

University of Stuttgart
Germany

Eye Tracking and Visual Analytics

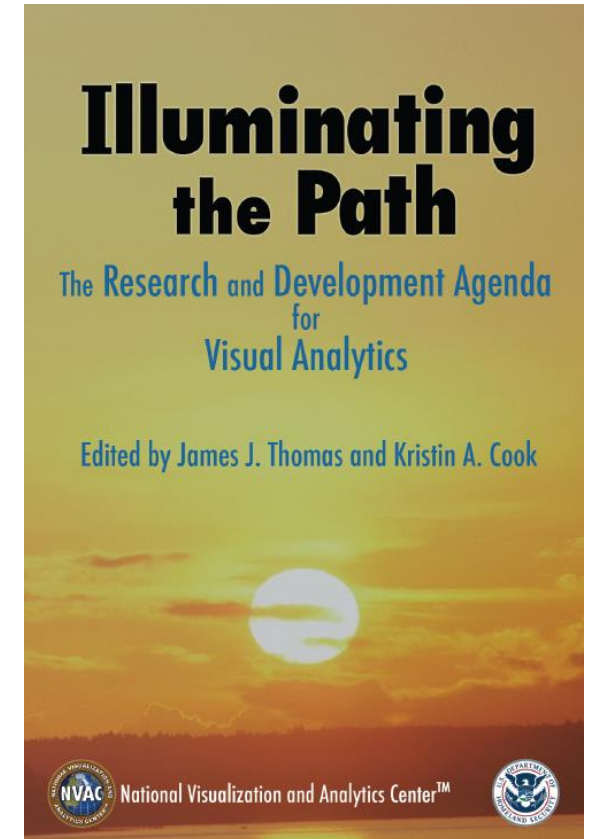
Michael Burch, Eindhoven University of Technology

ETRA 2018 - Tutorial: Eye Tracking and Visual Analytics – Warsaw, Poland

Visual Analytics

- Why visual analytics?
 - Recent challenges related to data analysis
 - Complex data
 - Large-scale data
- Definition:
“the science of analytical reasoning
facilitated by interactive human-machine interfaces”

[THOMAS J. J., COOK K. A. (Eds.): Illuminating the Path:
The Research and Development Agenda for Visual Analytics. IEEE Press, 2005]



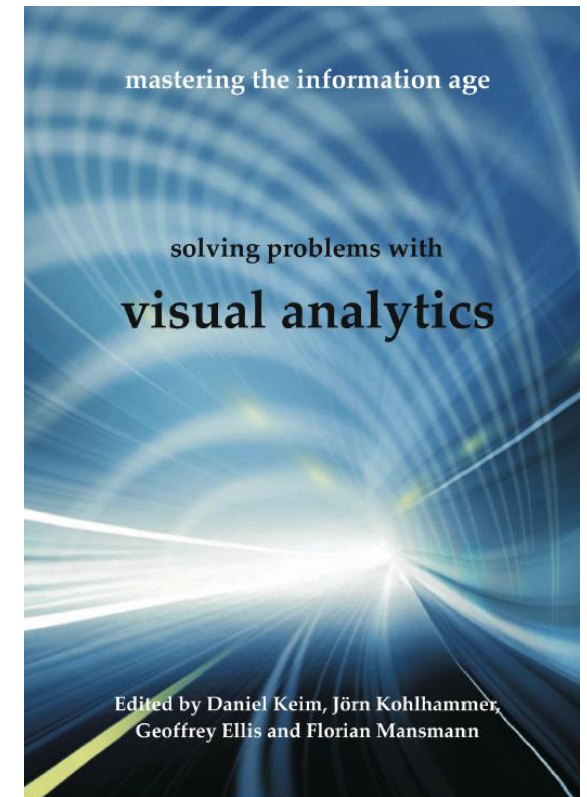
Refined Definition of Visual Analytics

“the creation of tools and techniques to enable people to:

- Synthesize information and derive insight from massive, dynamic, ambiguous, and often conflicting data.
- Detect the expected and discover the unexpected.
- Provide timely, defensible, and understandable assessments.
- Communicate these assessment[s] effectively for action.”

[KEIM D. A., KOHLHAMMER J., ELLIS G. P., MANSMANN F. (Eds.):

Mastering The Information Age – Solving Problems with Visual Analytics. Eurographics, 2010]



Simplified Definition

Visual analytics =

interactive visualization + automatic data analysis

Multidisciplinary Research

- Analytical reasoning
 - How to maximize human capacity to perceive, understand, and reason about complex and dynamic data and situations?
- Visual representations and interaction techniques
 - How to augment cognitive reasoning with perceptual reasoning through visual representations and interaction?
- Data representations and transformations
 - How to transform data into a representation that is appropriate to the analytical task and effectively conveys the important content?
- Production, presentation, and dissemination
 - How to convey analytical results in meaningful ways to various audiences

Cognitive science
Knowledge management

Visualization
Human-computer interaction

Data-mining
KDD
Statistical analysis

Knowledge management
Communication sciences

Multidisciplinary Research

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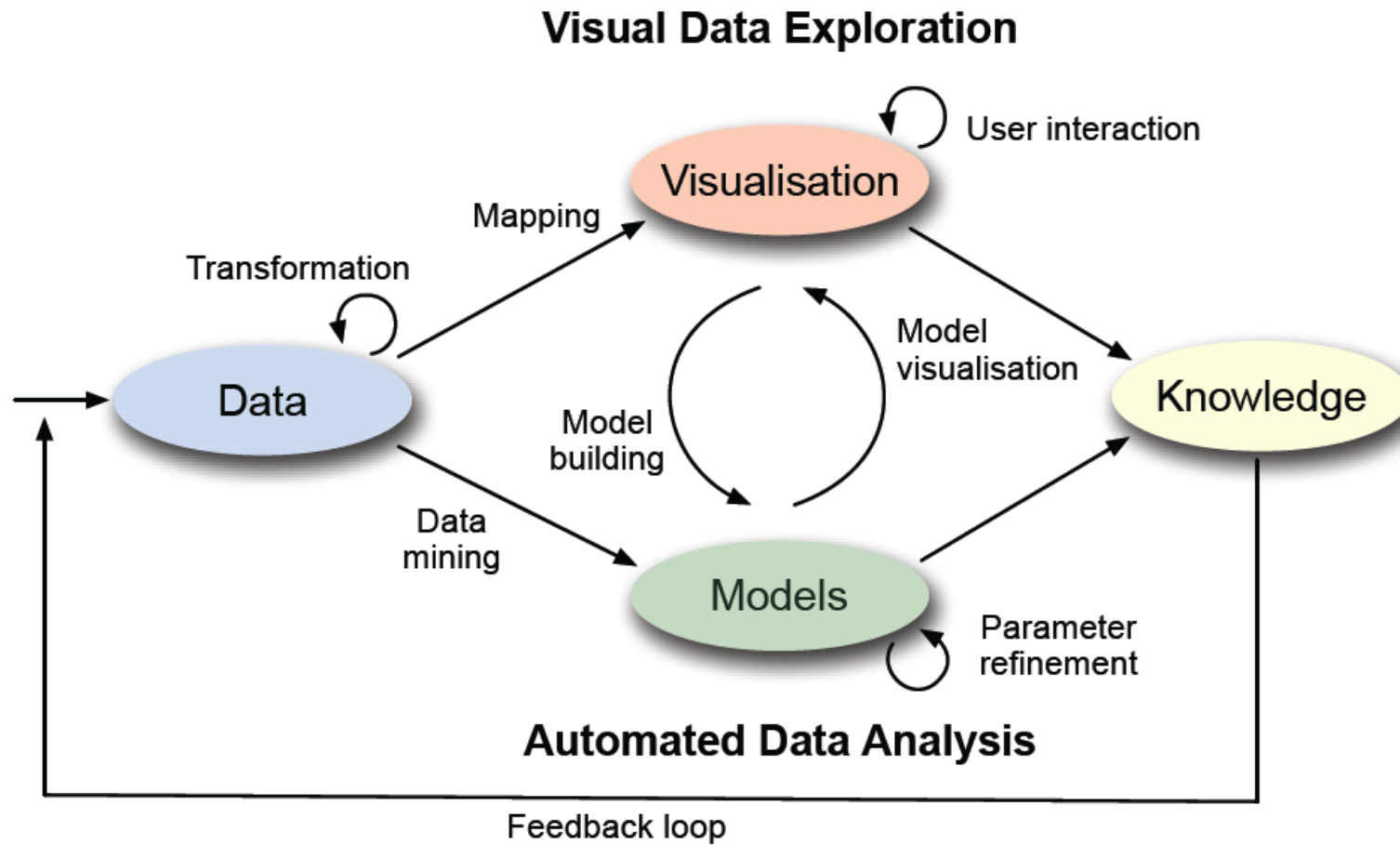
Cognitive science
Knowledge management

Visualization
Human-computer interaction

Data-mining
KDD
Statistical analysis

Knowledge management
Communication sciences

Visual Analytics Process



Why Visual Analytics for Eye Tracking Data?

