Visualizing Uncertainty and Alternatives in Event Sequence Predictions

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ABSTRACT

Data analysts apply machine learning and statistical methods to timestamped event sequences to tackle various problems but face unique challenges when interpreting the results. Especially in event sequence prediction, it is difficult to convey uncertainty and possible alternative paths or outcomes. In this work, informed by interviews with five machine learning practitioners, we iteratively designed a novel visualization for exploring event sequence predictions of multiple records where users are able to review the most probable predictions and possible alternatives alongside uncertainty information. Through a controlled study with 18 participants, we found that users are more confident in making decisions when alternative predictions are displayed and they consider the alternatives more when deciding between two options with similar top predictions.

CCS CONCEPTS

• **Human-centered computing → Visualization**.

KEYWORDS

Predictive visual analytics, uncertainty visualization, event sequence analysis, decision making

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1 INTRODUCTION

Sequences of timestamped events have been widely collected and analyzed to tackle various problems in domains such as healthcare, digital marketing, and education. For example, hospitals record patients' treatment histories, websites log users' page visits, and schools track students' learning activities. Key tasks in event sequence analytics include mining and summarizing frequent patterns, querying event sequences to build cohorts, and analyzing correlations between events and outcomes. With the emergence of machine learning techniques, predicting future events based on historical paths has also gained traction [53]. For example, marketing analysts may want to predict customers' next actions to foresee who might unsubscribe and send a retention offer before it happens; customer experience representatives may want to predict which customers might experience bottlenecks and provide support ahead of time.

Using statistical techniques, predictive models allow users to exploit patterns in their data and predict future trends and outcomes [35], with ever-increasing accuracy. The output of predictive models often includes uncertain information, such as ranges of expected values for numeric predictions or degrees of confidence for categorical predictions. Extensive research has shown that visual analytics improves users' understanding of large sets of event sequences in a wide variety of tasks: from timeline-based representations for inspecting individual journeys [45, 46] to aggregated overviews for exploring common patterns in a large number of records [41, 61] and integrated displays for analyzing how different sequences of events lead to different outcomes [18, 60].

However, most existing techniques focus on visualizing historical event sequences and few explore designs for supporting the analysis of probabilistic future events generated by predictive models. The added uncertainty information leads to difficulty in interpreting their results and discovering actionable insights, especially for event sequence predictions which have multiple steps, with multiple possible events at each step. While prior research broadly explored the design space of uncertainty visualization, the needs for seeing alternatives have not been sufficiently addressed. For example, besides the most probable prediction, what else may happen and how likely is it? Without information about alternatives, people may not be able to confidently make decisions.

Consider a scenario in digital marketing (i.e., advertising products or services through emails, display ads, paid search results, etc.). A marketer, Jill, is building an ad campaign for 1,000 customers that involves sending a series of emails. Using event sequence prediction models, she is able to predict the likely customer activities after receiving her emails. If there are three possible activities and she'd like to predict just the next five steps for each customer, the results will be 5,000 ordered lists of the three events for a total of 15,000 events, each associated with a probability, timestamp, and customer ID. Understanding these predictions, let alone making decisions from them, quickly becomes difficult. By taking the top-one prediction for each customer at each time-step, Jill can decrease the number of events to be reviewed, but in cases of uncertain top predictions or strong alternatives, she may miss important information.

We seek to fill this gap by designing and evaluating visualizations for exploring prediction results of event sequences. We begin by interviewing machine learning practitioners to collect design needs for visualizing event sequence predictions. We design and implement a novel alternative-aware uncertainty visualization to address users' needs of reviewing most probable predictions along with possible alternatives. A controlled study indicated that users are more confident in making decisions when alternative predictions are displayed and they consider the alternatives more when deciding between two options with similar most probable predictions. The direct contributions of this work are:

- Eight design needs for visualizing event sequence prediction results collected through interviews with five domain experts.
- An alternative-aware uncertainty visualization design for reviewing the most probable event sequence predictions along with possible alternatives.
- A controlled user study with 18 participants evaluating the effects of showing alternatives on people's decision making under uncertainty.

2 RELATED WORK

In this section, we survey and discuss related literature in decision making and visualization, with a focus on uncertainty data and event sequences.

Decision Making under Uncertainty

People often need to make decisions under uncertainty [22], which involves choosing actions based on imperfect observations with potential gains and risks [33]. Strategies for decision making under uncertainty have been extensively studied in a wide range of application scenarios, such as choosing medical treatments with uncertain diagnoses [23, 54], forecasting weather with estimated initial conditions [29, 30, 58], investing with a uncertain risks [24], or collaborative sensemaking under uncertain partner activities [19] and interruption time [20].

Despite that the tolerance toward risk is subjective [3, 31] and differs between domains [57], the importance of providing uncertainty information in predictive analysis has been agreed on and emphasized in many studies. For example, a laboratory study of flood forecasting [47] showed that the presence of estimated flooding probability leads to more optimal decisions and more coherent answers among individual decision makers. Similar results were also observed in public weather forecasting [37], where adding probabilistic uncertainty estimate improved both decision quality and people's trust in evacuation instructions in weather warnings.

Although the benefit of providing uncertainty (i.e., the probability of most probable prediction) in decision making had been well-studied in various application scenarios, the effects of showing alternative predictions (i.e., less probable predictions) has not been fully discussed in existing literature. In this paper, we investigate the needs of people to be aware of the alternative predictions and how the alternatives will affect people's decision making under uncertainty.

Visualization of Uncertainty

Properly presenting uncertainty information in data analysis tools can generally improve users' understanding of data and the quality of their decisions [21, 28, 51]. According to extensive surveys [5, 7, 55], two categories of designs are typically employed for presenting uncertainty information in combination with the data in static visualizations. The first category encodes uncertainty with the visual properties of the data points, such as blur or fuzziness [10, 39], grayscale, color, or transparency [1, 11, 26], and shape, dashing, or sketchiness [6, 17]. Overall, these visual encodings can create an intuitive effect that data with a higher uncertainty is harder to see or recognize [15], although blurring or fading out the visual elements may impair the readability of the visualizations [50].

Techniques in the second category incorporate uncertainty information by adding extra visual components in the form of glyphs [36, 38, 59], geometric features such as contour lines and isosurfaces [43, 48], or annotations [8]. These methods can display uncertainty with full details, but the added amount of visual complexity require more cognitive processing and may slow down users' exploration [2].

While prior research broadly explored the design space of uncertainty visualization, the needs for seeing alternatives have not been sufficiently addressed, i.e., beside the most probable prediction, what else may happen and how likely? Without information about alternatives, people may not be aware of the potential losses and gains when making decisions. In this work, we seek to fill this gap by designing and evaluating an alternative-aware uncertainty visualization for exploring event sequence predictions.

