might be interested in exploring cousin relationships and thus assign cousins higher interest values. Our system is modular and can be extended to incorporate alternative schemes. However, we leave the specification of new interest functions by genealogical analysts to future work.

Layout

Once DOI values are calculated, we compute the layout. The layout algorithm works by grouping genealogical elements into a three-level scenegraph consisting of nodes, local blocks, and global space (Figure 12). Nodes represent the bounding region for a specific lifeline. People either directly or transitively connected by marriage are grouped together to form a local block. Our algorithm first segments the graph into local blocks and performs a local layout for each, determining node bounds in the process. Blocks are then positioned by a global layout pass.

Local block segmentation A directed acyclic graph of blocks is constructed by traversing the genealogical structure in depth-first fashion and grouping conjugally-related people. Blocks may have more than one parent due to intermarriage. Our current approach has one limitation: it assumes that cross-generational incest (e.g., mothers marrying sons or sons-in-law) does not occur. We believe this to be a reasonable assumption for most real-world data sets.

Local layout and lifeline generation To perform local layout, we first arrange visible nodes along the time dimension relative to the origin of the block and determine node lengths. We then generate lifelines and set their vertical ordering. We also compute the position and style attributes of marks representing elements beneath the current DOI threshold (e.g., the partially elided elements in Figure 11).

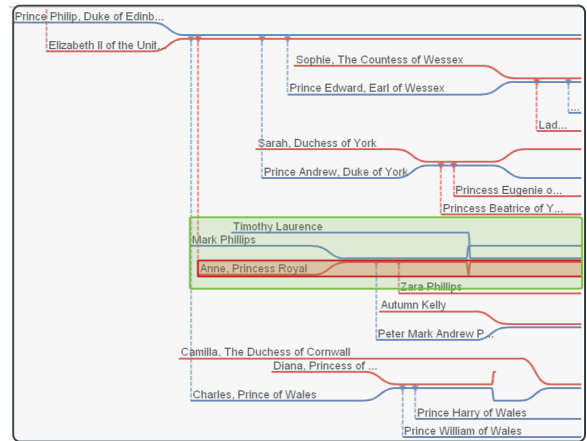


Figure 12: A three-level scenegraph groups nodes into local blocks within a global coordinate space.

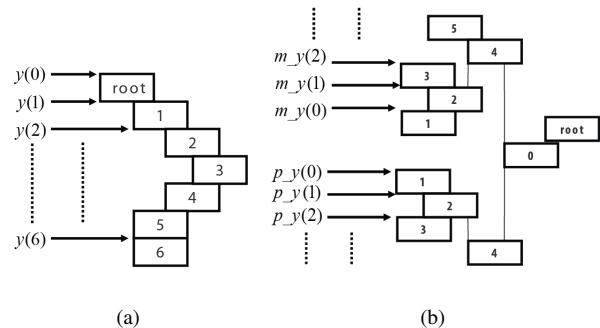


Figure 13: Global layout. (a) Descendants placed by pre-order traversal, (b) Ancestors by in-order traversal.

Lifelines are generated according to the design principles in the previous section. We maintain event points for temporal attributes of each person, including dummy event points to aid spline routing (e.g., between birth and marriage points). If divorce and re-marriage events occur in close spatial proximity, we perturb the event points along the horizontal dimension to ensure better perception of line crossings. We then place a label along (or in) the lifeline. If necessary, we truncate the label to fit the horizontal bounds of the lifeline.

The vertical placement of event points depends on a person’s computed DOI. We start by finding the person with maximal DOI in the block. We vertically oscillate this focal lifeline between a married and non-married position. The focal lifeline then serves as a reference line for spouses, whose lifelines converge to and diverge from the reference line (Figure 9). Different orderings are possible (Figure 5); the default is to order spouses vertically above the reference line.

