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TriPlan: an interactive visual analytics approach for better tourism route planning

Abstract Continuous research and development of novel tourism routes is necessary for tourism service providers to improve the tourist experience and industrial competitiveness. However, the route planning is cumbersome due to the time-consuming, extensive, and costly field study. Most of the existing route planning studies focus on recommending tourism routes for users based on attraction characteristics or tourist behavior features, which are generally unexplainable due to the black-box approaches they use. Other solutions allow users to customize itineraries through an interactive interface but often lack guidance from the aspect of route evaluation or destination image perception. In this paper, we thoroughly discuss the requirements and design tasks with domain experts and propose TriPlan, an interactive visual analytics system that provides intuitive planning guidance for tourism product developers. We design and improve multiple coordinated visualizations to facilitate analysis from the perspectives of overall route pattern and individual destination image. We also develop a hierarchical planning view to display the structural information of a plan. In addition, we introduce an automatic route optimization algorithm and multiple interactions to assist users in optimizing and adjusting the itineraries. Finally, we evaluate the usability and effectiveness of our system through three case studies and quantitative and qualitative interviews with the domain experts on real-world datasets.

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1 Introduction

Over the past decades, tourism has become one of the world's most prosperous economic sectors. Millions of jobs and businesses are dependent on a thriving tourism sector (OECD 2020; UNWTO 2019), and the tourism sector rests quite highly on the service providers available (Lopez-Cordova 2020). Taking China as an example, according to the China National Tourism Administration[1], the Chinese domestic tourists had exceeded 6 billion by 2019. Among them, 170 million people chose to book tours with a particular agency. There are approximately 39000 travel agencies in China. The travel intention of Chinese domestic tourists remains evident after the COVID-19 outbreak (Zhang et al. 2021).

To improve the industrial competitiveness or the quality of tourism products, tourism service providers need to continuously release various novel travel routes to enhance the tourist experience and encourage tourism differentiation and personalization (Ruiz-Meza and Montoya-Torres 2021). However, researching and developing a new itinerary is challenging for tourism service providers, as it still relies on extensive field researches and developers' experience (Tomej and Xiang 2020; Tussyadiah 2016). Such a method is costly, lengthy, and largely relies on the subjective idea of researchers, lacking objective data support.

Existing research on tourism route planning mainly focuses on automatic recommendation algorithms (Jiang et al. 2016; Lim et al. 2018; Gavalas et al. 2015) and self-service planning interface (Cenamor et al. 2017; Wang et al. 2018); either had a poor interpretability or just provided routes features than tourists' feedback information, which is an important factor for tourism service providers to determine whether a route is appropriate. For example, destination image, which is defined as the sum of one's beliefs, thoughts, and impressions about a destination (Crompton 1979; Gartner 1986), has been confirmed to be an integral and influential part of the tourist's destination decision process. Visual analysis provides an effective way to combine human intelligence with machine intelligence, enabling users to convert massive information into knowledge intuitively and efficiently and carry out reasoning. There have been a lot of research on the visual analytics of urban data. However, most related work focused on trajectory and regional patterns or OD pair characteristics, and did not combine trajectory with social network data to solve the problem of tourism route planning.

To address the above issues, we propose TriPlan (Fig. 1), an interactive visual analytics approach to provide comprehensive planning guidance for tourism service providers from the path and destination aspects. It integrates tourist online travel routes, user-generated content (UGC), and geographic information, which are released by tourists on web. It can reflect the route and destination information truly and comprehensively. We design multiple coordinated views and interactions, building up a comprehensive visual analysis framework including three modules: route mining and analysis, route planning, and destination analysis. The route mining and analysis module mines and visualizes frequent route patterns according to user preferences. The route planning module provides users with an intelligent path optimization function and allows users to modify routes through multiple interactions. The destination analysis module analyzes the affective images of the destinations, including time-series analysis and perceptual attribution of the destination image, providing users with decision-making guidance for modifying destinations in the route.

The contributions of this paper are summarized as follows:

- We proposed a novel visual analysis pipeline for tourism route planning through in-depth discussions with domain experts to guide the tourism service providers in the travel routes exploration and design.
- We designed and implemented a visual analysis system, named TriPlan, to help tourism service providers make an ideal itinerary interactively, where some novel visual designs and rich interactions are incorporated to support the smooth and comprehensive analysis of tourism routes.
- We conducted three case studies on real-world tourism dataset and user interviews with ten domain experts to demonstrate the usability and effectiveness of TriPlan.

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[1] http://zwgk.mct.gov.cn/zfxxgkml/

2 Related work

This section discusses recent studies related to tourism route planning and visual analytics of urban data.

2.1 Tourism route planning

Recent studies related to tourism route planning can be roughly categorized into automatic planning system and user self-service planning.

Automatic planning system mainly focuses on recommending travel routes or attractions by building a travel route recommendation model. Common modeling data include the popularity of POI (Lim et al. 2015, 2018), the interests of tourists (Chen et al. 2020), user request context (Zhang et al. 2019), and POI context (Majid et al. 2015). For example, Jiang et al. (2016) build a route recommendation system by automatically extracting POI admission fees, opening hours, and visiting seasons from geo-tagged photographs and travel websites. Some other researches focus on optimizing the tour sequence automatically by considering various factors, such as the traffic conditions (Chen et al. 2021; Gavalas et al. 2015), the level of POI category (Gionis et al. 2014), and the uncertainty of travel time (Liebig et al. 2014, 2017). However, the automatic methods are often plagued by the poor interpretability of their black-box models, making it difficult to trust and adjust the recommended results.

The self-service planning methods allow the user to customize the itinerary by providing an interactive operation interface. TouristHub (Stavrakis et al. 2020) and Cenamor et al. (2017) proposed user-friendly Web interfaces to enable users to create personalized itineraries based on user preferences and constraints. Providing rich interactive means, TripBuilder (Brilhante et al. 2014) and Aurigo (Yahi et al. 2015) allowed users to fine-tune the suggested itinerary personalized by considering both quantitative and qualitative preferences of the user. Some work utilized visualizations to provide users with more intuitive data guidance. For instance, the TISP system (Wang et al. 2018) visualizes the results of different types of queries. Wunderlich et al. (2017) visualize the delay uncertainty and its impact on tourists' train trip planning. Although user self-service planning schemes are more user-friendly, they often lack data support from the tourists' feedback perspective to guide users in planning.

Compared with the prior work, our work combines the advantages of both automatic and self-service methods. Not only do we provide users with multiple visualizations and interactions to facilitate flexible analysis and planning, but we also introduce a path optimization algorithm to enable users to an obtain time-optimal path result.

2.2 Visual analytics of urban data

A wider range of urban data have been generated and collected as the technology develops and urbanization accelerates. Zheng et al. (2016) categorized the frequently used urban data types in the field of visualization into six categories: human mobility data, social network data, geographic data, environmental data, healthcare data and others.