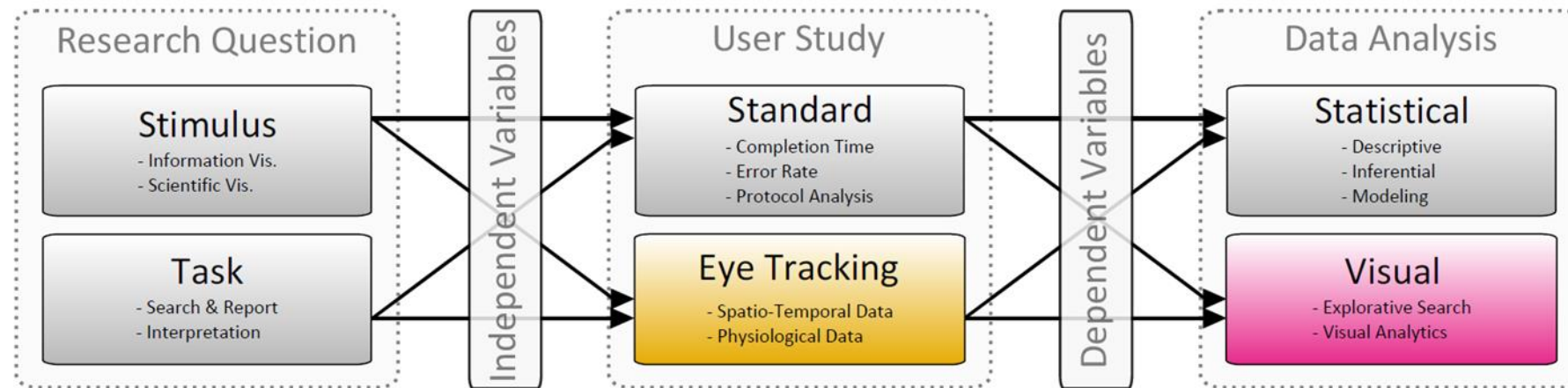
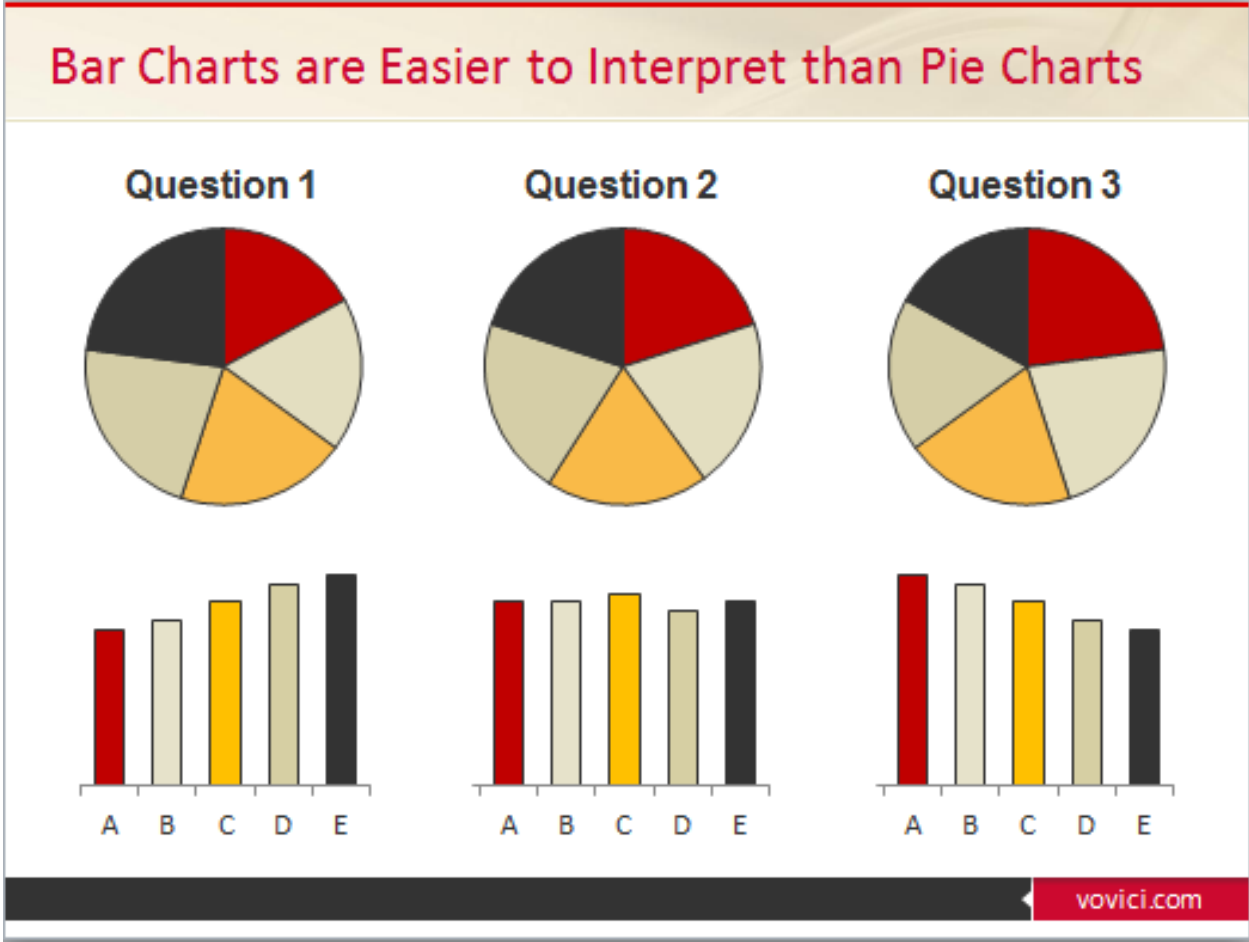


Figure 1: Pipeline of user-oriented evaluation. Stimulus and task represent the independent variables, measurements from a user study represent the dependent variables. The data analysis can then be performed with statistical methods, or in combination with a visual data analysis.

Traditional User Studies



Traditional User Studies



User Study Performance Measures

- Response times
- Error rates

→ **Dependent variables of traditional user studies**

→ **Typically statistically evaluated**

→ **Hypotheses confirmed/rejected**

Eye Tracking in Information Visualization

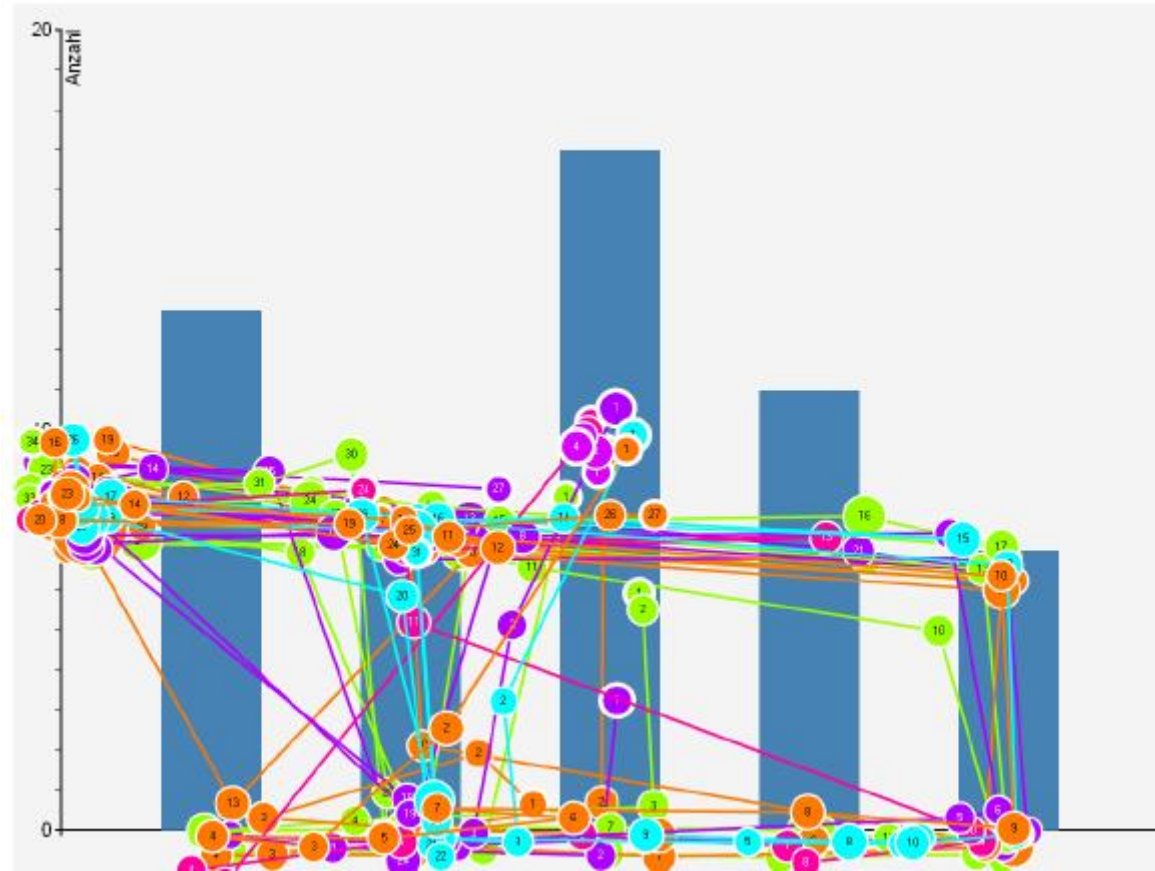
- Additional dependent variable in form of eye movements
 - Spatio-temporal data

→ **Challenge:**

Statistical evaluation of spatio-temporal eye movements with the goal to find common visual task solution strategies among the participants

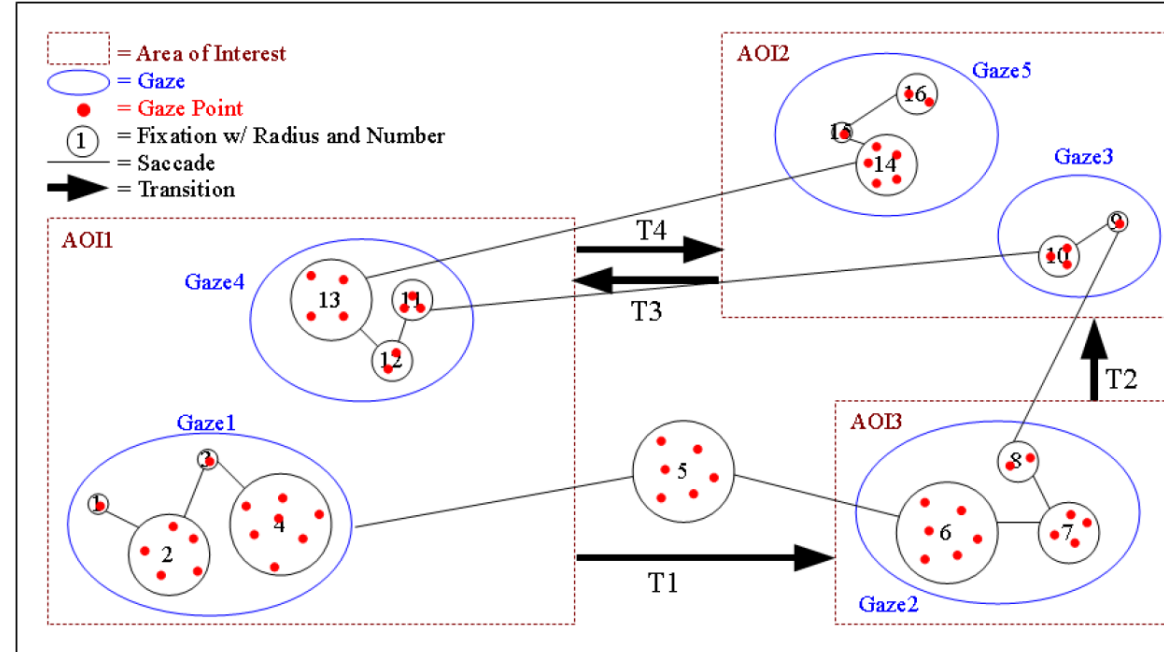
→ **Visual Analytics** (Algorithms, Visualization, Human User, Interaction, ...)