Global layout Once the block hierarchy is built, global layout is performed by positioning each block. First, we arrange blocks along the horizontal axis according to the minimum birth date in each block. Second, we perform the vertical layout, ensuring that the bounding boxes for local blocks do not intersect. We use different placement schemes for ancestors and descendants. For descendants, we traverse descendant blocks in pre-order, ensuring that the visit order is from the youngest child to the oldest child within each generation

(Figure 13a). Each block’s position is then assigned according to the visit order. As a result, the first-visited block is positioned below the root and the second-visited block is positioned below the first block, and so on. For ancestors, we visit blocks using in-order traversals (Figure 13b). Once layout is performed, we check if the vertical size fits the screen space. If not, we iteratively cull low-interest nodes and update the layout until it fits.

Interaction and Animation

Interactive navigation of TimeNets is similar to previous DOI-based visualizations [13]. Clicking a node makes it the current focus and updates the layout; control-clicking multiple elements defines multiple foci. In this way, one can navigate the graph and build up views of interest. Alternatively, one can type a search query; the result set is used as focal nodes. We use staged animations to communicate changes between interface states (c.f., [20]): the first stage fades out elements whose DOI has dropped beneath threshold, the second stage animates previously visible elements to their new positions, and the third stage fades in newly visible elements.

EVALUATION

To inform the iterative design of TimeNets, we conducted a formative evaluation comparing the effectiveness of generational “family tree” diagrams with TimeNets. Subjects were shown a genealogical diagram and asked comprehension questions. We hypothesized that **(H1)** traditional tree diagrams support faster and more accurate perception of structural family relations but that **(H2)** TimeNets better facilitate the apprehension of patterns with a temporal component.

Method

We asked subjects to complete tasks with two different visualizations: a modified descendant chart (Figure 14a) and a TimeNet chart (Figure 14b). We augmented the descendant chart design to support multiple marriages: spouses are listed in chronological order and each marriage is indicated by a curved edge annotated with marriage and divorce dates. Edges to children originate from these marriage markers. We used 600×600 pixel images depicting a fictitious family of 36 people. Each person was labeled with a common first name with either 5 or 6 letters. To avoid ambiguity all names of the same gender have a unique first letter. Names were varied between diagram conditions.

For each diagram, subjects were asked to answer comprehension questions (Table 1) grouped into three categories:

- *Structural* questions involving only kinship,
- *Temporal* questions involving only timing, and
- *Structural × Temporal* questions involving both.

There were 36 unique tasks in all, 18 for each diagram. Subjects were instructed to accurately answer questions as quickly as they could. A total of $N=22$ subjects participated via Amazon’s Mechanical Turk [12] and were paid \$0.10 USD per task. Before participating, subjects had to successfully complete a suite of qualification practice tasks. To combat known reliability issues with timing on MTurk [12], we used a “ready-set-go” interaction with each task and timed the tasks ourselves using JavaScript.

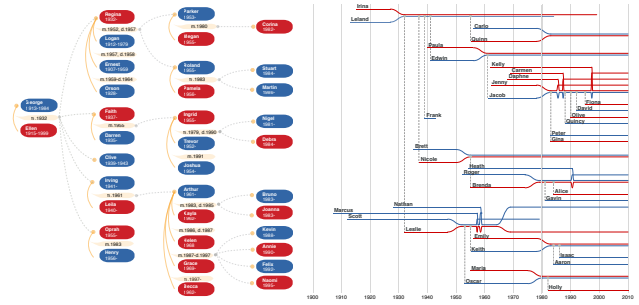


Figure 14: Genealogical diagrams used as experiment stimuli. (a) Descendant chart. (b) TimeNet.

Results

We analyzed both task accuracy and response time. To analyze accuracy, we first scored each subject response as either correct or incorrect; the overall accuracy rate was 90%. We found no significant differences between tree diagrams and TimeNets for structural ($\chi^2(1,211)=1.030, p=0.310$), temporal ($\chi^2(1,210)=0.072, p=0.789$), or structural \times temporal ($\chi^2(1,206)=1.603, p=0.205$) tasks.