Closely related to this paper, visualization methods of human mobility data often base on point (Andrienko et al. 2017; Liu et al. 2013), line (Sun et al. 2017; Meulemans et al. 2013), and area (Collins et al. 2009; Buchin et al. 2011). With the these visualization techniques, Weng et al. (2020) and Lu et al. (2017) focused on route selection, designing visualizations to analyze the properties of different trajectories to identify the optimum or defective routes. Focusing on regional characteristics, Zeng et al. (2013) presented an exchange ring diagram (ICD) that visualizes the traffic patterns; Shi et al. 2019 enabled users to find clusters at regional, site, and core site levels based on bike-sharing data. Focusing on multiple origin–destination (OD) pairs, Shin et al. (2021) provided multi-coordinated OD views to allow analysts to inspect, rank, and compare OD pairs; Yang et al. (2017) enhanced the traditional OD matrix by interactive features and geographic representation of links. Some other (Zhao et al. 2021b) work supports analysis from the perspective of mobility dataset construction.

Social network data representing by UGC are often combined with POI information to be used for destination image analysis. Li et al. (2018) extracted keywords from comments and embedded them in subregions to guide users to establish impressions of a city based on geographic location. Li et al. (2016) designed interactive views to analyze tourists' regional tendencies and emotional changes based on UGC data of tourism social networking sites. Hou et al. (2019) and Cao et al. (2020) analyzed the image differences of different platforms or destinations from the perspective of comparative analysis.

Fig. 1 TriPlan provides users with route research and planning guidance from the route and destination perspectives. **a** Route mining view: filtering and overviewing the theme dimension reduction of routes and setting parameters for route pattern mining. **b** Route analysis view: overviewing and comparing different patterns. **c** Route planning view: visualizing the hierarchical structure of the plan and providing interactions for flexible modification. **d** Destination analysis view: enabling emotional evolution analysis and perceptual attribution of the destination image

Different from previous studies, our work focuses on analyzing the dual performance of routes in terms of geographic location and tourist feedbacks by combining trajectory and social network data.

3 System overview

3.1 Requirement analysis

Following a user-centered design process, we worked closely with four domain experts from the tourism industry (D1-D4). D1 and D2 are product developers from a travel agency; D3 is a professor from the College of Tourism, Department of Tourism and Landscape Architecture; D4 is a doctor from the College of Tourism. We list the following three analysis requirements (R1-R3) derived from several rounds of iterative communication with domain experts guiding the system design.

R1: Identifying customized and ideal travel routes: Users expect to locate intriguing routes that meet their preferences rapidly from large-scale online travel route data, such as routes through both the "Forbidden City" and the "Great Wall." They also wish to identify ideal routes with a reasonable geographic distribution and excellent tourism ratings by comparative analysis.

R2: Planning route interactively: Users expect the system to provide interfaces and interactions to support flexible route planning, such as directly adding an existing route or sequentially adding destinations to the plan. Furthermore, users also want to adjust the plan intuitively, such as deleting a destination from the itinerary or adjusting the play duration and sequence.

R3: Offering insights into the destination image: To better assess the route's quality and provide data support for route adjustment and planning, users need to analyze the affective image of the destinations along the route in a fine-grained manner, such as the destination's popular seasons and the attribution of negative reviews on the destination.

3.2 Data processing

3.2.1 Data collection

To meet the analysis requirements listed above, we have combined travel routes, UGC, and geographic information data, examples of which are from Qyer.com[2], Mafengwo.com[3], and Amap API[4]. Among them, travel route data are used for route mining and analysis, UGC is used for constructing affective images of a tourism destination, and geographic information is used for spatial environment analysis of the route and destination.

The Qyer Itinerary Assistant website provides users with route sharing and customization services. It has more than 16.4 million registered users, and its total number of domestic itineraries released is over 160,000. Following a hierarchical route planning process (Xiang and Fesenmaier 2020), we divide the routes into the city and POI (Point of Interest) levels to facilitate users' planning with varied granularities. City-level routes take a city as the destination unit, while POI-level routes take the POI within a city as the destination unit, such as attractions, restaurants, traffic, and hotels. Overall, we crawl 30,000 domestic city-level routes and 70,000 POI-level routes, including attributes such as locations, planned travel duration, time spent, page views, and the number of having been copied.

Mafengwo is a travel forum website with UGC as its core competency. Its monthly active users has reached 100 million, and high-quality travel blogs written by users have surpassed 135,000 per month. UGC is the feedback on tourism websites, providing rich information for constructing a destination image. It mainly consists of long travel blog and short comment text. In this paper, we use the user comments on a POI as the UGC data. We crawl about 1.45 million short comment texts in the unit of POI, including attributes such as POI information, comment content, and evaluation ratings.

The Amap API gives developers programmatic access to various geographic data services, including IP locations, weather, geo-coding, driving, or public transport. We collect the geographic information of roughly 2000 cities (counties) and 30,000 POIs. The city geographic information includes attributes such as city name, geographic location, and city abbreviation. The POI geographic information includes POI name and type, geographic location, affiliated city, and other attributes.

3.2.2 Route theme classification

Route theme information, such as cultural trips, sea and beaches, and shopping and cities, can provide users with a better insight into that theme and further highlight route features (Moscardo 2010).

To establish data foundations for theme classification, we first merge the UGC data for each destination along the routes on different levels. At the city level, we aggregate the UGC data of all POIs within the corresponding city into one text. At the POI level, we merge the UGC data of each POI into one text directly. Then, we split the text into individual words using the Jieba Chinese Word Segmentation[5] and extract ten themes and their corresponding keywords using the latent Dirichlet allocation (LDA) algorithm (Blei et al. 2003). We use topic coherence measures (Röder et al. 2015) to divide themes in to K clusters. When K is equal to 10, the model evaluations and results have better semantics. Finally, we sort the keywords under each theme by probability and use top-ten high-probability keywords to represent the semantics of each theme. The theme classification results of both city-level and POI-level routes are shown in Tables 1 and 2, respectively. For users' better understanding, we named each theme according to its keywords' semantic (Robinson et al. 2011).

As shown in the table, the themes at the city level have strong regional characteristics. Users can quickly catch the district to visit based on these keywords and thus identify routes of interest. Themes at the POI level are more distinctive. For example, theme 3(Beach Holiday) represents the beach tourism scene, and theme 6(Leisure Tour) represents leisure tourism represented by snack street. With these keywords, users can overview the main features and sceneries of the routes and further narrow the scope of exploration.