Eye Tracking in Information Visualization



Eye Tracking Metrics

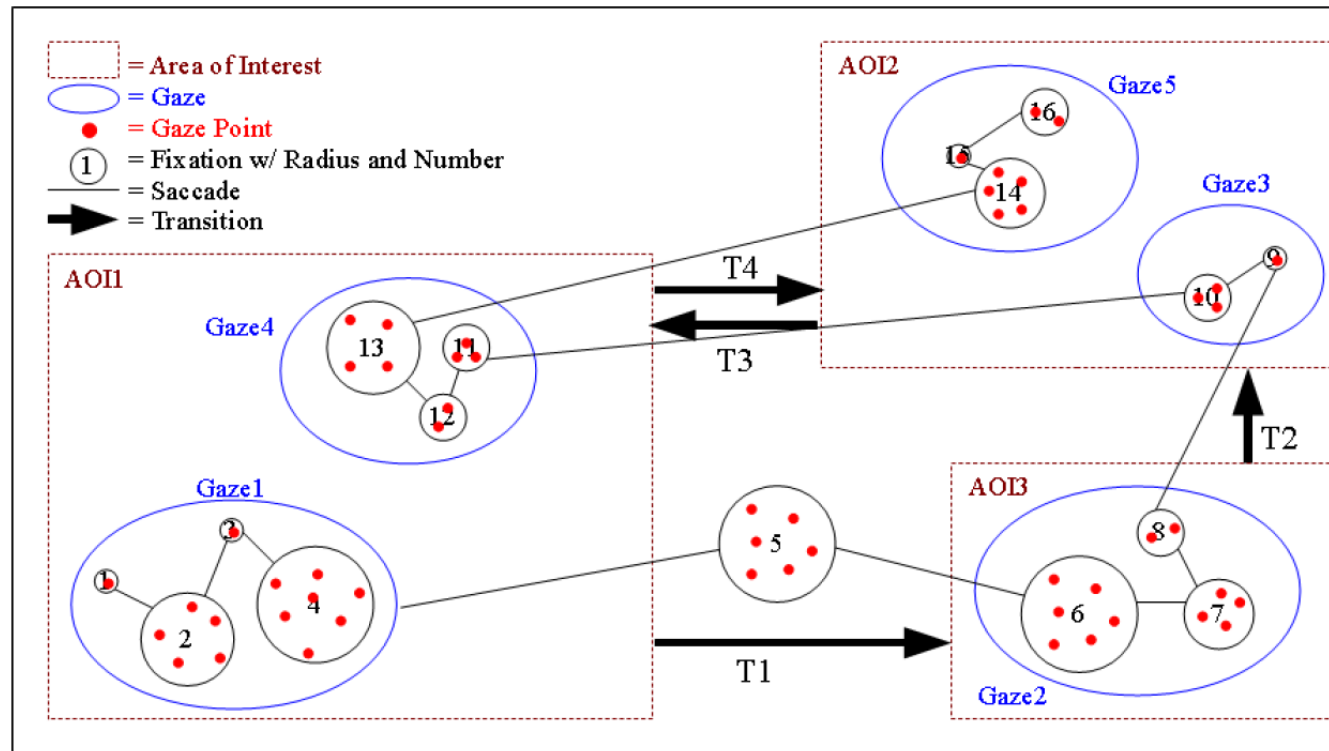
- Gaze points
- Fixations
- Gazes
- Areas of Interest
- Saccades
- Transitions
- Scanpaths



➔ **Inherent spatio-temporal nature**

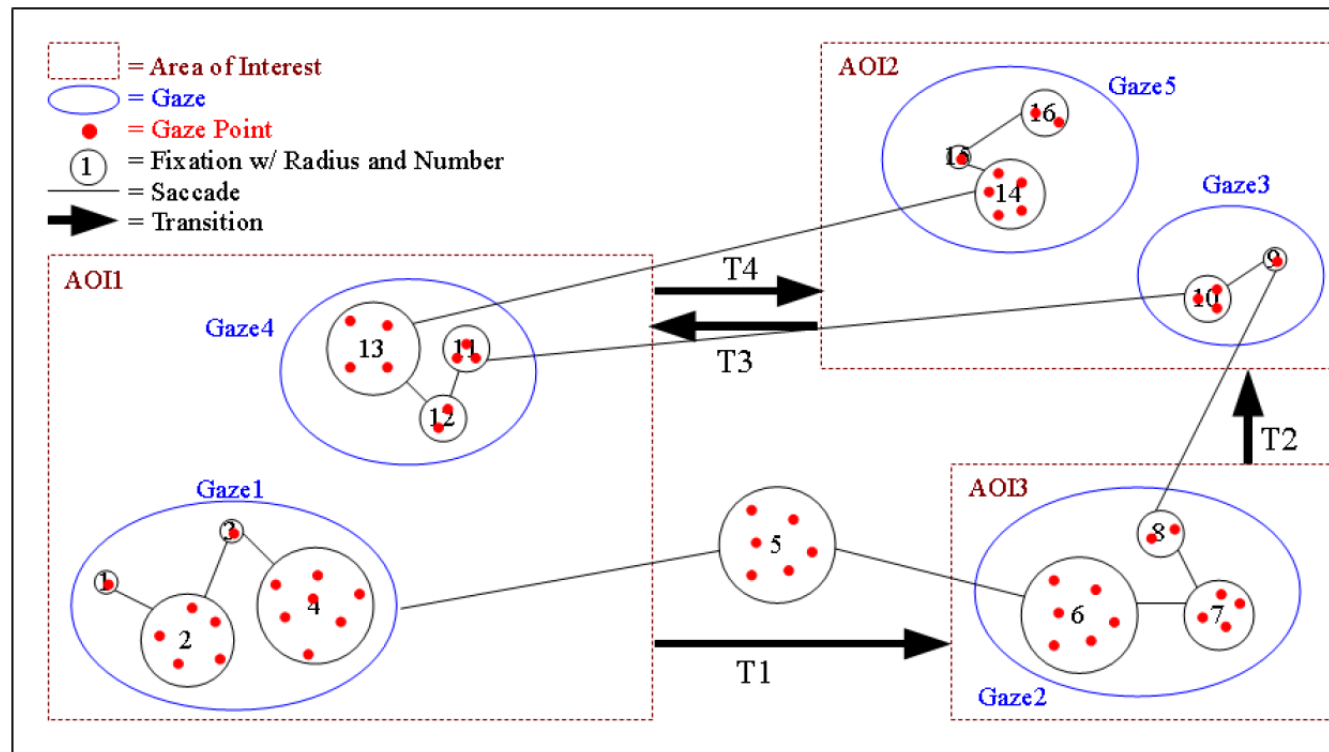
Eye Tracking Metrics

- Gaze points are spatially and temporally aggregated into fixations.



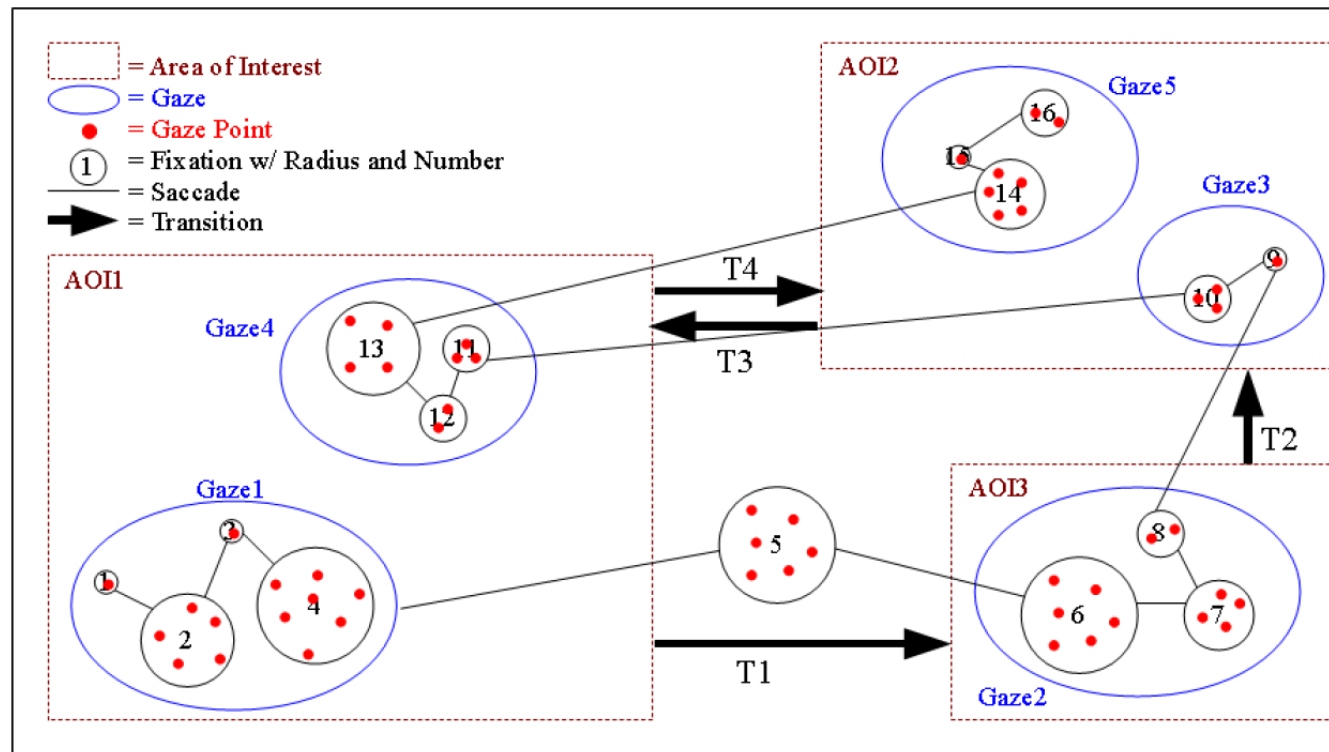
Eye Tracking Metrics

- Fixations are connected by saccades and have a certain duration represented by the radius.