Visualization of Event Sequences

Starting with LifeLines [45, 46], early research on event sequence analysis commonly uses a timeline-based representation to visualize individual traces with many successful applications in depicting a patient medical history [4, 25, 32]. These tools can be adapted for showing multiple records in a stacked manner but does not scale well to large datasets. To address the scalability issue, another group of techniques explored using a tree or graph structure to produce an overview of multiple records while preserving individual details. For example, LifeFlow [61], EventFlow [14, 41], and Scribe Radar [62] aggregate common subsequences on an alignment point using an Icicle tree representation. OutFlow [60] and CareFlow [44] introduce a state transition graph based the Sankey diagrams [49], which combine multiple event sequences into a graph of state nodes and show the step-by-step transitions.

Among visualizations for exploring historical events, several are capable of analyzing how different sequences of events lead to different outcomes, which can help analysts generate hypotheses about causation. For example, DecisionFlow [18], OutFlow [60], and CareFlow [44], aggregate similar event sequences into progression pathways and visually encode the correlations between the pathways and possible outcomes. CoCo [40] and MatrixWave [63] enable analysts to compare two groups of records with different outcomes by highlighting their differences in the composition of the event sequences. EventAction [12] and PeerFinder [13] help analysts search and refine a cohort of records similar to a seed record and to explore their activities and outcomes.

Compared to existing research on visualizing historical event sequences and definite outcomes of archived records, our work explores designs for supporting the analysis of probabilistic future events generated by predictive models. Specifically, we introduce a novel visualization technique to address users' needs of reviewing most probable predictions along with possible alternatives. In this work, we choose Sankey diagram as our primary representation, which is widely used in commercial systems (e.g., Adobe Analytics and Google Analytics) and familiar to analysts.

3 INFORMING THE DESIGN

Our development followed an iterative, user-centered design process [42]. To better understand existing approaches and problems, we began by conducting semi-structured interviews with five practitioners who use or build event sequence prediction models in their daily jobs at a large software company. We synthesized their responses into a set of user needs to guide our visualization design. We iteratively refined the design through multiple demos, discussions, and additional interviews with the initial participants as well as other practitioners. This section describes the formative interview study.

Interviews

We conducted two one-hour interviews with five machine learning practitioners (two females, aged 31–43, domain experience 7–15 years each). One session was with three marketing analysts (P1–3) interested in using predictive tools to analyze customer behaviors and another was with two data scientists (P4–5) who design predictive models for clients (e.g., software developers or data analysts). The interviews were semi-structured and guided by three topics, including the analytical tasks the practitioners applied prediction for, the predictive tools or models they have used, and the challenges they faced that have not been addressed by existing techniques. The interviews were not restricted to a particular use case. We encouraged the practitioners to describe examples of real situations in their jobs when discussing the tasks and challenges. One experimenter was responsible for taking notes during the interviews and coding the transcripts.

Results

Based on the feedback gathered during the interview study, we identified eight key design needs across three major themes. To ensure the commonality, each design need was supported by at least two interviewees (stated separately by two or stated by one and agreed on by another).

Support for Predicting both Outcomes and Activities. According to the three marketing analyst interviewees, predicting outcomes (long-term or intermediate) is a key functionality in many existing tools. They typically use regression or correlation analysis to answer queries such as *"what is the estimated conversion rate of these trial accounts?"* or *"for* *customers who have purchased product A and B, what else are they also likely to purchase?"* One issue that came up among all the marketing analysts was the lack of capability to **predict at the activity level (N1 | P1–3)**. For example, P1 explained *"we need not just outcome summaries but also their actual activities and behavior patterns."* P3 added that *"in hard situations when nothing look obvious (in the outcome predictions), seeing what they are likely to do will be especially useful."* The marketing analysts suggested **combining outcomes and activities in the prediction (N2 | P1–3)**. For example, P2 stated that *"I can identify customers with a low renewal probability and see what type of activities we need to engage them more."*

Support for Visually Exploring Event Sequences. When discussing how to present the prediction results, the marketing analysts expressed a desire for visualizations that can **support exploring historical activities and predictions simultaneously (N3 | P1–3)**. Specifically, P2 commented that their current audience management tool only shows summary activity metrics such as the numbers of website visits or product downloads and said: *"Visually reviewing what they (customers) have done before and what they may do next can help identify what type of content to send."* She added an example that *"for early customers, we often send them awareness emails to introduce our products and for advanced users, we send them renewal promotions."* While all five interviewees agreed that it is useful to **show multiple event sequences at a time (N4 | P1–5)** to accelerate the analysis, the three marketing analysts also emphasized the importance of **being able to inspect individual records with full details (N5 | P1–3)** to help provide a personalized marketing experience. In addition, two data scientists, P4 and P5 pointed out that people often forget about uncertainty when using predictive models and suggested **showing the uncertainty and reminding users that more than one situations may happen (N6 | P4–5)**.

Support for Making Personalized Action Plans. One common need brought up by the marketing analysts was to help them personalize customers' experience. P1 explained that *"I hope this tool can help us identify the real problem faced by each customer, prioritize where we need to focus more, and select appropriate content in a data-driven way."* The other two marketing analysts had the same feeling and P2 added: *"It takes a lot of effort to put together assets for an email and days to see its performance."* They wished to have a prediction tool that allows them to **quickly try out different types of intervention plans on different audience (N7 | P1–3)** and **predict how certain interventions impact their behaviors (N8 | P1–3)**.

Discussion

In an attempt to bound the scope of our work to the design of uncertainty visualization under the context of event sequence predictions, we will mainly focus on addressing N3−6 in this paper. While the remaining needs are also important to fully support users' analytical workflow, N1−2 are more related to the choice of prediction models and N7−8 are at the level of application functionalities. Existing technologies, such as next-action prediction models and outcome classifiers [9] could be used to address N1−2 and partial dependence diagnostics [34] can be used for N7−8.

4 VISUALIZATION DESIGN ITERATIONS

Informed by the design needs gathered from the interview study, we iteratively designed a visualization for exploring prediction results of event sequences. The final design was developed over a three-month period where the feedback was collected from 12 machine learning practitioners (4 analysts, 2 researchers, 1 product manager, and 5 from the original interviews). Over a dozen prototypes were piloted before settling on the final design (Fig. 1−3 highlight a selection of the designs). To allow the pilot users to assess our designs in realistic settings, we developed and demonstrated prototypes based on a real digital marketing dataset, which consisted of 30-day behavior logs of 38,155 customers.

In this section, we begin by describing the predictive model used and our method for aggregating its results. Then, we describe the evolution and key design decisions for the alternative-aware uncertainty visualization.

Predictive Model

We generated predictions of future activities based on a Time-Aware Recurrent Neural Network (TRNN) [9]. TRNN is the state-of-the-art technique for "next action" prediction. The input of the model is a sequence of events. Each event is a combination of event categories and timestamp. Each event category is characterized by a one-hot representation and the feature vector of each event is generated based on the representation of the corresponding event category extended with the normalized timestamp. The model is built based on LSTM networks [16], which contains a list of chained LSTM units. The input of each unit is the feature vector of an event in the sequence, and the output of each LSTM unit is sent to the next unit for iteration.