Table 1 Route theme keywords (city level)

Theme	Keywords
1: Cultural tourism	Museum, resort, attraction, architecture, ancient city, ticket, antiquity, culture, building, city wall
2: Northwest loop	Xining, grassland, Saka Salt Lake, Kumbum Monastery, Lhasa, Lanzhou, Itinerary, Qinghai, Danxia, big
3: Pearl river delta	Guangzhou, Shenzhen, Pearl River, New Town, port, park, Shekou, subway, airport, wharf
4: HK-macau tour	Hong Kong, Macau, architecture, tourist, church, street, hotel, university, statue, coffee
5: Shanghai fashion tour	Shanghai, world, dream, queuing, bar, paradise, cuisine, park, visit, movie
6: Park-theater tour	Square, architecture, arboretum, country, theater, royal, ticket, China, price, avenue
7: Southwest leisure tour	Chengdu, Yading, alley, Chongqing, tour, marketplace, hot pot, panda, sausage, shopping
8: Landscape scenery	Fisherman, park, hotel, Guilin, island, beach, sandbeach, blue, Sanya, terraces
9: Watery towns	Hangzhou, West Lake, Nanjing, Wuzhen, Broken Bridge, park, square, bookstore, wetland, moon
10: Yunnan landscape	Lijiang, Dali, Lugu Lake, Erhai Lake, small, ancient town, village, ancient city, hike, snow-capped mountain

Table 2 Theme keywords (POI level)

| Theme	Keywords
1: Resort tour	Park, resort, wetland, university, street, environment, facilities, beauty, convenience, play
2: Landscape tour	Waterfall, funicular, ancient town, snow-capped mountain, temple, bell tower, ruins, Onsen, canyon, climbing
3: Beach holiday	Couples, roundabout, promenade, ferry, sea, beach, romance, seafood, bathing, photograph
4: City tour	Architecture, mansion, open, prosperous, design, subway, dessert, city, hotel, center
5: Shopping tour	Lively, night view, shopping, stadium, beauty, foreign, brand, bar, milk tea, shop
6: Leisure tour	Shopping, alley, culture, snacks, taste, cuisine, street, market, tea, hot pot
7: Cultural tour	Memorial, showroom, history, old town, ticket, palace, queue, photograph, ancient, square
8: Historical place	Ancient city, ancient town, inn, life, Lijiang, bar, visit, art, construction, Jiangnan
9: Religious tour	Church, rose, headquarter, beautiful, urban, performance, fountain, luxury, culture, elegance
10: Self-guided walking tour	Grassland, hike, walk, ride, altitude, glacier, sunrise, road, village, along the way

3.2.3 Indicator computation

We propose two evaluation indicators to quantify the characteristics of each destination along the route: visit popularity and tourist rating.

The visit popularity index is calculated by route popularity and comment popularity. The route popularity, at the POI level, refers to the number of POI-level routes that pass through the corresponding POI, and comment popularity refers to the number of comments under that POI. At the city level, route popularity refers to the number of POI-level routes that pass through the corresponding city, and comment popularity refers to the total number of comments on all POIs within that city. Due to the significant differences in the order of magnitude, we linearly normalize the route popularity and comment popularity separately and then take their average value as the visits popularity for each city (POI).

The tourist rating index is calculated by online rating and comment rating. At the POI level, the online rating is derived directly from user rating on the POI introduction page of the website, and comment rating is the average user rating of all reviews under that POI, all on a scale of 0–5. At the city level, the online rating refers to the average online ratings of all POIs within the city, and the comment rating refers to the average of all POIs' comment ratings. The final tourist rating of each city (POI) is the average of the online rating and comment rating.

3.3 System pipeline

Based on the above-mentioned requirements, we have designed TriPlan, an interactive visualization system (Fig.1), to provide comprehensive visual guidance and interactive planning methods for tourism product developers. The pipeline of our system is shown in Fig. 2. We crawl and collect three types of data: route, UGC, and geographic information as our source data, calculate the theme and various analysis indicators of each route or destination and store them in the database structurally. The visual design can be divided into three modules according to analysis requirements: route mining and analysis, route planning, and destination
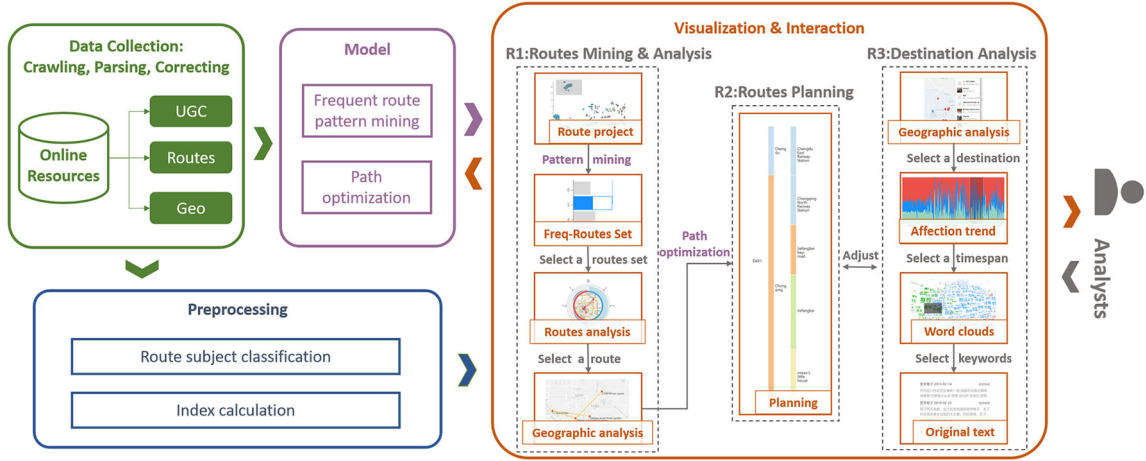
Fig. 2 Pipeline of TriPlan. Routes, UGC, and geographic information are used as data sources to support three aspects of exploration: route mining and analysis, route planning, and destination analysis. Rich multi-view interactions (gray arrows) provide users with flexible analysis and modification functions

analysis. It enables users to select and analyze data freely, reveals potential route patterns, and presents pattern characteristics, planning results, and destination affective image. In addition, the system supports explorations based on user preferences or input by providing multiple interactions, allowing users to customize or justify their planning flexibly.

4 Visual design

This section describes the design tasks and the designs of interactive visualization views in TriPlan.

4.1 Design tasks

We identified the following visual design tasks (T1-T5) by discussing the analysis requirements (R1-R3) and the limitations of existing technologies. Specifically, our design focuses on enabling tourism product developers to mine, analyze, and plan ideal routes rapidly.

T1 Outlining route collection and identifying target route subset (R1): To assist users in identifying the route subset of interest quickly, it is necessary to allow users to put forward their preferences or constraints and provide an overview of large-scale route data collection.

T2 Mining and displaying frequent route patterns (R1): To make the route analysis results more statistically significant, it is necessary to mine the frequent route patterns from the target route subset. To assist users in comparing and analyzing different routes, the visualization should display the corresponding statistical information of the patterns.