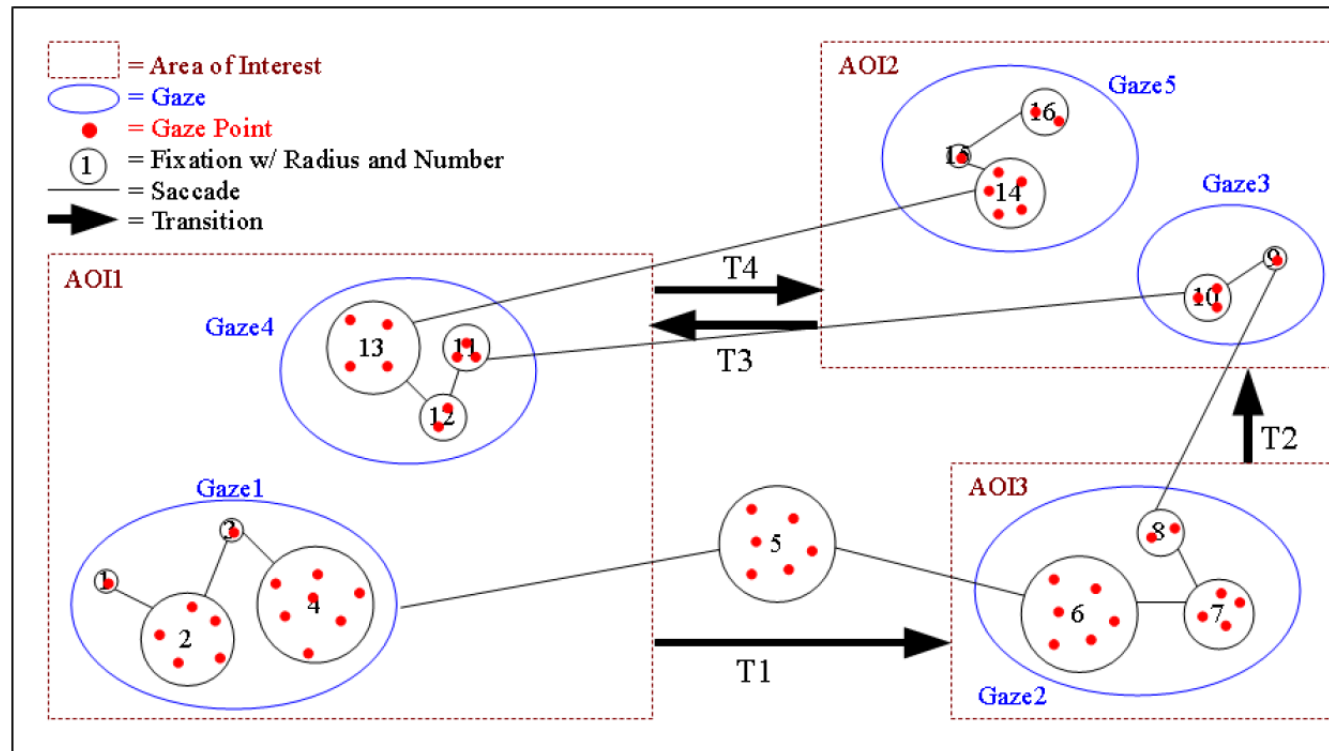
Eye Tracking Metrics

- A temporal order of fixations is a gaze, however, only if the fixations are within an AOI.



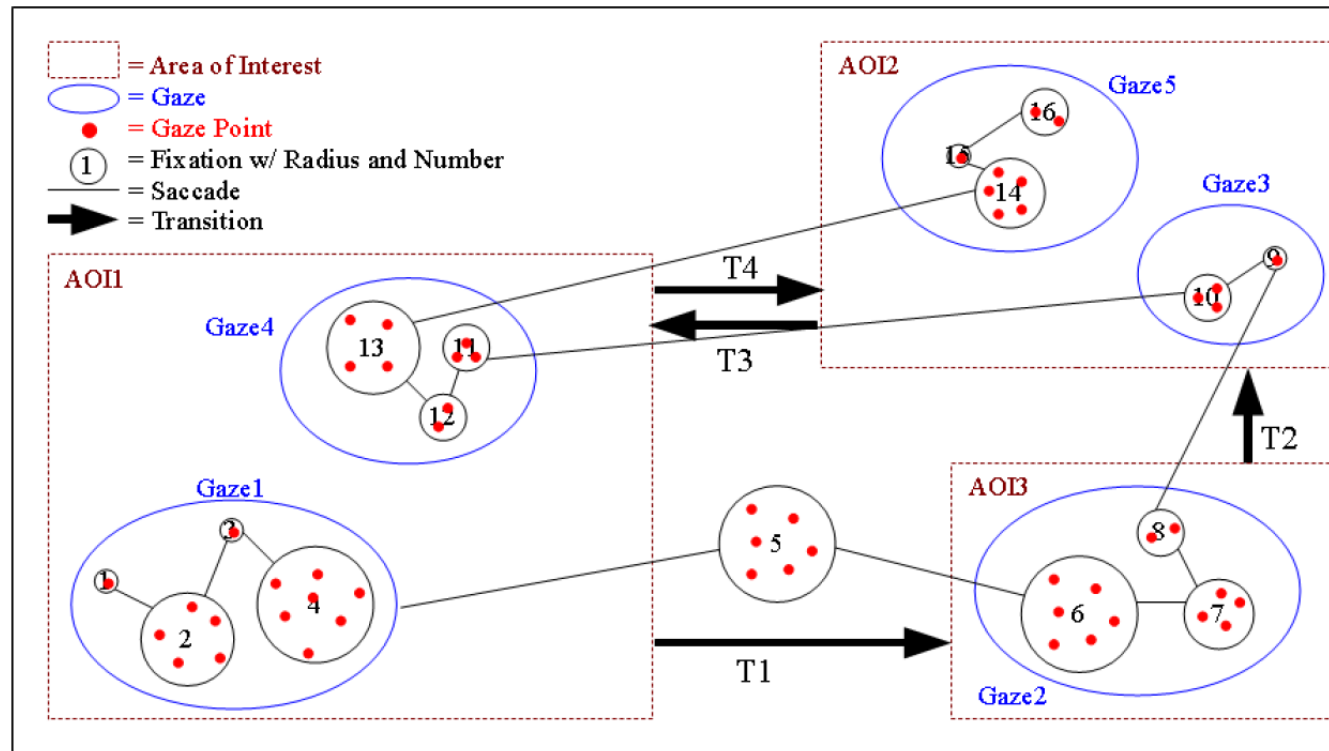
Eye Tracking Metrics

- An AOI is a region of specific interest on the stimulus.



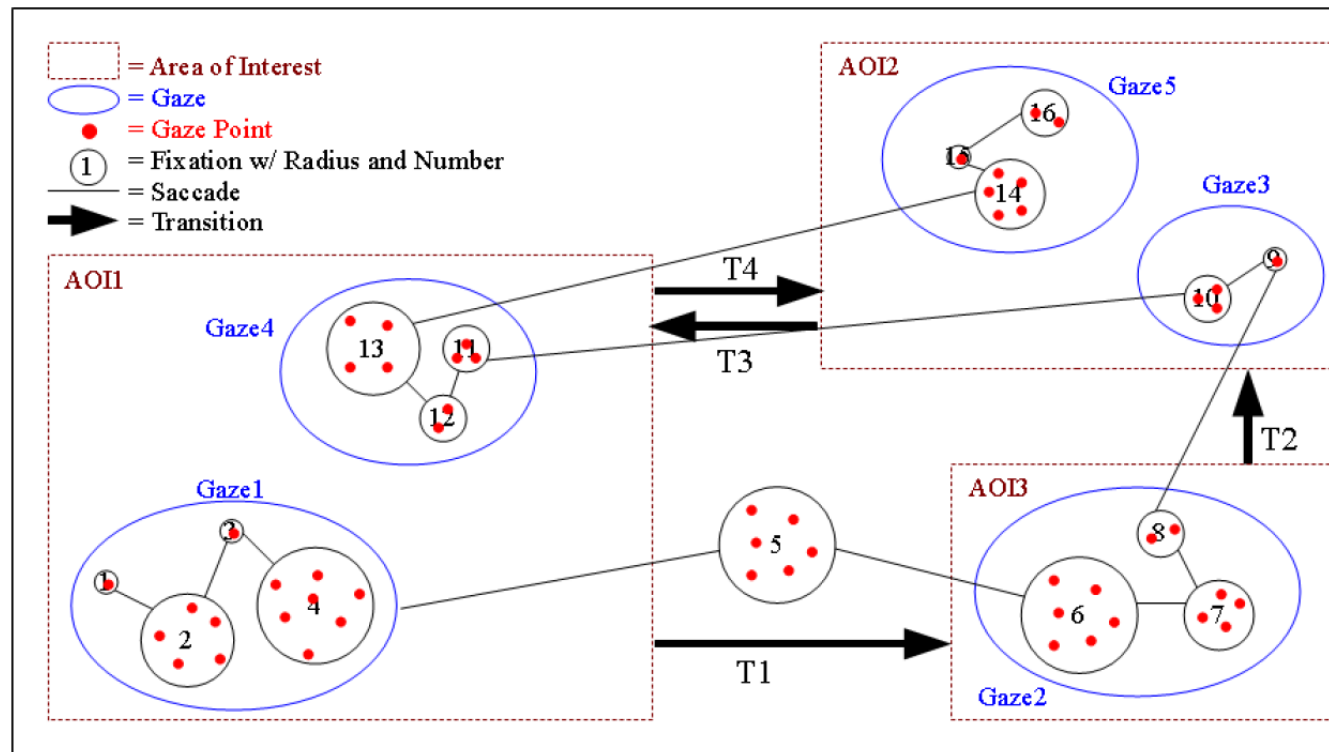
Eye Tracking Metrics

- A saccade from one AOI to the next is called a transition.



Eye Tracking Metrics

- A complete sequence of fixations and saccades is called a scanpath.