The output of each LSTM unit is recursively computed based on the input of the current unit and the output of the previous unit. The model is trained based on the softmax regression on the weighted output of each LSTM unit, which intuitively represents the probability of each event category being the next event. The optimization goal is to maximize the probability of the actual next event. Once the model is

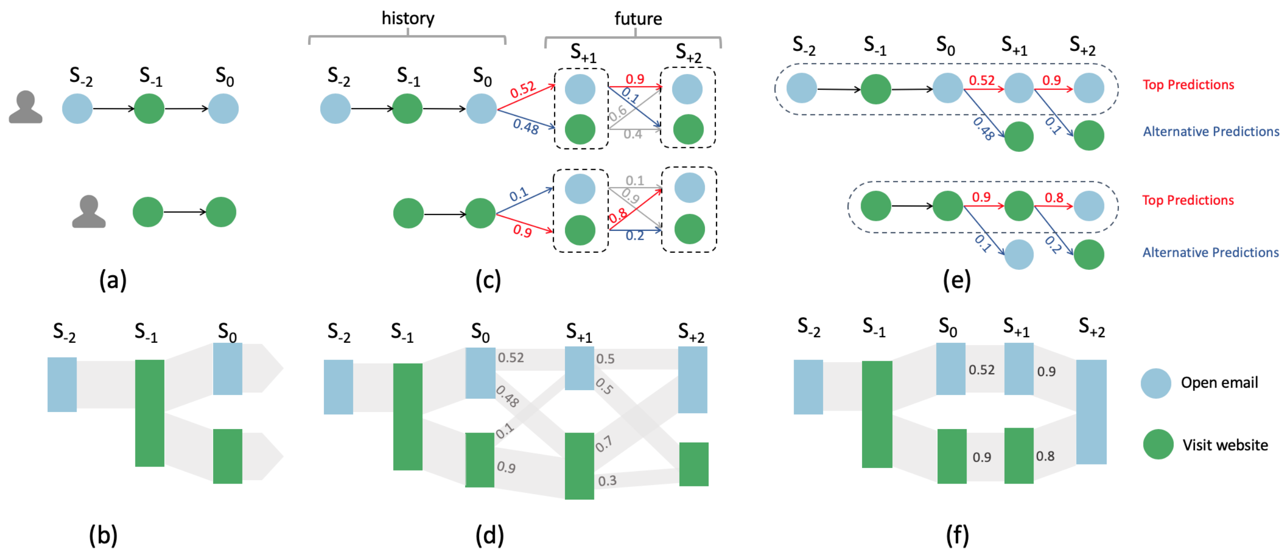

Figure 1: (a) Historical event sequences aligned by their most recent events. (b) Historical sequences aggregated in Sankey diagram. (c) The probabilistic future events of each sequence. Each step in the prediction is a probability distribution over all available event categories, which leads to exponential growth of the number of possible paths. (d) Probabilistic paths of all sequences aggregated in Sankey diagram, with the sizes of nodes and widths of links proportional to the probabilities. (e) Most probable future paths derived by preserving only the most probable event at each prediction step. (f) Most probable future paths aggregated in Sankey diagram, with the sizes of nodes and widths of links proportional to the aggregated population.

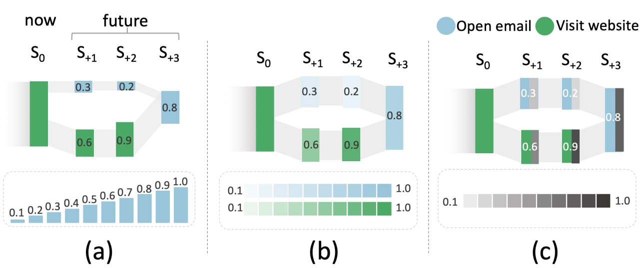

Figure 2: The explored choices for visualizing top prediction uncertainty: (a) size-oriented design, which uses the size of nodes to distinguish the probabilities, (b) color saturation-oriented design, which encodes probabilities with the color saturation for each event category, and (c) opacity-oriented design, which separate the event probability from the event category with a grey-scale (opacity) encoding.

trained, when given an event sequence as input, a probability distribution of the next event can be derived from the output of the last LSTM unit. We can predict probabilistic future paths by iteratively appending the most probable next event to the input sequence.

Aggregating Probabilistic Event Sequences

Unlike historical event sequences where each event belongs to a certain category and each record has a certain path, events predicted by the TRNN model are represented by probability distributions over all the event categories, resulting in up to m^n probabilistic future paths for each record (Fig. 1(c)), where m represents the number of event categories and n is the number of steps. The added complexity leads to great difficulty in producing an overview of the future activities of multiple records. The simplest solution involves taking only the most probable prediction at each step. However, as previously discussed, this obfuscates possible alternative paths or uncertain predictions.

To address this challenge, our first design aggregated the paths by calculating the average probability of each event, e, at each step, S, across all records. This design showed the overall probability distributions between two steps but lost track of individuals' identities (**N5**) and which alternatives correspond to which top events. Additionally, after reviewing this preliminary prototype with pilot users, we noticed that they tended to focus more on paths with high probabilities and paid less attention to the less probable ones.

The final aggregation method is a combination of the previous two iterations: we preserve and aggregate records by their top prediction at each step (Fig. 1(f)) and alternate predictions are aggregated by average probability. The new aggregation method produces an overview of the most probable future activities of all the records (**N3, N4**) and supports reviewing individual's details (**N5**).

We visualize the most probable future paths as a Sankey diagram. We then explored designs for encoding the uncertainty information associated with each prediction and a

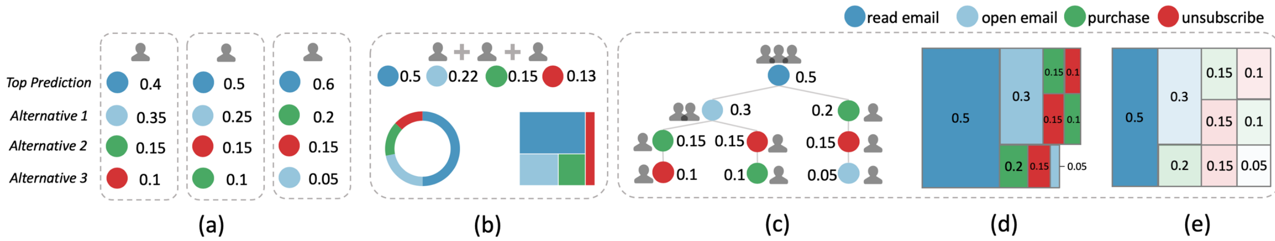

Figure 3: (a) Three records with the same top prediction and thus to be aggregated into one node. Design choices for aggregating and presenting their top prediction's probabilities and varied alternative predictions are: (b) composition-oriented choices (e.g., pie chart, treemaps), which directly aggregate the probabilities of both top predictions and alternatives by categories. (c-e) hierarchical-oriented choices, where the prediction results are organized into (c) a hierarchical tree and can be compactly arranged through horizontal icicle layout, encoding the average probability with (d) the width of each rectangle or (e) the color opacity. Our final design improved the layout and probability encoding of the hierarchical-oriented choices.