T3 Displaying route planning results and supporting interactive route planning (R2): The interactions should support overall route addition, interactive route planning, and flexible route modification. The visualization should intuitively present the planning result. Considering the time cost of user interaction, it is also necessary to provide users with an automatic path optimization function.

T4 Providing statistical affective information of the destination image (R3): To discover the periodic properties of tourist experience fluctuation, evaluate the quality of the route, and provide data support for planning and modification, the visualization should also show the time-series characteristics and keywords of the destination affective image.

T5 Supporting geo-awareness of route and destination (R1, R3): To assist users in optimizing the route design, the visualization should show the commercial environment around a route or destination, such as the distribution of hotels and restaurants.

4.2 Visualization and interaction

We propose TriPlan, an interactive visual analysis system, to accomplish the above tasks. The system can help tourism product developers identify and customize ideal travel routes and reduce the survey and planning costs. The visualization and interaction module of TriPlan consists of four parts of views:

(1) *Route mining view*: As shown in Fig.1a, it includes a control panel and a route projection view, which enables users to select a set of routes of interest by setting spatiotemporal constraints and overviewing route collection characteristics, and to further mine frequent patterns of routes from the routes subset (T1, T2).

(2) *Route analysis view*: As shown in Fig.1b, it includes frequent route set view, frequent route analysis view, and spatial map to compare and analyze various indicators and geo-spatial environment of different route patterns (T2, T5).

(3) *Route planning view*: As shown in Fig.1c, the hierarchical route planning view displays information such as the spatiotemporal distribution and sequence of the route plan and provides interactions to enable users to modify the arrangements that do not meet their expectations (T3).

(4) *Destination analysis view*: As shown in Fig.1d, it displays the temporal change of destination affective image, comment keywords, and keywords co-occurrence relationships, as well as the original comment texts (T4).

4.2.1 Route mining view

The route mining view aims at helping users quickly identify the route subset of interest from the large-scale online travel route data and narrow down the data to be analyzed.

The control panel (Fig. 1a1) allows users to filter the routes collection according to personal preferences. The route projection view (Fig. 1a2) uses the t-SNE method [28] to reduce the dimensionality of the routes according to the route theme (see Sect. 3.2.2). A point represents a route, and each route has ten theme probability values. The color encodes the highest probability theme (Fig. 3). The control form (Fig. 1a3) supports frequent pattern mining of routes. The form items, respectively, specify the minimum support, minimum and maximum number of destinations in the pattern for subgraph mining. We use a proposed graph-based substructure pattern mining algorithm called gSpan (Yan and Han 2002) to mine frequent route patterns that meet the constraints from the selected route subset.

Interaction Users can specify the spatial constraint (City or POI that must pass through) and temporal constraint (departure time range) in the control panel to obtain an initial route set which will be projected in route overview view. Following a hierarchical analysis process, users always filter city-level routes first, then change the analysis level to POI level under the corresponding city by clicking the city name in Fig. 1a1, and filter the POI routes within the corresponding city. Moreover, users can brush a target route subset in the route projection view to further narrow the scope of the dataset, which will be used for frequent patterns mining. By hovering the mouse over a route scatter point, users can view the complete information of the route through a floating frame, including its destinations and the probability of each theme.

4.2.2 Route analysis view

The route analysis view aims at providing a multi-level analysis of frequent route patterns. Following an exploration guideline, "overview first, zoom and filter, then details on demand (Shneiderman 2003)," we
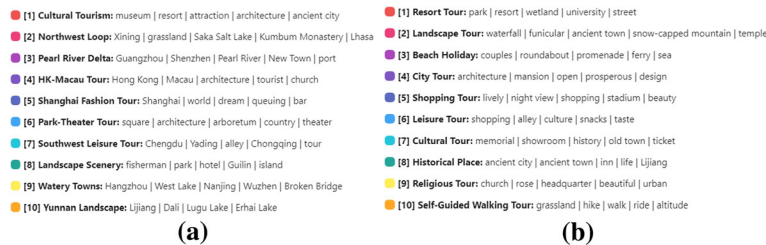

- **[1] Cultural Tourism:** museum | resort | attraction | architecture | ancient city
- **[2] Northwest Loop:** Xining | grassland | Saka Salt Lake | Kumbum Monastery | Lhasa
- **[3] Pearl River Delta:** Guangzhou | Shenzhen | Pearl River | New Town | port
- **[4] HK-Macau Tour:** Hong Kong | Macau | architecture | tourist | church
- **[5] Shanghai Fashion Tour:** Shanghai | world | dream | queuing | bar
- **[6] Park-Theater Tour:** square | architecture | arboretum | country | theater
- **[7] Southwest Leisure Tour:** Chengdu | Yading | alley | Chongqing | tour
- **[8] Landscape Scenery:** fisherman | park | hotel | Guilin | island
- **[9] Watery Towns:** Hangzhou | West Lake | Nanjing | Wuzhen | Broken Bridge
- **[10] Yunnan Landscape:** Lijiang | Dali | Lugu Lake | Erhai Lake

(a)

- **[1] Resort Tour:** park | resort | wetland | university | street
- **[2] Landscape Tour:** waterfall | funicular | ancient town | snow-capped mountain | temple
- **[3] Beach Holiday:** couples | roundabout | promenade | ferry | sea
- **[4] City Tour:** architecture | mansion | open | prosperous | design
- **[5] Shopping Tour:** lively | night view | shopping | stadium | beauty
- **[6] Leisure Tour:** shopping | alley | culture | snacks | taste
- **[7] Cultural Tour:** memorial | showroom | history | old town | ticket
- **[8] Historical Place:** ancient city | ancient town | inn | life | Lijiang
- **[9] Religious Tour:** church | rose | headquarter | beautiful | urban
- **[10] Self-Guided Walking Tour:** grassland | hike | walk | ride | altitude

(b)

**Fig. 3** Color legend for different themes at city level (**a**) and POI level (**b**)

divide the exploration process into three levels: set overview, route overview, and spatial details, which are laid out from left to right as frequent route set view, frequent route analysis view, and spatial map.

The frequent route set (Fig. 1b1) groups and counts the results of pattern mining by the number of nodes (destinations), and presents them in the form of a histogram, allowing users to observe the numerical distribution of the frequent routes with different length.