Eye Tracking Metrics

→ Space and time dimensions make statistical evaluation of the data more complicated

Example Scenario: Metro Map Design

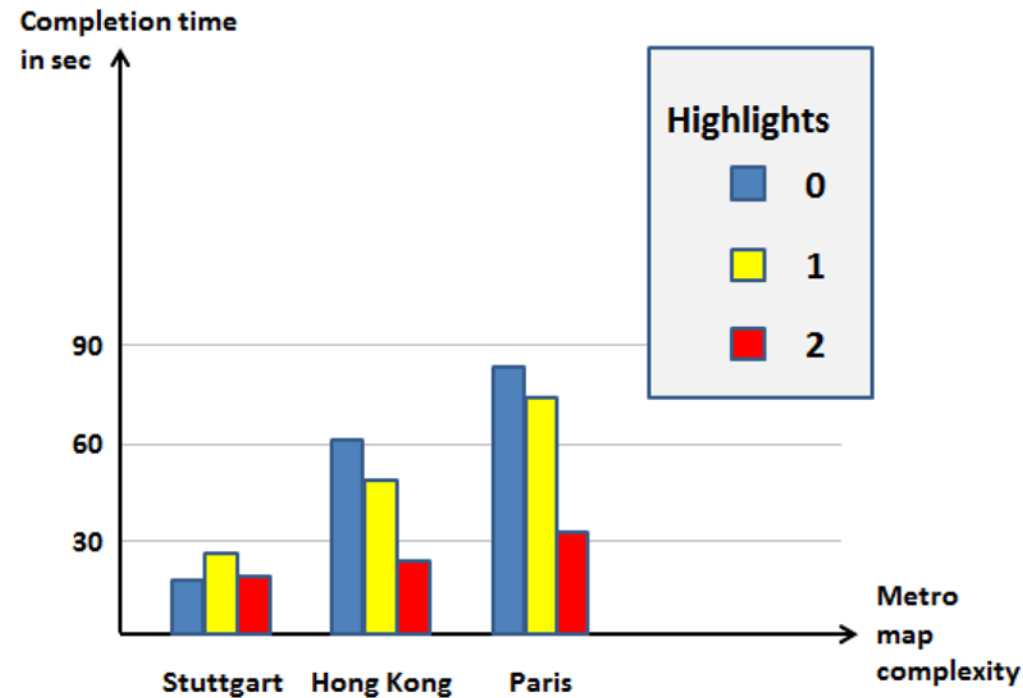
- Michael Burch, Kuno Kurzhals, and Daniel Weiskopf
Visual Task Solution Strategies in Public Transport Maps
Eye Tracking for Spatial Research 2014

Goal

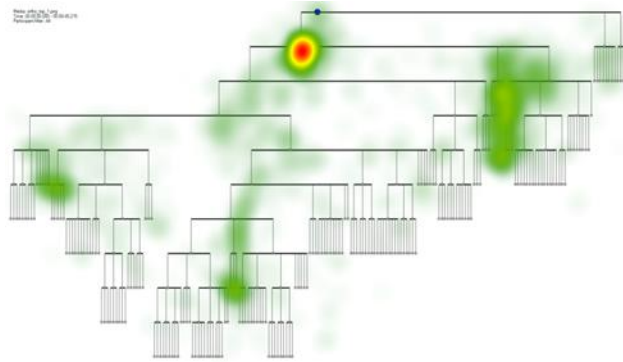
Understand how people read metro maps

Example Scenario: Metro Map Design

- Results on completion times and error rates

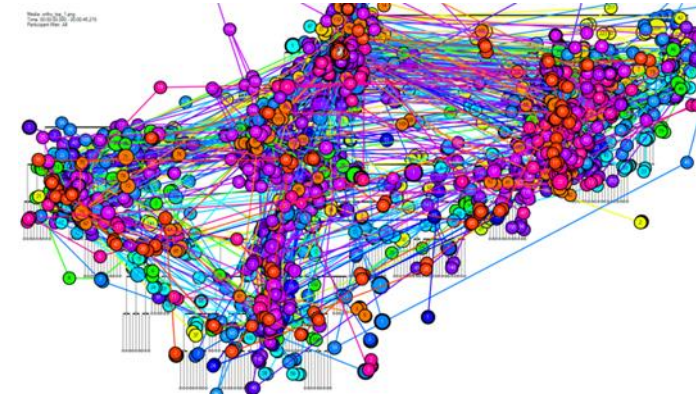


Traditional Information Visualization Techniques



Heat map

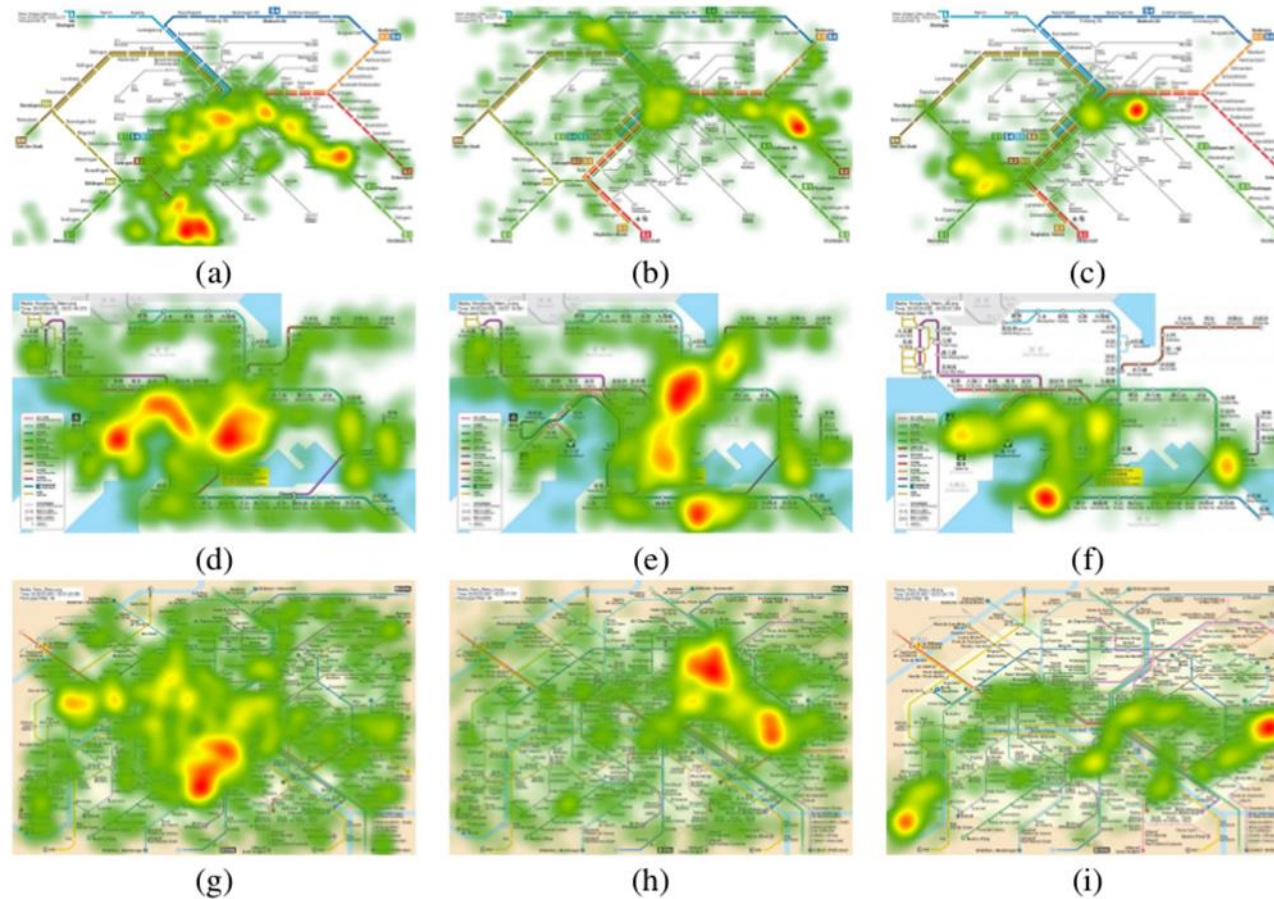
vs.



Gaze plot

Example Scenario: Metro Map Design

- Results on reading strategies



Example Scenario: Metro Map Design

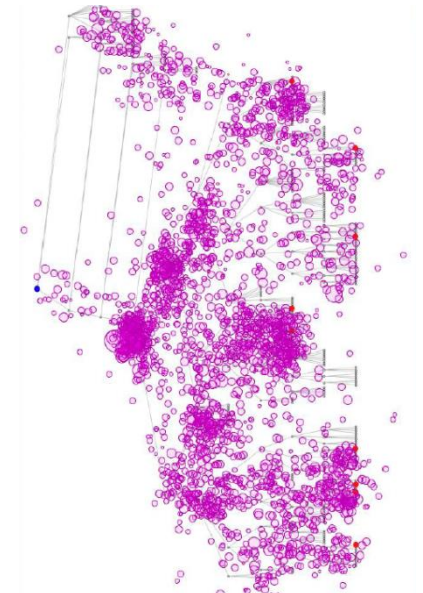
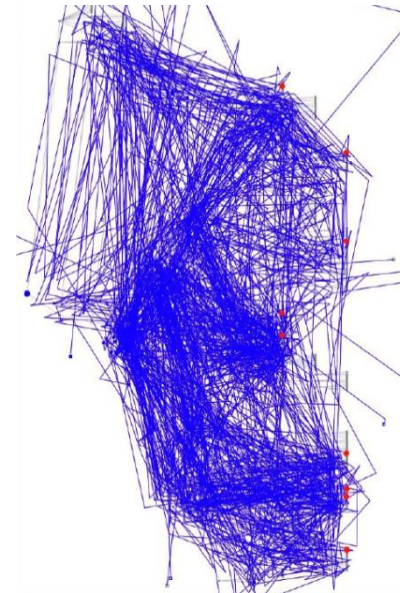
- Identified visual task solution strategy
 - 1.) Searching and locating start and destination stations
 - 2.) Finding a geodesic path between start and destination stations
 - 3.) Building a set of possible metro lines
 - 4.) Estimating possible interchange points
 - 5.) Partially solving the route finding task between interchange points
 - 6.) Cross checking the complete found route