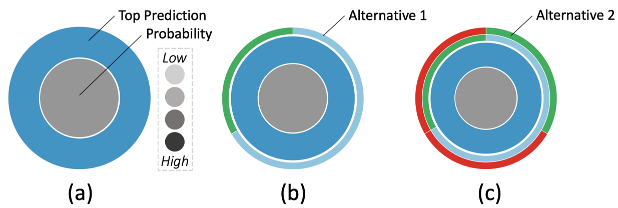

Figure 4: The final design: (a) Only the top prediction (color of the thick ring) and its probability (darkness of the inner circle) is displayed at the start. (b-c) Alternative predictions are added level-by-level (thin rings).

novel glyph design for revealing possible alternatives beside the most probable predictions.

Visualizing Uncertainty of the Top Prediction

Motivation. Previous work has shown that conveying uncertainty improves decision making and trust [37, 47]. Furthermore, extensive work has been done on visualizing uncertainty [5, 7, 55]. We used Tak et al.'s survey [55] combined with Vosough et. al.'s flow diagram study [56] as a basis for the design space: size, blur, color saturation, gradient, and transparency. Based on their findings, we removed blur, gradient, and fuzziness due to low perceived visualization quality and low dependability. Thus, we explored size, color saturation, and transparency.

Size-Oriented Designs. We first used the size of nodes to distinguish the probabilities (Fig. 2(a)). However, this led to many of our pilot users ignoring low-probability paths completely and only focusing on the most probable paths. Further, pilot users tended to emphasize the events where the population was small but probability was high.

Color Saturation-Oriented Designs. Because we use color as the event-category encoding, we were inspired by Correl's Value-Suppressing Uncertainty Palettes (VSUP) [11] to encode uncertainty with the event categories. However, because event categories are typically categorical without any natural ordering, it is impossible to create a VSUP with more than three events. We piloted a matrix palette using saturation (Fig. 2(b)), but our pilot users found the colors confusing and hard to distinguish between event categories, especially as the number of categories increased.

Opacity-Oriented Designs. Finally, we encoded the probability of the top prediction in its own glyph with a grey-scale (opacity) encoding (Fig. 2(c)). Because the encoding was separated from the event-category, users were more easily able to distinguish which events were more certain, even between events of different categories, and also placed an accurate emphasis on large versus small populations.

Visualizing Alternatives and Their Uncertainties

Motivation. Our motivation for showing alternatives in uncertainty visualizations was originated from design need **N6**: besides the most probable prediction, what else may happen and how likely? Here, we use a simplified marketing example to illustrate this need. As shown in Fig. 1(c), the top prediction of the first customer in step one is "open email." However, the probability of this top prediction is only 0.52 and the alternative prediction "visit website" has a probability of 0.48, which is very close to the top prediction. In this case, the alternative prediction also requires analysts' attention. Moreover, only showing the top prediction may conceal potential values and risks which tend to have a low probability, such as "purchase" or "unsubscribe."

Composition-Oriented Designs. To show the top prediction and alternatives, we first explored graphs and charts that are commonly used for summarizing categorical data, including pie charts and treemaps (Fig. 3(b)). In the visualization, the size of the group is proportional to the size of the chart, the event categories are shown as sub-areas in different colors, and the average probability of each event category is proportional to the sizes of the sub-areas. While the visualization provides a clear overview of the probability composition of the prediction regarding event categories, showing all alternatives adds significant visual clutters to the display and may distract users from reviewing the top predictions. Also, averaging the probabilities for all alternative predictions at different levels may lead to biases [52].

Hierarchical-Oriented Designs. We then explored designs that can preserve the hierarchical structure of the prediction results. As illustrated in Fig. 3(a), each record's next action prediction is a probability distribution over all available event categories, ordered by probabilities. The most probable one is called the top prediction and the rest are alternative predictions. The prediction results of multiple records are arranged into a hierarchical tree if they have the same top prediction (Fig. 3(c)). Starting from the root node (i.e., the top prediction), these records split into branches at the n-th level if they have different n-th alternative predictions. Based on this data structure, we designed a horizontal icicle layout (Fig. 3(d)) to show the next action predictions of a group, where the leftmost rectangle is the root of the tree and the partitions are the tree nodes. Each rectangle of the partitions represents a subset of records having the same alternative prediction at the same tree level. The height of the rectangles encodes the number of records and the width encodes their average probability.

This hierarchical-oriented design mitigates the biases of averages since only the probabilities at the same tree level are aggregated. Also, users can choose to only review a few levels of alternatives to simplify the visualization while not losing predictions with a relatively high probability. However, due to the variance of the probabilities, partitions at the same level may fail to align with each other. In addition, we found these rectangular designs fail to intuitively imply the order of the levels and users were not sure about how to read the visualization (i.e., row-by-row or column-by-column).

Our final design uses a circular glyph to address the usability issues of the rectangular designs while preserving the hierarchical structure of the prediction results. As illustrated in Fig. 4, only the top prediction (Fig. 4(a)) is displayed at start. The color of the first outer ring represents the common top prediction of a group of records. Users can get started by exploring the top predictions to see the most probable future paths. Then, depending on the granularity of the analysis, alternative predictions can be added level-by-level, which are represented by the outer rings growing from inside (Fig. 4(b,c)). Arcs in the outer rings correspond to the rectangle partitions in Fig. 3(e), colored by event categories. The probabilities of alternative predictions are dynamically illustrated in the inner circle on mouse hover. Users can also set a threshold to hide alternative predictions with a probability lower than the threshold. Compared to the rectangular designs, the circular glyph intuitively implies the order of the different levels of the predictions, explicitly encodes the uncertainty, and is more space efficient as users can incrementally add levels of alternatives.

5 EVALUATION

We conducted a controlled user study with 18 participants to investigate the effects of showing alternatives on people's decision making under uncertainty. In this section, we introduce the design of the experiment, analyze quantitative results, and summarize participants' subjective feedback gathered from post-study interviews.

Hypotheses

Extensive studies in decision making have found that communicating uncertainty information can influence people's choices and their confidence in their choices [3, 30, 37]. Therefore, we pose our research question as to understand *how alternative predictions affect people's choices and their confidence in making decisions under uncertainty.*

We developed four hypotheses around this research question. Research by Arshad [3] showed that presenting uncertainty as supplementary information for decision making can significantly improve user confidence. We hypothesize that the additional context about alternative predictions will enhance this benefit:

H1. Overall, users will be more confident in making decisions when alternative predictions are displayed.

As suggested in several recent studies, uncertainty information may become less helpful for improving users' estimates when the uncertain measurements have similar readings [21] and that users tend to make random decisions when the prediction uncertainties are high [29]. We hypothesize that showing alternative predictions will be especially beneficial in these situations:

H2. Showing alternatives predictions has a greater impact on users' confidence when deciding between two options with similar top predictions compared to options with different top predictions.

H3. Showing alternative predictions has a greater impact on users' confidence when deciding between two options with uncertain top predictions compared to options with certain top predictions.

Lastly, as observed in experiments [30, 37], showing uncertainty can improve decision quality and reduce risk-seeking behaviors, we hypothesize that showing alternatives along with uncertainty information will enhance this effect:

H4. Showing alternative predictions may change users' decision when the alternatives contain risk or value compared to when the alternatives are normal.