The frequent route analysis (Fig. 1b2) aims to summarize and overview statistic information such as the geographic mode, the themes involved, and the popularities and ratings of the patterns so that users can quickly grasp and compare the overall pictures of the routes. The route patterns are sorted from top to bottom by support. Each pattern consists of three parts from the inside to the outside. The innermost geographic map (Fig. 4a) uses a thumbnail to show the route pattern's geographic features and tour order in graph (Zhao et al. 2021a). Numerical markers on the map indicate the tour order of route nodes. The middle donut chart (Fig. 4b) shows which themes of routes the frequent route pattern is mined from and the proportion of routes with different themes, which are represented by the angle of θ_k in the figure. Different colors encode different themes according to the theme colors in the route projection view. The outermost annular area chart (Fig. 4c) shows the popularity (left) and rating (right) index information (see Sect. (3.2.3) of the destinations along a route. The polar axis angle represents the i_{th} order of the destinations along the route, which are even-distributed along the outer ring and denoted by θ_h^i and θ_s^i, respectively, in the figure. The polar diameter length is used to express the numerical value, which are represented by ρ_h^i and ρ_s^i, respectively. By observing the changes in popularity and ratings, and the relationship between them, it is possible for users to find such as less popular but higher-rated routes or routes that alternate between hot and cold destinations.

The spatial map (Fig. 1b3) is laid on the far-right side. It occupies the largest visual area, making it convenient for users further to observe the geographic distribution and its commercial environment nearby.

Interaction Users can select a frequent route set according to the ideal length of the route and display it in the frequent route analysis view. The selected set is highlighted in blue. Users can further expand and show a target route pattern on the map by clicking. To reduce users' memory load, a tooltip will pop up when user hovers over a target pattern, showing its theme composition. Or users can open a theme color legend by clicking on the "!" icon. Furthermore, users can click a path on the map to add it to the hierarchical route planning view as a plan (Sect. 4.2.3). For route added directly to a plan, we use an efficient genetic algorithm (Moon et al. 2002) to optimize the tour order by considering constraints including traffic time, total time, and time difference between the visit duration and traffic time. It can optimize the rationality of the plan and reduce users' interaction costs in the modification process. Users can also choose to add a single destination to the plan or open its destination image in the destination analysis view (Sect. 4.2.4).
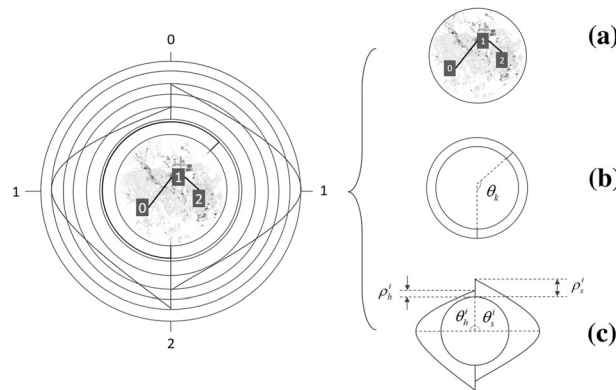
Fig. 4 Visual coding design of frequent route analysis view. It consists of (**a**) geographic map, (**b**) donut chart, and (**c**) annular area chart from the inside to the outside

4.2.3 Route planning view

The purpose of the hierarchical route planning view (Fig. 1c) is to help users intuitively grasp the temporal and spatial distribution of destinations in the plan, and their category proportions, to interactively evaluate and adjust the order or duration of the visit.

Drawing on the design idea of the column tree chart, we designed a two-layer stacked column chart with a vertical layout. The view is divided into three levels: date, city, and POI. The date layer is the outermost frame, nesting the cities to be visited under the corresponding date as the city layer, and the city layer nests the POIs to be visited within the corresponding city as the POI layer. POIs are arranged from top to bottom in the order of visit. The height of the POI column takes 1 hour as the minimum length unit and is calculated according to the visit duration of the corresponding destination. The column height of the city level is calculated by the sum of its nested POI column heights. The colors of the columns at the POI level indicate different POI types, including attraction (green), food (orange), transportation (blue), and accommodation (yellow). The color of the columns at the city level is determined by their nested POI type that accounts for the largest proportion.

Interaction As shown in Fig. 5, this view supports interactions such as hovering, selection, addition (Fig. 7b1), dragging (Fig. 5a), deletion, and modification (Fig. 5b). The selection interaction enables users to focus on a destination for further analysis by clicking the corresponding column. The dragging and modification interactions enable users to adjust the visit sequence or adjust the visit duration planned for a destination.

4.2.4 Destination analysis view

The destination analysis view aims at assisting users in analyzing the image of a destination. Several definitions of the destination image generally divide it into cognitive and affective components (Gartner 1994). The cognitive image represents tourists' knowledge of and beliefs regarding a place, while the affective image refers to their feelings or emotional responses. We help users catch tourists' affective responses toward or knowledge of a place from three levels.

The time-series affection view (Fig. 1d1) uses a time-series flowchart to express the variations in affective states of visitors' comments over time. Green, blue, and red encode positive, neutral, and negative
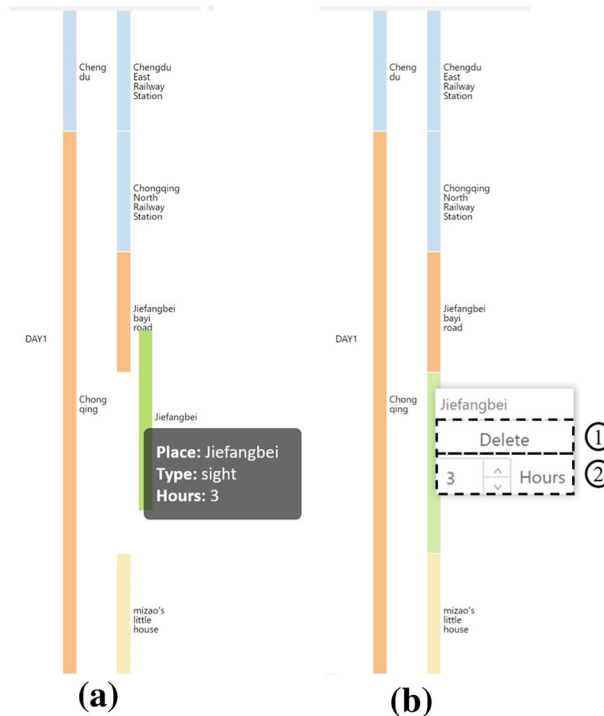
Fig. 5 Interactions designed for hierarchical route planning view

sentiments, respectively. The proportion of different colors in the vertical direction corresponds to the proportion of different sentiments in comments in the corresponding time range.

The sentiment word clouds (Fig. 1d2) are designed to analyze the affective tendency, comment keywords, and the specific factors that influence a destination's evaluation by establishing a co-occurrence relationship between keywords. Keywords are extracted from the UGC comments on the corresponding destination. Its color encodes the corresponding type of sentiment in-line with time-series affection view, and size indicates its frequency of occurrence in the comment collection. We construct a relationship matrix of keywords based on the co-occurrence times of keywords in sentences to describe the relationship between keywords. Then, we consider two constraints, sentiment proportion and force guidance, as our layout rules. Sentiment proportion constraint divides the width occupied by keywords of different sentiment into three parts according to the proportion of different sentiment in the comment collection. All sentiment types of keywords are only drawn in the corresponding constrained area. The force guidance constraint defines the gravity between keywords based on the co-occurrence matrix and takes the charge repulsion and collision detection into account to ensure an elegant layout. The final layout results from the joint action of the two constraints.