Mining Eye Movement Data

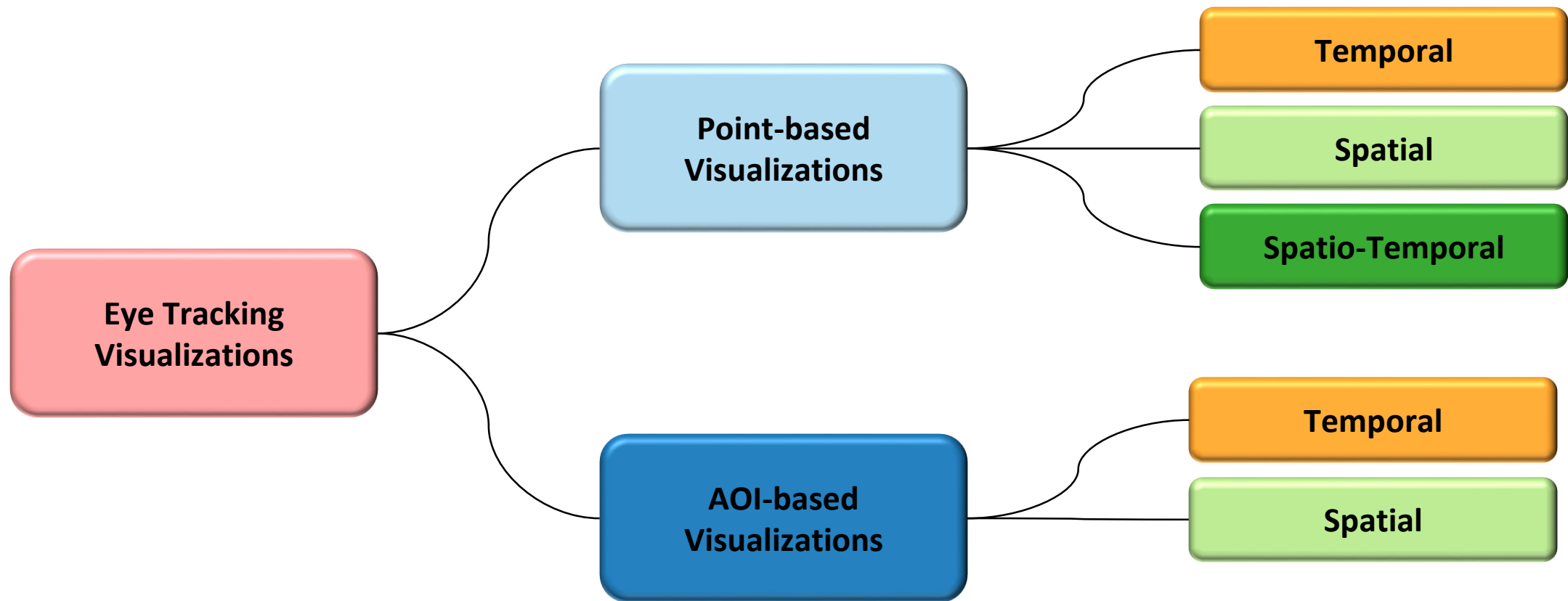


Why Visual Analytics for Eye Tracking Data?

- Complex and large data
 - Gaze information, fixations, saccades
 - Spatiotemporal data
 - Participant groups
 - AND: Stimulus data (spatiotemporal as well)
- Visualization alone may fail
- Automatic or statistical analysis less suited for data exploration and hypothesis building
- Combine best of both worlds!

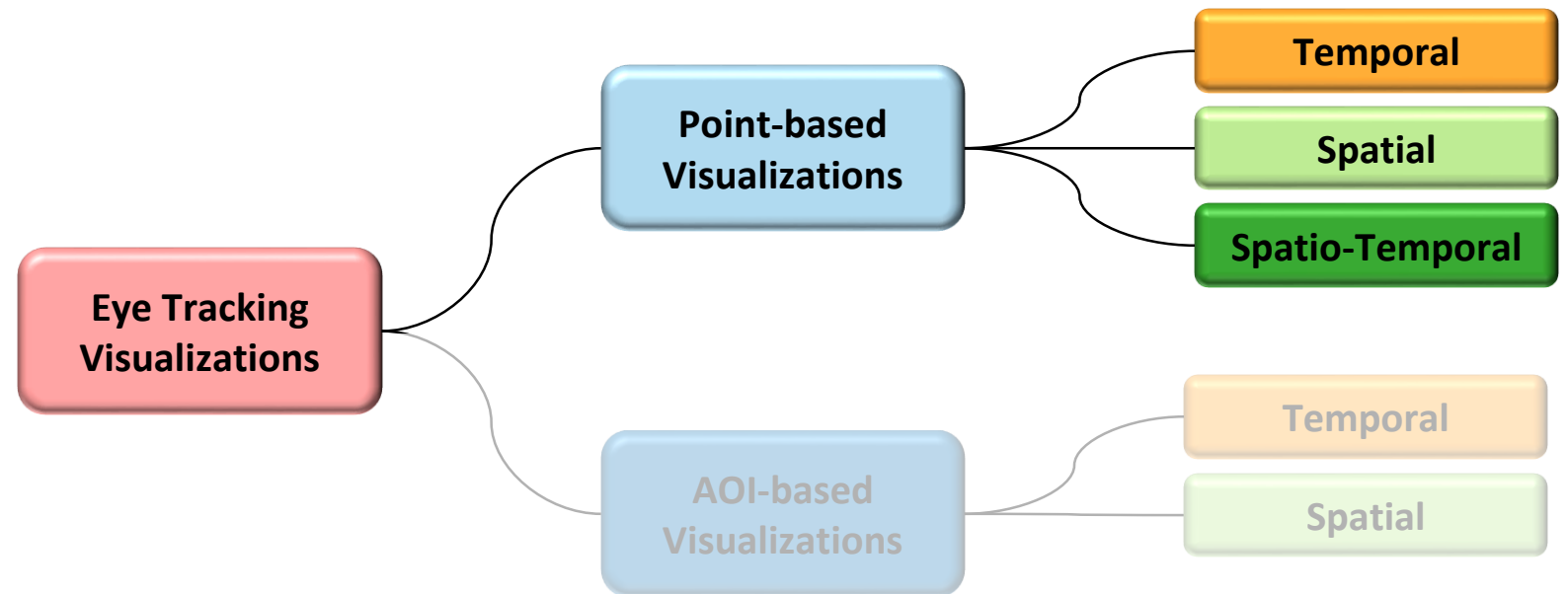


Revisiting: Classification of Eye Tracking Visualizations



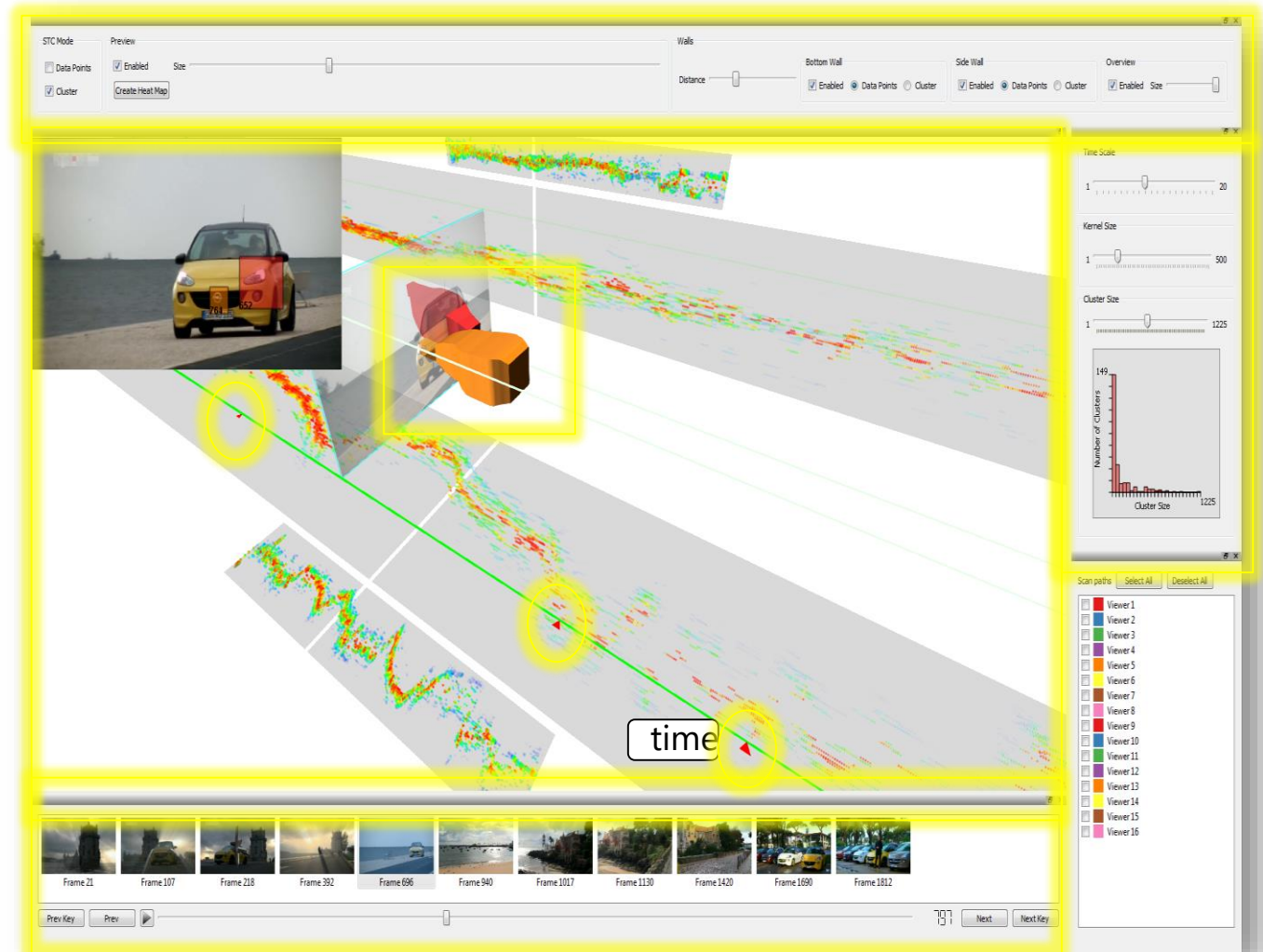
Space-Time Visual Analytics

- Focus on point-based aspects
- Focus on spatio-temporal information
- Include (dynamic) stimulus