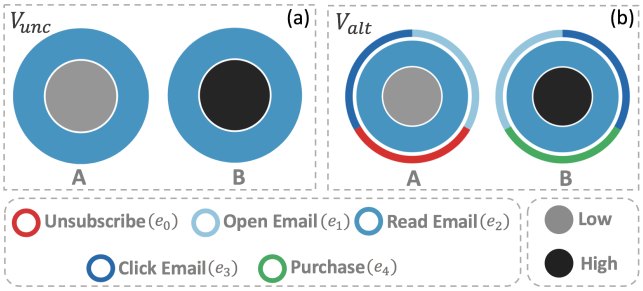

Figure 5: Example tasks presented in (a) V_{unc} and (b) V_{alt}. In these examples, the top predictions of both options represent "Read Email" but have different probabilities. V_{alt} reveals that one-third of the customers have an alternative prediction "Unsubscribe" after receiving email A and have an alternative prediction "Purchase" after receiving email B.

	V_{unc}	V_{alt}
Top Prediction	e_0, e_2, e_4	e_0, e_2, e_4
Probability	*Low*, *High*	*Low*, *High*
Alternative	-	(e_2, e_4), (e_0, e_4), or (e_0, e_2)
Combinations	6	12
Comparison Tasks	15	66
Participants	18	
Total Tasks	1,512	

Table 1: The design of the study tasks.

Experiment Design

Guided by the taxonomy of evaluating uncertainty visualizations [27], we designed a full-factorial, within-subject study to test our hypotheses by comparing two uncertainty visualization designs: V_{unc} (Fig. 5(a)) and V_{alt} (Fig. 5(b)). We derived V_{unc} and V_{alt} from our final alternative-aware visualization design (as introduced in Fig. 4), where V_{alt} shows both top and alternative predictions but V_{unc} shows only the top prediction. Their visual encodings were kept the same to ensure the fairness of the comparison.

Participants and Apparatus

We recruited 18 participants (10 males and 8 females, aged 20–30, $M = 24.72$, $SD = 2.16$) through an intern email list in an industrial research lab. Two of the participants were undergraduate students and 16 were postgraduate. 10 had hands-on experience in digital marketing during their three-month internship. 14 were familiar with data analysis, machine learning, or software engineering. The other 4 had limited technical backgrounds but studied marketing, human resources, or graphic design at school. We made sure all the participants had taken statistics courses and had no difficulty in understanding the probabilities in prediction. Each participant received 10 dollars. A laptop computer was used, with a 13-inch display of resolution 2560×1600 pixels.

User Tasks and Data

The study was performed using hypothetical tasks in a digital marketing scenario: *"Imagine you are an email marketer deciding between two emails to send. You have a visualization tool that shows the predicted customer reactions to each email. Which email do you send?"* We used a decision task in a specific context since it can help participants give realistic responses [27]. We pose the scenario on email sending since it is one of the most popular marketing channels. However, we ensured that the task was simple and easy to understand by participants without marketing knowledge.

As shown in Fig. 5, in each task, the participant was given two visual glyphs (A and B) representing the prediction results of the customers' next actions after receiving either of the two emails. The participants were asked to provide an answer using a 7-point Likert scale (definitely A, probably A, possibly A, not sure, possibly B, probably B, definitely B), reflecting both their decision and confidence. We generate study tasks using a synthetic dataset, which included 5 event types (e_0: unsubscribe, e_1: open email, e_2: read email, e_3: click email, e_4: purchase). These five event types are used to cover 3 types of situations: purchase (e_4) represents a desired good reaction, unsubscribe (e_0) represents a bad reaction to avoid, and (e_1, e_2, e_3) are normal reactions.

We considered 3 variables in generating the testing data: top prediction, top prediction's probability, and alternative predictions. The top predictions had 3 possible values representing the 3 situations (bad as e_0, normal as e_2, good as $e4$). Top predictions' probabilities had two levels of certainty (low probability as U, high probability as C). The alternative predictions included 3 events. Two were consistently filled with two normal events (e_1, e_3) for the purposes of diversity. The remaining one was chosen from e_0, e_2, e_4 to represent one of the 3 situations (bad, normal, good) in the alternative predictions. Since events contained in top predictions will not appear in alternative predictions, each type of top prediction only has two possible alternatives. For example, if the top prediction is e_2, its alternative predictions can only be $(e_1, e_3, \underline{e_0})$ or $(e_1, e_3, \underline{e_4})$.

The glyphs in each study task were generated in pairs by iterating over all the conditions (Table 1). To focus on the study goals and ensure each study session can be completed within one hour, we did not vary the population and the probability of the alternative predictions. Participants were told that the alternative predictions in each glyph have the same probability.

Procedure

Each study session started with a 10-minute tutorial, introducing top predictions, uncertainties, and alternative predictions. We also explained our visualization designs (V_{unc},

V_{alt}) and the study task. Then the participants used our study system to perform two training tasks using each design. Participants were encouraged to ask questions and we made sure they fully understood the experiment. The formal study began, which was divided into two sessions for V_{unc} and V_{alt}, respectively. The order of the sessions was counterbalanced using a Latin Square. The order of the tasks within each session and the order of the glyphs in each task were randomized. In V_{alt}, alternative predictions were randomly ordered in the outer ring. We conducted post-study interviews to understand the reasons behind participants' decisions and gather their feedback.

Results

Confidence. We first compare V_{unc} and V_{alt} in terms of users' average confidence in making decision in different experiment conditions. We inferred users' confidence by taking the absolute value of each choice in 7-point Likert scale (0=not sure, 3=very confident). A Wilcoxon signed-rank test was used at a significance level of 0.05. The means, Z-scores, and p-values are reported in Fig. 6 where comparisons with significant differences are highlighted in a white background.

As reported in Fig. 6, among all 15 comparison conditions with different top predictions and probability levels, we found that V_{alt} ($M = 2.56, SD = 0.72$) generally had a higher average confidence compared to V_{unc} ($M = 2.30, SD = 0.78$) and the differences were significant in 6 conditions, which supports **H1**. Among the 6 conditions with a significant difference, 5 represented a situation when both options had similar top predictions (i.e., $e_i.*$ v.s. $e_j.*$, where $|i - j| \leq 2$) with only one exception where the top predictions were extremely different ($e_0.U$ v.s. $e_4.U$), confirming **H2**. Moreover, alternative predictions had significantly increased the average confidence in all the three conditions where the top predictions of both options were uncertain. Surprisingly, we also found significant differences in three conditions where one of the top predictions was certain. These results partially supported **H3** and also indicated that showing alternatives has an impact on both certain and uncertain top predictions.

Decision Changes. Next, we investigate if the participants had made different choices when deciding between two options using V_{unc} and V_{alt}. We counted the 18 participants' choices on all 66 tasks when using V_{alt}, excluding "not sure" answers. The numbers of choices were further broken down according to the 15 comparison conditions with different top predictions and probability levels. We identified the decision changes by contrasting each participant's choices made with V_{unc} and V_{alt}.