The original comment text view (Fig. 1d3) displays all the original comment texts containing the selected keywords so that users can more accurately catch the information expressed by the keywords and sentiment and verify the accuracy of the extracted destination image.

Interaction Users can locate a time period by brushing in the time-series affection view, expanding the comment keywords published in the corresponding time period in the sentiment word clouds view. Similarly, by brushing a set of keywords, users can expand the original comment texts containing the selected keywords.

5 Evaluations

We conducted three case studies and interviews with ten new domain experts to demonstrate the usability and effectiveness of TriPlan.

5.1 Case study

Taking planning an itinerary through Chengdu and Chongqing as an example, we show the system's ability in route analysis, planning, and modification from three case studies: route selection and analysis, route planning, and destination analysis. The users involved in our case studies are ten new domain experts from the tourism industry (see Sect. 5.2).

5.1.1 Route selection and analysis

In this case, we describe how TriPlan helps tourism product developers to identify a route of interest that satisfies their expectations from large-scale route data.

Firstly, in the control panel, the users searched for Chengdu and Chongqing, respectively, as the spatial constraints and selected the default time range as the temporal constraints. Then, a set of routes that satisfy the constraint, i.e., routes through Chengdu and Chongqing, were filtered and projected in 2D space (Fig. 6a1). It can be seen that the routes of different themes have been clustered into different clusters. After that users selected routes whose themes were dominated by the southwest scene because Chengdu and Chongqing are in the southwest of China. Further, they set the minimum support to 3 and the node number range to 3-5 to mine frequent patterns from the selected routes, since experts believe that 3 as minimum support is enough to avoid accidental factors and can avoid ignoring some unpopular but high-quality routes. Besides, 3-5 is a rational length for city-level routes to ensure that the journey would not be too long. The mining results were shown in Fig. 6a2–a4. Then, users tried to observe the routes containing three destinations (Fig. 6a2), as it is a reasonable length for intercity travel. By comparing the geographic distribution, the variation of popularity and ratings, and the thematic probability distribution of different routes, as shown in Fig. 6a3, users found that the fourth route can be used as a high-quality candidate. Its geographic extent is moderate (Fig. 6a4), ratings are relatively average, and themes distribution is rich and diverse, including theme elements such as ancient buildings in theme 1(Cultural Tourism).
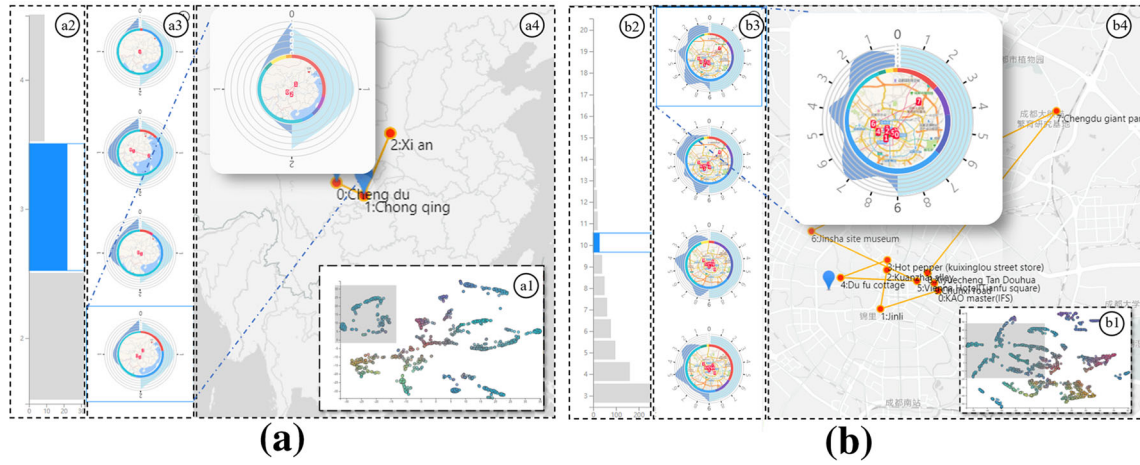
Fig. 6 Results of mining and analysis at city level (**a**) and POI level (**b**)

After finding an idea city-level route, users further planned the POI-level route. Taking the POI within Chengdu as an example, users wanted to formulate a compact itinerary, which focuses on food and culture and meeting shopping needs. Users firstly expand the route projection view of Chengdu (Fig. 6b1). It can be seen that these trips in Chengdu are dominated by theme 6(Leisure Tour), theme 8(Historical Place), and theme 4(City Tour), which is consistent with the experts' experience that Chengdu is known for its leisure culture, culinary culture, panda ecosystem, and ancient Shu civilization. Then, users chose the routes related to themes 6 and 7, namely leisure tour and cultural tour. After a set of interactions like frequent route mining, route set selection (Fig. 6b2), comparative analysis of patterns in the route analysis view (Fig. 6b3), users added the POI routes to the map to evaluate the POIs distribution and traffic conditions of each route in detail. Finally, users chose a route with ten destinations in Fig. 6b3, which has higher support, high and balanced ratings. It also contains cold but high-rating destinations, which users thought were good choices because since the COVID-19, the original demand for outbound travel has backed to China, and people yearn for minority destinations. And this route accounts for a more significant percentage of cuisine (theme 6, blue) and cultural (theme 7, turquoise) themes, satisfying the requirements aforementioned. Besides, the distribution of destinations in this route is relatively concentrated, and the transportation cost is appropriate.

5.1.2 Route planning

In this case, we discuss how the self-service planning interactions and automatic route optimization algorithm combined to assist users in completing planning work rapidly. After finding the idea POI route in the above case, users tried to add it to the plan directly by clicking on it. Then, it was displayed in the hierarchical route planning view.

Figure. 7a, b shows the result of planning arranged in default order and optimized by algorithm, respectively. By default, all destinations were set into one day, and the visit sequence is unreasonable, which will cause a lot of transportation costs. This arrangement requires lots of interactive operations for users to re-adjust the route sequence and date arrangement, leading to a significant increase in interaction costs. By algorithm, the itinerary was divided into three days automatically, and the daily scheduling duration was limited to a reasonable range. At the same time, the algorithm further improved the rationality of the schedule by converging to a solution with relatively the shortest traffic time.

It should be noted that the optimization results of the algorithm did not consider complex constraints. For example, in Fig. 7b1, the accommodation on the first day was arranged after lunch, and there was no meal on the third day. In this case, the users need only a few simple interactions such as dragging or adding based on the optimization result to complete planning and adjustment.