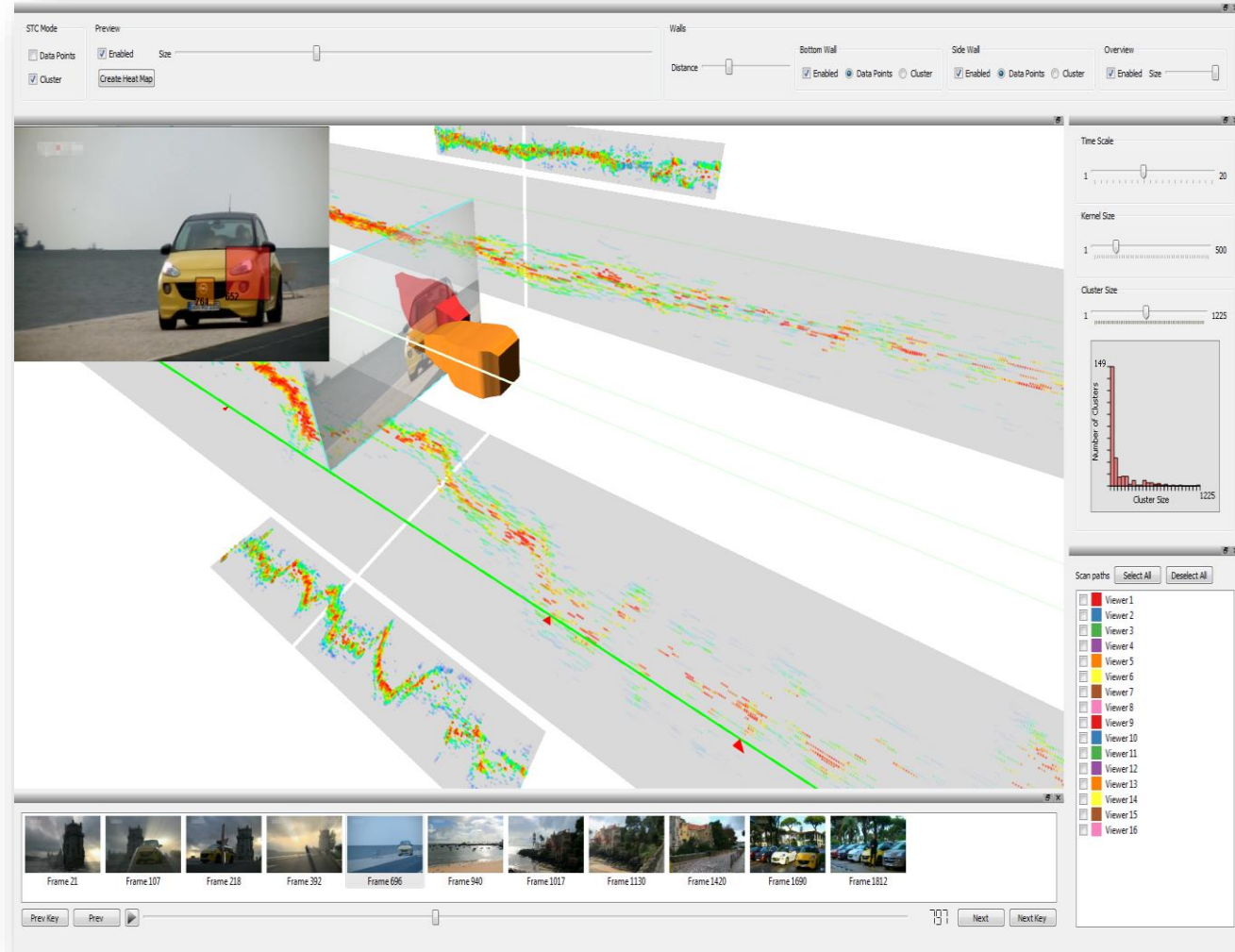
Space-Time Visual Analytics

- Static overview
- Data mining and computer vision
 - Shot detection
 - Gaze clustering
- Interaction
 - Density filter
 - Cluster size filter
- Multiple coordinated views



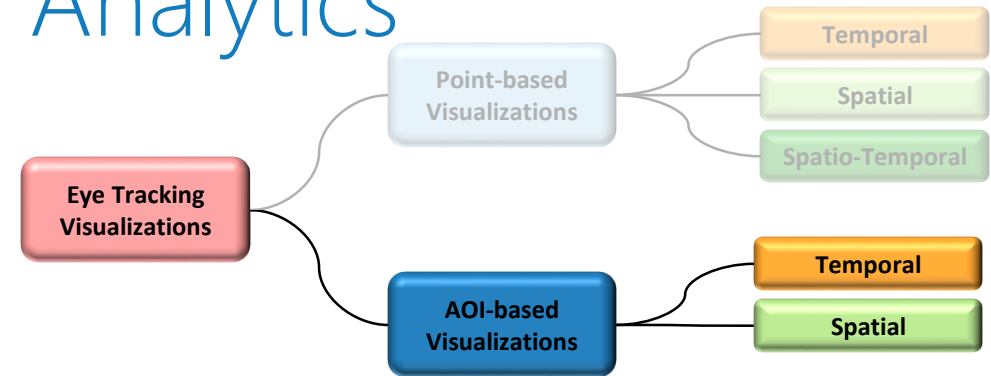
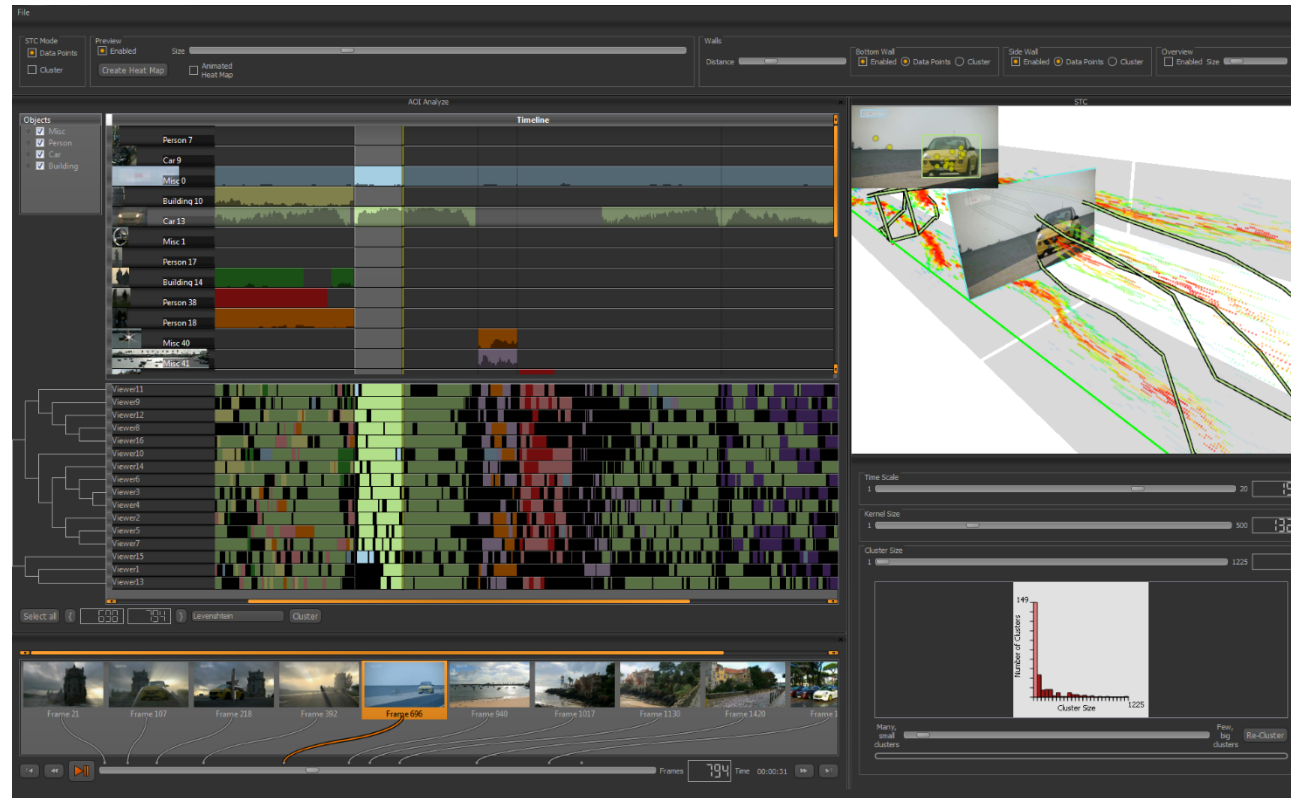
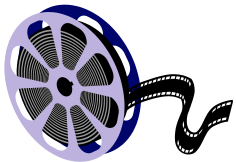
Space-Time Visual Analytics

- Other components
 - Bee swarm
 - Heat maps
 - Static
 - Dynamic
 - Motion compensated
 - 3D scanpaths



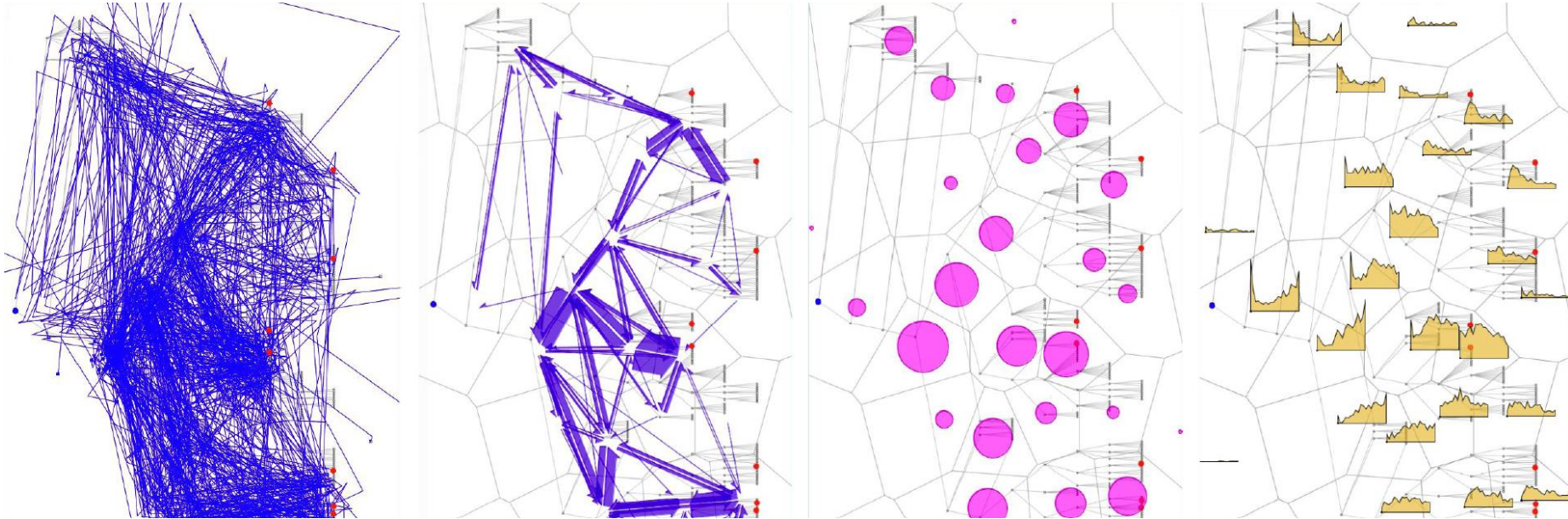
Complementary AOI-Based Visual Analytics

- AOI definition
- Hierarchical clustering of AOI scan paths
- Scarf plots



Geospatial Visual Analytics for Eye Tracking

- Additional analytical techniques?
- Can we make use of existing visual analytics techniques from GIScience?