In Fig. 7, we highlighted in red the numbers of different choices in each comparison condition and annotated the alternative predictions of each option. Overall, most decision changes occurred when two options had similar top predictions but extremely different alternative predictions (i.e., e_0 and e_4 as alternative predictions). By referring to the observations in Fig. 6, we also found in these comparison conditions, participants' confidence was lower than usual when using V_{unc} and significantly increased when using V_{alt}. These findings partially supported **H4** and indicated that the participants considered more alternative predictions that contained potential risk or value when deciding between two options with similar top predictions. In contrast, when top predictions were different, their decisions were hardly changed by alternatives.

Feedback

We summarized participants' feedback around the usefulness, utility, and ease of understanding of our alternative-aware uncertainty visualization.

Usefulness. All study participants gave positive answers when asked if seeing alternative predictions was useful. One commented: *"I turned to alternative predictions when it is hard to choose from the top prediction."* Another said that: *"I compared the alternative predictions when the top predictions of both options are not certain."* One participant thought showing alternative predictions was critical for risk control and said: *"When the top prediction is good but has a low certainty, then I will consider alternative predictions to make sure that, in the worst case the top prediction does not come out, the result is still tolerable."* Moreover, two participants mentioned that alternative predictions can sometimes determine the nature of top prediction. One explained: *"For example, when I compare two medium top predictions with different level of certainty, I could not decide which one is better unless I know the alternative predictions."* This also explains why $e_2.C/e_2.U$ shows most decision changes in Fig. 7.

Utility. We asked the participants to rank the importance of top prediction, top prediction's probability, and alternative predictions. 13 out of 18 chose top prediction as most important, followed by top prediction's probability, and then alternatives. One explained: *"I will check the top prediction first and then compare uncertainty when the top predictions are the same. If I still cannot decide, I will consider alternative predictions."* Two others had the same rankings, but felt that top prediction and uncertainty should be considered together without explicit ordering. Three participants put alternative predictions prior to uncertainty and one marketing student commented: *"I would take any risk for purchase because it is the ultimate goal in marketing. If one side contains a good outcome, I would go for it."* This feedback indicate the subjective nature of how people perceive risk and value and shed

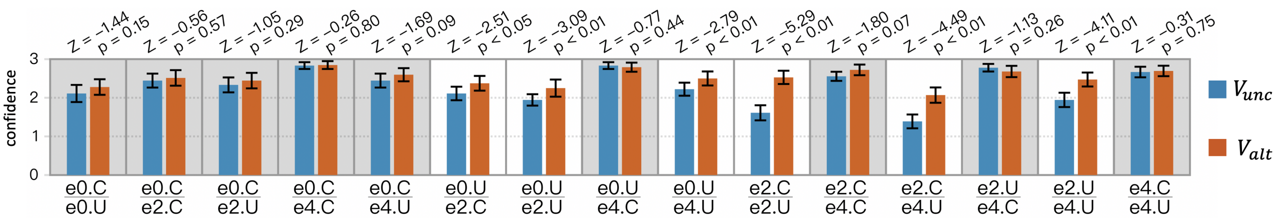

Figure 6: Users' average confidences when using V_{unc} or V_{alt} under 15 comparison conditions with different top predictions and probability levels. Alternative predictions varied when using V_{alt} and the results are aggregated. Significant differences ($p < 0.05$) are highlighted in a white background. Error bars show 95% confidence intervals.

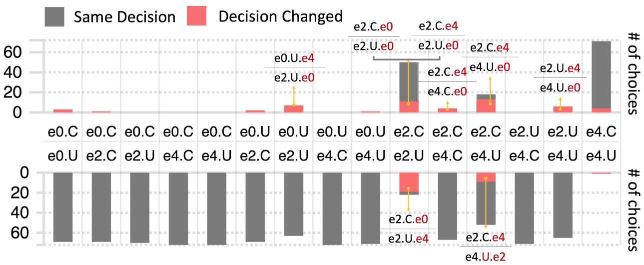

Figure 7: The distribution of the 18 participants' choices on all 66 tasks when using V_{alt}. Decision changes are identified by contrasting each participant's choices made with V_{unc} and V_{alt} and highlighted in red.

light into our unexpected observation that alternatives had significant effects even when top predictions were certain.

Ease of Understanding. We asked the participants to rate *"how easy was the visualization to understand"* on a 7-point Likert Scale (1=very difficult, 7=very easy). On average, the participants felt the visualization was easy to understand ($M = 6.17$, $SD = 0.62$). One with a graphical design background commented: *"The design is well aligned with people's cognition. The top prediction and probability shown in the middle indicates their highest priority. The surrounding alternatives represent additional information."* Another with a data science background suggested an improvement for our uncertainty encoding: *"Using darkness to show probability is intuitive but I also want to see specific values to make a more accurate comparison and decision."*

6 DISCUSSION

All hypotheses were confirmed in the user study results, with a larger impact than expected. Despite that the most significant impact was when the top predictions were similar, one exception stood out: when comparing two very different top predictions (uncertain e_0 v.s. uncertain e_4), the presence of alternative predictions changed users' decision making, indicating that alternative-aware visualizations could also be beneficial even when one top prediction is obviously superior to another. Also, despite that we found no difference in all conditions where both top predictions are certain, we surprisingly found significant results in three conditions where only one top prediction was certain, indicating that showing alternative predictions has an impact in both certain and uncertain situations.

We only tested the particular task of sending marketing emails in the user study, but our needs analysis, visualization designs, and study findings can provide useful guidance to many other digital marketing channels (e.g., display ads, paid search results), where customer activities are similarly defined (e.g., views, clicks) and the risks and gains are comparable (e.g., dropout, conversion). Our design can also be adapted to visualize event sequence data in other domains, such as patients' electronic health records and students' academic histories. However, since people's perception and tolerance toward risks differ among domains [57], the impact of showing alternatives requires further investigation to verify for specific applications.

Finally, while this paper only focused on addressing four design needs related to uncertainty visualization design for event sequence predictions, we believe that there is value in clarifying the remaining needs so as to inspire others to develop better solutions to support decision making.

Limitations and Future Directions

Our visualization design has several limitations. We used darkness to encode uncertainty information in consideration of its intuitiveness and enabling fast comparison. However, participants with a background in data science expressed the need for reviewing exact uncertainty values for making more accurate comparisons and decisions. Therefore, we recommend showing both darkness and exact values in applications of our design. Moreover, unlike general uncertainty visualizations, our design was tied to the event sequence data and may not be an optimal solution to other data structures.

Our user study also has several limitations. First, our participants may not fully represent experts with long domain experience and the task may not fully represent real-world situations. We still need long-term case studies with domain experts to advance our understanding of the usefulness of our design in real-world analytical tasks. Second, our study did not formally compare different design options for uncertainty encoding, since we focus more on understanding the effects of the added alternative predictions. In future work, we will incorporate alternative visualization into other uncertainty displays and produce generalized design guidelines.