Next, we examined response times. As the data are not normally distributed, we used a non-parametric test (Mann-Whitney U) to compare conditions. For structural tasks, the median response time using TimeNets is 2.8s slower (19.9s vs 17.1s, 14%) than tree diagrams. This difference, however, is not significant ($U(108,103) = 5353, p = 0.637$). For other tasks, TimeNets exhibit a statistically significant advantage. The median response time using TimeNets is 4.3s faster (14.6s vs 18.9s, 23%) for temporal tasks ($U(104,106) = 4408, p = 0.012$) and 6.0s faster (18.1s vs 24.1s, 25%) for structural \times temporal tasks ($U(103,103) = 4430, p = 0.041$).

Discussion

Our results provide scant evidence for **H1**: we found no significant differences in accuracy across chart types, and while the descendant charts were slightly faster for structural tasks, the difference was not significant. On the other hand, we did find evidence for **H2**: tasks requiring the use of temporal attributes were completed significantly faster using TimeNets, resulting in a $\sim 25\%$ time savings. Our results suggest that

Structural	How many daughters does Irina have?
	How many half-siblings does Peter have?
	Who is Isaac and Holly’s closest male ancestor?
	Which person has had the most marriages?
	Which mother of two is still married to her first husband?
Which woman has step-children but not biological children?	
Temporal	How many people were alive in 1950?
	Which person was born during the 1920s?
	Were Marcus and Carmen alive at the same time?
	Who was born most recently?
	Who died in infancy?
Who has the longest lifespan?	
Temp \times Struct	How many couples got married in the 1970s?
	Which of Leslie’s sons was the last to get married?
	Who did Brenda marry after divorcing Roger?
	Who was half the age of their spouse when they married?
	Which uncle is younger than some of his nephews?
Who is at least 10 years younger than all their siblings?	

Table 1: Representative User Study Tasks.

- (a) TimeNets can be learned quickly by a lay audience and
- (b) TimeNets facilitate the perception of temporal trends in genealogical data better than tree diagrams.

In addition to establishing concrete benefits for TimeNets, our study also provided qualitative insights for improving future designs. From subjects' comments and our own test runs we learned that visual search for a person's name often dominates task time regardless of diagram type. This observation suggests that search and highlighting mechanisms for finding individuals could facilitate interactive use of either diagram type. Also, more sensitive studies (e.g., using eye tracking) might be able to separate the effects of diagram type on visual search versus decoding and inference.

These results provide promising formative evidence for the use of TimeNets in genealogical research: TimeNets appear to be well-suited for conveying structural and temporal data in an integrated fashion, and may prove a useful tool for analyses involving temporal attributes and/or complex marriage relations. Still, further evaluation is needed to more deeply understand the strengths and weaknesses of genealogical visualization techniques. New studies might examine depictions of data uncertainty, and case studies with practicing genealogists are necessary to assess the effectiveness of these techniques in real-world contexts.

CONCLUSION

In this paper we presented TimeNets, a time-based representation of genealogical data. By depicting individuals as timelines which converge and diverge to depict marriage, TimeNets represent a number of real-world phenomena—including divorce, remarriage, plural marriage, and out-of-wedlock births—that are either difficult or impossible to represent using standard genealogical diagrams. By using degree-of-interest techniques, TimeNets also support scalable, interactive exploration. In a controlled experiment we found that TimeNets exhibited significant advantages over family tree diagrams for tasks involving temporal data: TimeNets accelerated task times ~25% without diminishing accuracy. These results suggest that TimeNets could serve as a useful tool for genealogical researchers and hobbyists.

Though we have focused on human genealogical data, we believe our techniques can be applied to other domains concerned with time-varying branching and merging phenomena. Examples include academic genealogy, biological evolution, artistic movements, computer systems (e.g., multi-threading), and organizational structures (e.g., firms and subsidiaries [14]). Exploring such domains may also suggest new variations of TimeNets. For example, the use of ordinal time, alternative degree-of-interest functions, and additional means of communicating structural units (e.g., a nuclear family) are all potentially useful extensions of our technique.