In summary, the path optimization function integrated into our system can significantly reduce the user's initial interaction cost and obtain a plan with the shortest travel time. And further, through a structural visual analysis method, users can intuitively evaluate each activity's distribution and duration and modify the plan that does not meet their expectations with fewer interactions.
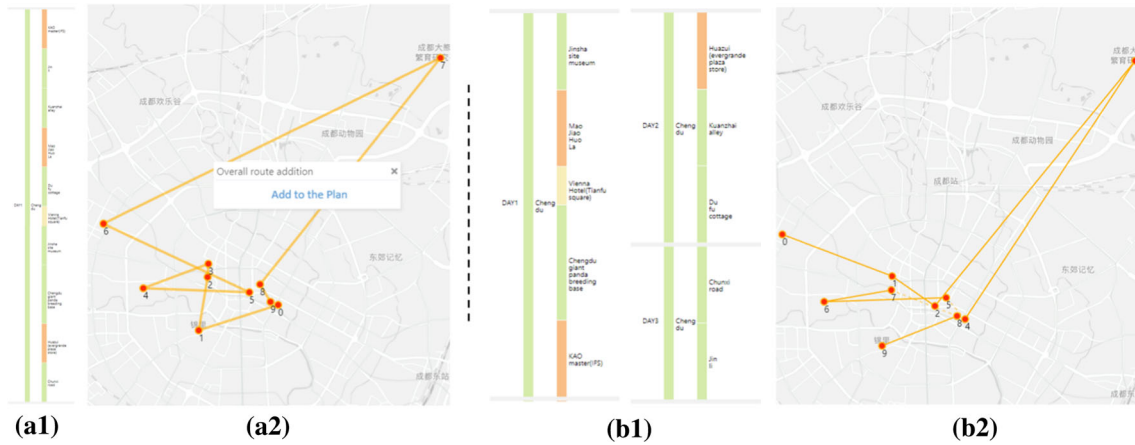
Fig. 7 Comparison between default plan (**a**) and plan after algorithm optimization (**b**)

5.1.3 Destination analysis

Taking Chengdu as an example, its time-series affection view is shown in Fig. 8. The affective image of Chengdu changes periodically, and the evaluation in the past two years has a downward trend. To analyze whether Chengdu is suitable to be one of the main destinations and the periods during which visitors can have a better play experience, users brushed the period (a) which has more negative reviews and period (b) which has more positive reviews, respectively, to further analyze the specific factors and reasons that influence the visitors' evaluations from the keywords composition.

As shown in Fig. 8a, period (a) is from the second half of 2017 to the beginning of 2018. The proportions of these three sentiment types show that negative reviews account for more than positive ones. Among them, the commercial streets such as *Jinli* and *Kuanzhai Alley* in the (a1) are closed to negative words such as *Crowded*, *Disappointed*, and *Expensive*. Users speculated that most tourists have poor travel experiences in these commercial streets. Besides, the *Snacks* is closed to *Not Delicious*, which means that the attractions in a commercial street in Chengdu should be chosen carefully as destinations for pleasure and dining. In the (a2) area, words such as *Park* and *Down Jacket* are concentrated, reflecting the seasonal characteristics of parklike attractions in winter, and are also connected closely with negative words such as *Desolate* and *Cold*. Hence, users understood that winter is not suitable for visiting Park attractions in Chengdu. The neutral words in the (a3) area are mainly festival words such as Spring *Festival* and *Temple Fair*, and these words are closed to positive words such as *Lively*, *Good* and *Like*. Users could know that Chengdu will hold multiple celebrations such as Temple Fairs during festivals and tourists always have good experiences. When planning tourism products during Spring Festival, Chengdu can be considered one of the cities to visit, and related Temple Fair attractions are also worthwhile candidates.

As shown in Fig. 8b, period (b) is approximately from the spring to the summer of 2018. In the high-frequency word area (b1), there are some attractions such as *Qingcheng Mountain* and *Dujiangyan* around Chengdu connect closely with positive words such as *Leisure*, *Wide,* and *Cool*. It shows that short trips around Chengdu are very popular with tourists in spring and summer, where the natural landscape is delightful. In the area (b2), there are some nouns such as *Panda*, *Hot Pot*, and other local characteristic travel entities, while there are few related descriptive adjectives around. To understand the specific images of these entities more clearly, the users brushed the area (b2) and expanded the original comment text containing these keywords.

As shown in Fig. 9, most of the comments about *Panda* come from the Chengdu Research Base of Giant Panda Breeding. Most of the comments suggest tourists go as soon as the door opens in the morning to avoid big crowds. Users summarized that when arranging the Chengdu Research Base of Giant Panda Breeding as a travel destination, it is better to let it be the first stop of a day. Some comments also mention that there are many foreign tourists in the Base, and the information board is marked in multiple languages. Therefore, when planning travel products involving foreigners, it is an excellent choice to consider Chengdu Research Base of Giant Panda Breeding as one of the main destinations.
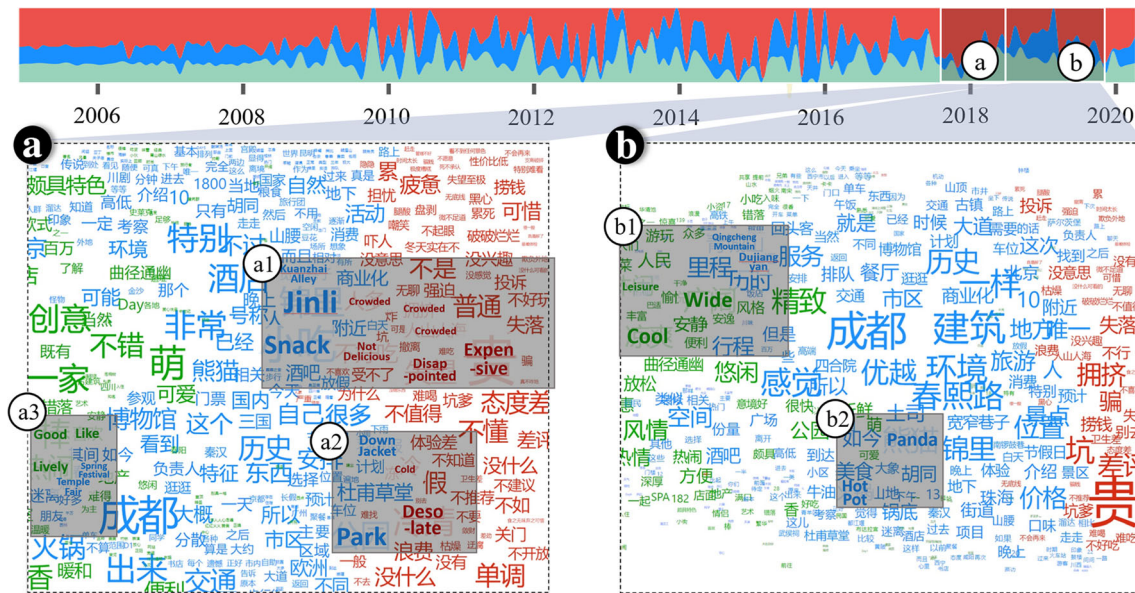
Fig. 8 Comment keywords on Chengdu in period **a** and **b**