7 CONCLUSION

Predicting next events to gain insights about the future is an emerging event analytics task. Informed by interviews with five machine learning practitioners, we have designed an alternative-aware uncertainty visualization for exploring event sequence predictions. Our study suggests that people are more confident in making decisions when alternative predictions are displayed and they consider the alternatives more when deciding between two options with similar top predictions. Based on the study results and participants' feedback, we have discussed when, why, and how showing alternative predictions is useful or has limitations.

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REFERENCES

[1] Jeroen CJH Aerts, Keith C Clarke, and Alex D Keuper. 2003. Testing popular visualization techniques for representing model uncertainty. *Cartography and Geographic Information Science* 30, 3 (2003), 249–261.

[2] Anthony D Andre and Henry A Cutler. 1998. Displaying uncertainty in advanced navigation systems. In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, Vol. 42. 31–35.

[3] Syed Z Arshad, Jianlong Zhou, Constant Bridon, Fang Chen, and Yang Wang. 2015. Investigating user confidence for uncertainty presentation in predictive decision making. In *Proceedings of the Annual Meeting of the Australian Special Interest Group for Computer Human Interaction.* 352–360.

[4] Ragnar Bade, Stefan Schlechtweg, and Silvia Miksch. 2004. Connecting time-oriented data and information to a coherent interactive visualization. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems.* 105–112.

[5] Georges-Pierre Bonneau, Hans-Christian Hege, Chris R Johnson, Manuel M Oliveira, Kristin Potter, Penny Rheingans, and Thomas Schultz. 2014. Overview and state-of-the-art of uncertainty visualization. In *Scientific Visualization.* Springer, 3–27.

[6] Nadia Boukhelifa, Anastasia Bezerianos, Tobias Isenberg, and Jean-Daniel Fekete. 2012. Evaluating sketchiness as a visual variable for the depiction of qualitative uncertainty. *IEEE Transactions on Visualization and Computer Graphics* 18, 12 (2012), 2769–2778.

[7] Ken Brodlie, Rodolfo Allendes Osorio, and Adriano Lopes. 2012. A review of uncertainty in data visualization. In *Expanding the Frontiers of Visual Analytics and Visualization.* 81–109.

[8] Andrej Cedilnik and Penny Rheingans. 2000. Procedural annotation of uncertain information. In *Proceedings of the Conference on Visualization.* 77–83.

[9] Charles Chen, Sungchul Kim, Hung Bui, Ryan Rossi, Eunyee Koh, Branislav Kveton, and Razvan Bunescu. 2018. Predictive analysis by leveraging temporal user behavior and user embeddings. In *ACM International Conference on Information and Knowledge Management.*

[10] Christopher Collins, M Sheelagh T Carpendale, and Gerald Penn. 2007. Visualization of uncertainty in lattices to support decision-making.. In *EuroVis.* 51–58.

[11] Michael Correll, Dominik Moritz, and Jeffrey Heer. 2018. Value-suppressing uncertainty palettes. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems.* 642.

[12] Fan Du, Catherine Plaisant, Neil Spring, and Ben Shneiderman. 2016. EventAction: Visual analytics for temporal event sequence recommendation. In *Proceedings of the IEEE Visual Analytics Science and Technology.* 61–70.

[13] Fan Du, Catherine Plaisant, Neil Spring, and Ben Shneiderman. 2017. Finding similar people to guide life choices: Challenge, design, and evaluation. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems.* 5498–5544.

[14] Fan Du, Ben Shneiderman, Catherine Plaisant, Sana Malik, and Adam Perer. 2017. Coping with volume and variety in temporal event sequences: strategies for sharpening analytic focus. *IEEE Transactions on Visualization and Computer Graphics* 23, 6 (2017), 1636–1649.

[15] Richard Finger and Ann M Bisantz. 2002. Utilizing graphical formats to convey uncertainty in a decision-making task. *Theoretical Issues in Ergonomics Science* 3, 1 (2002), 1–25.

[16] Felix A Gers, Jürgen Schmidhuber, and Fred Cummins. 1999. Learning to forget: Continual prediction with LSTM. (1999).

[17] Jochen Görtler, Christoph Schulz, Daniel Weiskopf, and Oliver Deussen. 2018. Bubble treemaps for uncertainty visualization. *IEEE Transactions on Visualization and Computer Graphics* 24, 1 (2018), 719–728.

[18] David Gotz and Harry Stavropoulos. 2014. DecisionFlow: Visual analytics for high-dimensional temporal event sequence data. *IEEE Transactions on Visualization and Computer Graphics* 20, 12 (2014), 1783–1792.

[19] Nitesh Goyal and Susan R Fussell. 2016. Effects of sensemaking translucence on distributed collaborative analysis. In *Proceedings of the ACM Conference on Computer-Supported Cooperative Work and Social Computing.* 288–302.

[20] Nitesh Goyal and Susan R Fussell. 2017. Intelligent interruption management using electro dermal activity based physiological sensor for collaborative sensemaking. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 1, 3 (2017), 52:1–52:21.

[21] Miriam Greis, Aditi Joshi, Ken Singer, Albrecht Schmidt, and Tonja Machulla. 2018. Uncertainty visualization influences how humans aggregate discrepant information. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems.* 505:1–505:12.

[22] Miriam Greis, Hendrik Schuff, Marius Kleiner, Niels Henze, and Albrecht Schmidt. 2017. Input controls for entering uncertain data: Probability distribution sliders. *Proceedings of the ACM on Human-Computer Interaction* 1, EICS (2017), 3:1–3:17.

[23] Paul KJ Han, William MP Klein, and Neeraj K Arora. 2011. Varieties of uncertainty in health care: A conceptual taxonomy. *Medical Decision Making* 31, 6 (2011), 828–838.

[24] William Harbaugh, Kate Krause, and Lise Vesterlund. 2002. Prospect theory in choice and pricing tasks. (2002).

[25] Beverly L Harrison, Russell Owen, and Ronald M Baecker. 1994. Timelines: An interactive system for the collection and visualization of temporal data. In *Graphics Interface.* 141–141.

[26] Shiping Huang. 2005. *Exploratory visualization of data with variable quality.* Ph.D. Dissertation. Worcester Polytechnic Institute.

[27] Jessica Hullman, Xiaoli Qiao, Michael Correll, Alex Kale, and Matthew Kay. 2019. In pursuit of error: A survey of uncertainty visualization evaluation. *IEEE Transactions on Visualization and Computer Graphics* 25, 1 (2019), 903–913.

[28] Susan Joslyn and Jared LeClerc. 2013. Decisions with uncertainty: The glass half full. *Current Directions in Psychological Science* 22, 4 (2013), 308–315.

[29] Susan Joslyn, Karla Pak, David Jones, John Pyles, and Earl Hunt. 2007. The effect of probabilistic information on threshold forecasts. *Weather and Forecasting* 22, 4 (2007), 804–812.

[30] Susan L Joslyn and Jared E LeClerc. 2012. Uncertainty forecasts improve weather-related decisions and attenuate the effects of forecast error. *Journal of Experimental Psychology: Applied* 18, 1 (2012), 126.

[31] Daniel Kahneman and Amos Tversky. 2013. Prospect theory: An analysis of decision under risk. In *Handbook of the Fundamentals of Financial Decision Making*. 99–127.