Looking forward, the design of TimeNets is one step in a larger research agenda. Genealogical research is an attractive domain for studying rich, collaborative sensemaking practices [11]: it engages millions in a social process of foraging for data, evaluating multiple uncertain data sources, analyzing the data, and then disseminating the resulting products. As a first step in this domain, we designed TimeNets to be

able to aggregate and represent genealogical data more representative of real-world families. We hope to extend TimeNets to the web to study and support the collective curation, analysis, and dissemination of genealogical data.

REFERENCES

1. S. K. Card and D. Nation. Degree-of-Interest Trees: A component of an attention-reactive user interface. In *Advanced Visual Interfaces*, pages 231–245, 2002.
2. S. K. Card, B. Suh, B. A. Pendleton, J. Heer, and J. W. Bodnar. Time tree: Exploring time changing hierarchies. In *IEEE VAST*, pages 3–10, 2006.
3. Cousin, Dec 2009. <http://en.wikipedia.org/wiki/Cousin>.
4. G. M. Draper and R. F. Riesenfeld. Interactive fan charts: A space-saving technique for genealogical graph exploration. In *8th Workshop on Technology for Family History and Genealogical Research*, 2009.
5. J. Fails, A. Karlson, L. Shahamat, and B. Shneiderman. A visual interface for multivariate temporal data: Finding patterns of events over time. In *IEEE VAST*, pages 167–174, 2006.
6. Freebase, Dec 2009. <http://www.freebase.com/>.
7. G. W. Furnas. Generalized fisheye views. In *ACM CHI*, pages 16–23, 1986.
8. The GEDCOM Standard Release 5.5, Jan 1996. The Church of Jesus Christ of Latter-day Saints.
9. Genelines, Dec 2009. <http://progenygenealogy.com/>.
10. Genopro, Dec 2009. <http://www.genopro.com/>.
11. J. Heer and M. Agrawala. Design considerations for collaborative visual analytics. *Information Visualization*, 7(1):49–62, 2008.
12. J. Heer and M. Bostock. Crowdsourcing graphical perception: Using Mechanical Turk to assess visualization design. In *ACM CHI*, 2010.
13. J. Heer and S. K. Card. DOITrees revisited: Scalable, space-constrained visualization of hierarchical data. In *Advanced Visual Interfaces*, pages 421–424, 2004.
14. K. Ito and E. L. Rose. The genealogical structure of Japanese firms: Parent-subsidiary relationships. *Strategic Management Journal*, 15, 1994.
15. R. McClure. *The Complete Idiot's Guide to Online Genealogy*. 1997.
16. M. J. McGuffin and R. Balakrishnan. Interactive visualization of genealogical graphs. In *IEEE InfoVis*, 2005.
17. E. S. Mills. Genealogy in the 'information age': History's new frontier? In *National Genealogical Society Quarterly* 91, 2003.
18. R. Munroe. XKCD #657, Dec 2009. <http://xkcd.com/657/>.
19. P. Pirolli and S. K. Card. Information foraging. *Psychological Review*, 106:643–675, 1999.
20. C. Plaisant, J. Grosjean, and B. B. Bederson. SpaceTree: Supporting exploration in large node link tree, design evolution and empirical evaluation. In *IEEE InfoVis*, pages 57–64, 2002.
21. C. Plaisant, B. Milash, A. Rose, S. Widoff, and B. Shneiderman. Lifelines: Visualizing personal histories. In *ACM CHI*, pages 221–227, 1996.
22. J. Priestley. *A Chart of Biography*. J. Johnson, St. Paul's Church Yard, 1765.
23. F. van Ham and A. Perer. Search, show context, expand on demand: Supporting large graph exploration with degree-of-interest. *IEEE TVCG*, 15(6):953–960, 2009.