**Fig. 9** Part of the original comment texts containing the keywords in b2 area

5.2 Expert interview

We collected users' feedback and comments on TriPlan through in-depth interviews with ten experts from the tourism industry, including five tourism product developers (E1-E5), three cultural tourism researchers (E6-E8), and two data visualization researchers (E9-E10). Firstly, we explained the tasks and visual encoding designs of TriPlan for experts. Secondly, we showed an example to illustrate the process of route pattern mining, analysis, planning, and modification to help experts get familiar with the system. Then,

Table 3 User questionnaire

Q1	TriPlan is very easy (difficult) to learn.
Q2	TriPlan is very easy (difficult) to use.
Q3	The visual design of the TriPlan are easy (difficult) to understand.
Q4	The visual interactions of the TriPlan are easy (difficult) to use.
Q5	I am very willing (unwilling) to use TriPlan in tourism route planning.
Q6	It is very easy (difficult) to identify the target route subset of interest.
Q7	It Is very easy (difficult) to catch the characteristics of frequent route patterns.
Q8	It Is very easy (difficult) to find the ideal frequent route.
Q9	The destination image analysis provided by TriPlan is very useful (useless) for destination decision.
Q10	TriPlan can (cannot) help me plan my ideal travel route.
Q11	TriPlan can (cannot) improve my efficiency in travel route planning.

Q1-5 focus on assessing the usability of TriPlan, and Q6-11 evaluate its effectiveness in facilitating tourism route planning
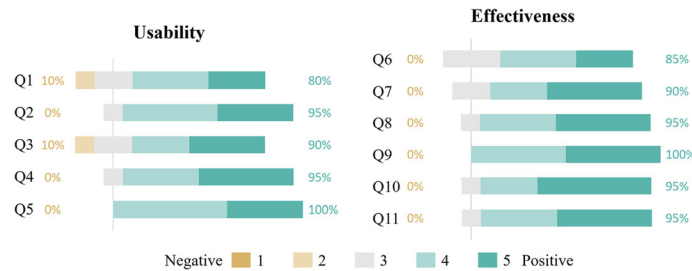
Fig. 10 Results of our questionnaire. The percentage number on the left represents negative responses (1 and 2), while the right represents positive responses (4 and 5). Neutral responses (3) are not included

experts were required to explore the functions of our system and use their domain knowledge to analyze and plan itineraries. We also required the participants to think aloud and ask questions freely during their exploration. Finally, we designed a questionnaire with ten questions, as shown in Table 3, using the five-point Likert scale (Likert 1932) to measure experts' attitudes. The questionnaire results are shown in Fig. 10 with reference to the statistical method used by Lin et al. (2021). Besides, we conducted one-on-one interviews with ten experts to summarize their comments and advice. We summarized our observations and experts' feedback as follows.

5.2.1 System usability

 Most participants can use the system freely after a short period of learning. Even experts who have never been in contact with this kind of visual analysis system can easily understand the visual design of our system. E2 and E3 are relatively unfamiliar with the concept of the frequent pattern mining and the interactions provided by the hierarchical route planning view, but after a period of familiarity, they can explore the system well.

5.2.2 System effectiveness

The questionnaire shows that most participants can find ideal route patterns through filtering and analysis. For example, through continuous screening and exploration, E2 found attractions such as Luzhen and Nanhu Park, which are not covered by conventional travel routes but are well rated. And they commented that "the visualizations and interactions provided by our system involve users in the entire planning process, making the planning more transparent and customized comparing to the automatic recommendation algorithm." However, E9 proposed that polygon selection may be more suitable as an interactive method for selecting data in the projection view to support more accurate data selection and improve user experience. Most experts commented that the hierarchical planning view is very distinct and intuitive, and E6 and E10 also believe that this view can be applied to more scenarios. Experts also agreed that the route pattern analysis and destination image perception methods can provide comprehensive planning guidance for users. For example, the analysis of sentiment keywords is critical in decision-making and can get more detailed tour suggestions. E1 proposed that the keyword extraction process is time-consuming, and pre-filtering

uncommon keywords can reduce the volume of comments selected by users and improve the speed of interaction.

6 Discussion

Our evaluation demonstrates the effectiveness of our work. This section summarizes the lessons we learned during our collaboration with experts, and the limitations and generalizations of TriPlan.

6.1 Lessons Learned

The most impressive lesson is to communicate closely with domain experts. For the requirement analysis, we summarized the ideal process of route planning and divided it into several stages, such as pattern discovery, evaluation, and iterative planning. Design tasks were carefully designed for each stage. For system design, we combined existing achievements in the tourism field with visualization to solve problem more effectively, such as combining path optimization algorithms to reduce user's interaction costs. For evaluation, we went through several rounds of prototype iterations to make the system fit the domain.

6.2 Limitation

(1) Data scope: The frequent route analysis method proposed in this paper mainly considers selected indicators such as the rating, popularity, and proportion of different themes. At a customer-oriented level, the characteristics of target tourists, such as the number of tourists, the age characteristics, and the background of the tour group, could be considered to recommend routes in a more customized way. (2) Algorithm: The path optimization algorithm used in this paper takes the minimum travel time as the optimization goal. Allowing users to customize the algorithm's optimization objectives or constraint rules could get a more comprehensive result, such as continuous touring time and accommodation area, but this is not the focus of this paper.

6.3 Generalization

TriPlan is designed to analyze the routes and destinations for tourism planning. But its applications are not limited to the tourism planning domain and can also be extended to other application scenarios that combine graph data with text data. For example, in public opinion analysis, different news topics may have different broadcast modes. TriPlan can be extended to analyze public opinion propagation patterns based on social network data, like tracking and analyzing the development trend and evolution pattern of network public opinion.

7 Conclusion

In this paper, we proposed TriPlan, a visual analysis system that assists tourism service providers in mining and formulating ideal itineraries. The system mines frequent route patterns from large-scale online travel routes and integrates multiple coordinated views and interactive operations to facilitate analysis. The insights learned from the exploring process further guide tourism product developers to design and adjust a travel route. We presented three case studies on real-world travel data and interviewed ten domain experts from the tourism industry. The results demonstrated the usability and effectiveness of TriPlan in exploring, analyzing, and adjusting the plans. In future work, we plan to introduce more data resources and analytical indicators in tourism route planning to enable more fine-grained route analysis and planning, as well as to integrate more automatic recommendation algorithms to support planning in a more automated and personalized manner.

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