[32] Gerald M Karam. 1994. Visualization using timelines. In *Proceedings of the ACM International Symposium on Software Testing and Analysis*. 125–137.

[33] Mykel J Kochenderfer. 2015. *Decision Making Under Uncertainty: Theory and Application.* MIT Press.

[34] Josua Krause, Adam Perer, and Kenney Ng. 2016. Interacting with predictions: Visual inspection of black-box machine learning models. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. 5686–5697.

[35] Max Kuhn and Kjell Johnson. 2013. *Applied Predictive Modeling*. Vol. 26. Springer.

[36] Alexander Kumpf, Bianca Tost, Marlene Baumgart, Michael Riemer, Rüdiger Westermann, and Marc Rautenhaus. 2018. Visualizing confidence in cluster-based ensemble weather forecast analyses. *IEEE Transactions on Visualization and Computer Graphics* 24, 1 (2018), 109–119.

[37] Jared LeClerc and Susan Joslyn. 2015. The cry wolf effect and weather-related decision making. *Risk Analysis* 35, 3 (2015), 385–395.

[38] Mengchen Liu, Shixia Liu, Xizhou Zhu, Qinying Liao, Furu Wei, and Shimei Pan. 2016. An uncertainty-aware approach for exploratory microblog retrieval. *IEEE Transactions on Visualization and Computer Graphics* 22, 1 (2016), 250–259.

[39] Alan M MacEachren. 1992. Visualizing uncertain information. *Cartographic Perspectives* 13 (1992), 10–19.

[40] Sana Malik, Fan Du, Megan Monroe, Eberechukwu Onukwugha, Catherine Plaisant, and Ben Shneiderman. 2015. Cohort comparison of event sequences with balanced integration of visual analytics and statistics. In *Proceedings of the International Conference on Intelligent User Interfaces*. 38–49.

[41] Megan Monroe, Rongjian Lan, Hanseung Lee, Catherine Plaisant, and Ben Shneiderman. 2013. Temporal event sequence simplification. *IEEE Transactions on Visualization and Computer Graphics* 19, 12 (2013), 2227–2236.

[42] Tamara Munzner. 2009. A nested process model for visualization design and validation. *IEEE Transactions on Visualization and Computer Graphics* 6 (2009), 921–928.

[43] Alex T Pang, Craig M Wittenbrink, and Suresh K Lodha. 1997. Approaches to uncertainty visualization. *The Visual Computer* 13, 8 (1997), 370–390.

[44] Adam Perer and David Gotz. 2013. Data-driven exploration of care plans for patients. In *CHI Extended Abstracts on Human Factors in Computing Systems*. 439–444.

[45] Catherine Plaisant, Brett Milash, Anne Rose, Seth Widoff, and Ben Shneiderman. 1996. LifeLines: Visualizing personal histories. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. 221–227.

[46] Catherine Plaisant, Rich Mushlin, Aaron Snyder, Jia Li, Daniel Heller, and Ben Shneiderman. 1998. LifeLines: Using visualization to enhance navigation and analysis of patient records. In *Proceedings of the AMIA Symposium*. 76–80.

[47] Maria H Ramos, Schalk J Van Andel, and Florian Pappenberger. 2013. Do probabilistic forecasts lead to better decisions? *Hydrology and Earth System Sciences* 17, 6 (2013), 2219–2232.

[48] Philip J Rhodes, Robert S Laramee, R Daniel Bergeron, Ted M Sparr, et al. 2003. Uncertainty visualization methods in isosurface rendering. In *Eurographics*, Vol. 2003. 83–88.

[49] Patrick Riehmann, Manfred Hanfler, and Bernd Froehlich. 2005. Interactive Sankey diagrams. In *IEEE Symposium on Information Visualization*. 233–240.

[50] Maria Riveiro. 2007. Evaluation of uncertainty visualization techniques for information fusion. In *International Conference on Information Fusion*. 1–8.

[51] Dominik Sacha, Hansi Senaratne, Bum Chul Kwon, Geoffrey Ellis, and Daniel A Keim. 2016. The role of uncertainty, awareness, and trust in visual analytics. *IEEE Transactions on Visualization and Computer Graphics* 22, 1 (2016), 240–249.

[52] Sam L Savage and Harry M Markowitz. 2009. *The Flaw of Averages: Why We Underestimate Risk in the Face of Uncertainty.* John Wiley and Sons.

[53] Eric Siegel. 2013. *Predictive Analytics: The Power to Predict Who Will Click, Buy, Lie, or Die.* Wiley Hoboken.

[54] Vlad V Simianu, Margaret A Grounds, Susan L Joslyn, Jared E LeClerc, Anne P Ehlers, Nidhi Agrawal, Rafael Alfonso-Cristancho, Abraham D Flaxman, and David R Flum. 2016. Understanding clinical and non-clinical decisions under uncertainty: A scenario-based survey. *BMC Medical Informatics and Decision Making* 16, 1 (2016), 153.

[55] Susanne Tak, Alexander Toet, and Jan van Erp. 2014. The perception of visual uncertainty representation by non-experts. *IEEE Transactions on Visualization and Computer Graphics* 20, 6 (2014), 935–943.

[56] Zana Vosough, Dietrich Kammer, Mandy Keck, and Rainer Groh. 2017. Visualizing uncertainty in flow diagrams: A case study in product costing. In *Proceedings of the International Symposium on Visual Information Communication and Interaction*. 1–8.

[57] Elke U Weber, Ann-Renee Blais, and Nancy E Betz. 2002. A domain-specific risk-attitude scale: Measuring risk perceptions and risk behaviors. *Journal of Behavioral Decision Making* 15, 4 (2002), 263–290.

[58] Robert L Winkler. 2015. The importance of communicating uncertainties in forecasts: Overestimating the risks from winter storm Juno. *Risk Analysis* 35, 3 (2015), 349–353.

[59] Craig M Wittenbrink, Alex T Pang, and Suresh K Lodha. 1996. Glyphs for visualizing uncertainty in vector fields. *IEEE Transactions on Visualization and Computer Graphics* 3 (1996), 266–279.

[60] Krist Wongsuphasawat and David Gotz. 2012. Exploring flow, factors, and outcomes of temporal event sequences with the Outflow visualization. *IEEE Transactions on Visualization and Computer Graphics* 18, 12 (2012), 2659–2668.

[61] Krist Wongsuphasawat, John Alexis Guerra Gómez, Catherine Plaisant, Taowei David Wang, Meirav Taieb-Maimon, and Ben Shneiderman. 2011. LifeFlow: Visualizing an overview of event sequences. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. 1747–1756.

[62] Krist Wongsuphasawat and Jimmy Lin. 2014. Using visualizations to monitor changes and harvest insights from a global-scale logging infrastructure at Twitter. In *IEEE Conference on Visual Analytics Science and Technology*. 113–122.

[63] Jian Zhao, Zhicheng Liu, Mira Dontcheva, Aaron Hertzmann, and Alan Wilson. 2015. MatrixWave: Visual comparison of event sequence data. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. 259–268.