[Andrienko et al. 12]

Characteristics of Data and Analysis Tasks

- Commonalities between eye tracking and geospatial data:
 - Importance of 2D space and spatial relationships
 - Temporal evolution
 - Trajectories (movement) as highly relevant pieces of information
 - Groups of multiple moving objects / participants' gaze
- Differences:
 - Instantaneous jumps (saccades) over relatively long distances
 - Intermediate points between the start and end positions less meaningful
 - No interpolation
 - Linking to underlying stimulus

More Details on Tasks in Eye Movement Analysis

- Attention distribution:
 - What areas attract user's attention? How much attention?
 - Does the user find predefined AOIs? How easily?
 - How does the attention change over time?
 - What differences exist between users, displays, interfaces?
- Attention movement:
 - How much movement? How far? How complex is the path?
 - How is the path related to the display content? What is the sequence of attending the AOIs?
 - What is the search, exploration, problem-solving strategy?
 - Where are difficulties?
 - What differences exist between users, displays, interfaces?

Guidelines

- Some geospatial visual analytics techniques carry over, others do not
- Guidelines: <http://geoanalytics.net/and/papers/vast2012em/index.html> [Andrienko et al. 12]

Guidelines for eye tracking analysis method selection and use depending on analysis tasks

The following table provides guidelines for selecting methods and method combinations for analyzing eye movement data depending on the analysis tasks. The task listed in the first column. The second column specifies the size of the data set or subset for which the methods listed in the third column can be effective. In most cases size is specified in terms of the number of users whose eye trajectories are analyzed; however, in some cases it is the number of user groups or the number of different displays (visual stimuli), for which the eye movements are compared. The visual analytics methods are listed in the third column. Each method is represented by its name and an image. Clicking on the name or image opens the page with an illustrated description of the method. The last column contains references to relevant papers, which are listed below the table.

Some of the methods involve **data transformations**, such as generalization and aggregation. Before applying various analysis methods, it may be useful to **transform temporal references** in the data.

Note about the illustrations

The images that were used as the visual stimuli in the eye tracking experiment are shown in the background of most of the illustrations. Although the original images have very high resolution (1920x1200 pixels), they appear as low resolution in the illustrations. This is the effect of the automatic scaling of the images for fitting the size of the display window.

Tasks	N of users	Methods	Ref
Overall spatial pattern of movements; relation to display content or structure	multiple	Map display of trajectories (MT) Flow map (FM)	[11]
General character of movements; individual spatial pattern of movements; relation to display content or structure; individual search strategy	1-few	Map display of trajectories (MT) with interactive filtering Space-time cube (STC) Flow map (FM) with interactive filtering and dynamic aggregation	[3]

Clustering of time intervals

Clustering of time intervals is applied to results of **spatio-temporal aggregation** of eye movement data. Before that, it is reasonable to **transform the time references to the common start and end times**, i.e., to relative times with respect to the total duration of task fulfillment. The data are aggregated by small time intervals, for example, 1-2% of the total duration of the task completion.

For the clustering, each time interval is represented by a feature vector consisting of values of aggregate attributes referring to the generalized places (areas of interest) or attributes referring to the connections between the places (flows). Any partition-based clustering algorithm can be applied to these feature vectors, for example, the k-means method from the Weka library (www.cs.waikato.ac.nz/ml/weka/). The method uses the Euclidean distance between feature vectors as the measure of dissimilarity.

Clustering of time intervals by similarity of the spatial patterns of flows (CTF)

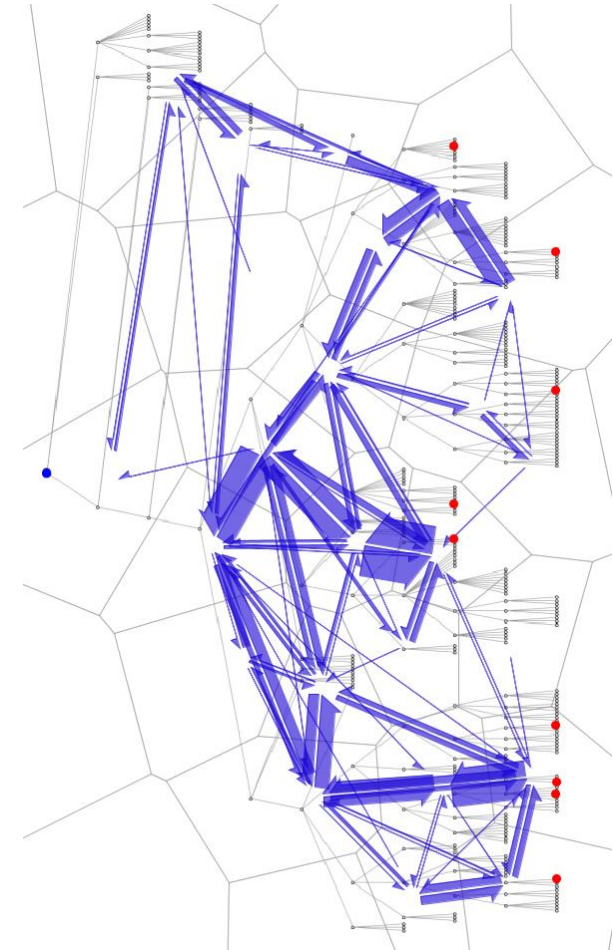
The goal of this analysis is to divide the whole time of task fulfillment into intervals so that the intervals correspond to different kinds of activities, such as tracing the tree perimeter, exploring subtrees, tracing branches by following the links, and checking the candidate solution. For this purpose, the data are **aggregated** by small time intervals (e.g. 1% length of the task duration). Then the combinations of time-dependent attribute values associated with the connections (flows) between the places are taken as feature vectors describing the time intervals. Thus, for each time interval and each connection there is a corresponding count of eye movements. The vector consisting of the counts for all connections is taken as the feature vector of this time interval. These feature vectors are used to cluster the small time intervals. Several consecutive small intervals having similar feature vectors will be united into longer time intervals. However, non-contiguous time clusters can also be obtained. This may mean that different types of activities are not performed in a strict order or in the same order by all users.

The results of the clustering can be visualized on small multiple flow maps as shown below. The maps summarize the eye movements in the time clusters by representing the average values of the attribute that was used for the clustering, i.e., for each connection and each time cluster, the mean of the values from the time intervals included in the cluster is computed. The attribute means are represented by visual features of the flow symbols, i.e., by widths or color coding.

The image below illustrates the approach. We have aggregated the data by time intervals of 1% of the task duration. Then we applied k-means clustering algorithm to the vectors of the move counts corresponding to the time intervals. We tested different values of the parameter k (number of clusters) for obtaining well discriminable and interpretable spatial patterns. The image shows the results for k=9. Lower values of k mix some of the patterns observable with k=9 and higher values reveal finer differences but not additional types of activities. The colored caption of each map signifies the time cluster represented by the map; the colors have been obtained by projecting the cluster centers onto a two-dimensional color space as illustrated on the right. The temporal positions of the clusters are shown by the segmented bar at the bottom of the figure. The sizes (i.e., total durations) of the time clusters are given in the table in the lower right corner.

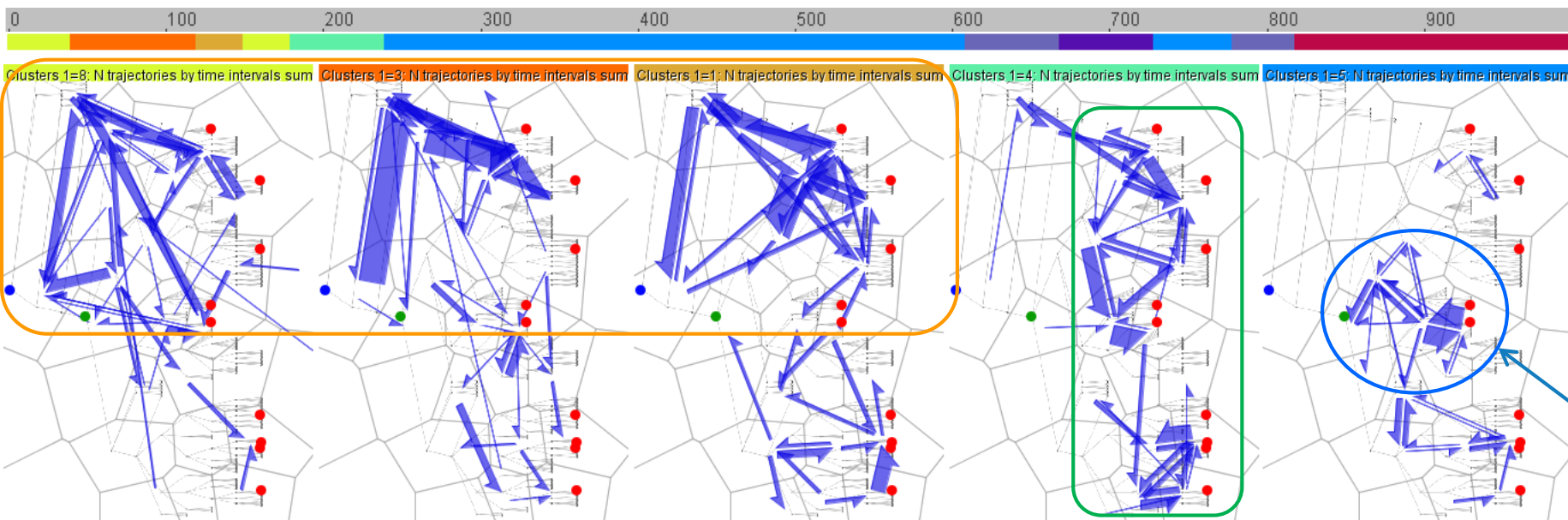
Example: Eye Tracking Study on Tree Visualization

- Study: readability of variants of node-link tree visualization [Burch et al. 11]
- Visual analysis of the gaze data [Andrienko et al. 12], [Burch et al. 13]



[Andrienko et al. 12]

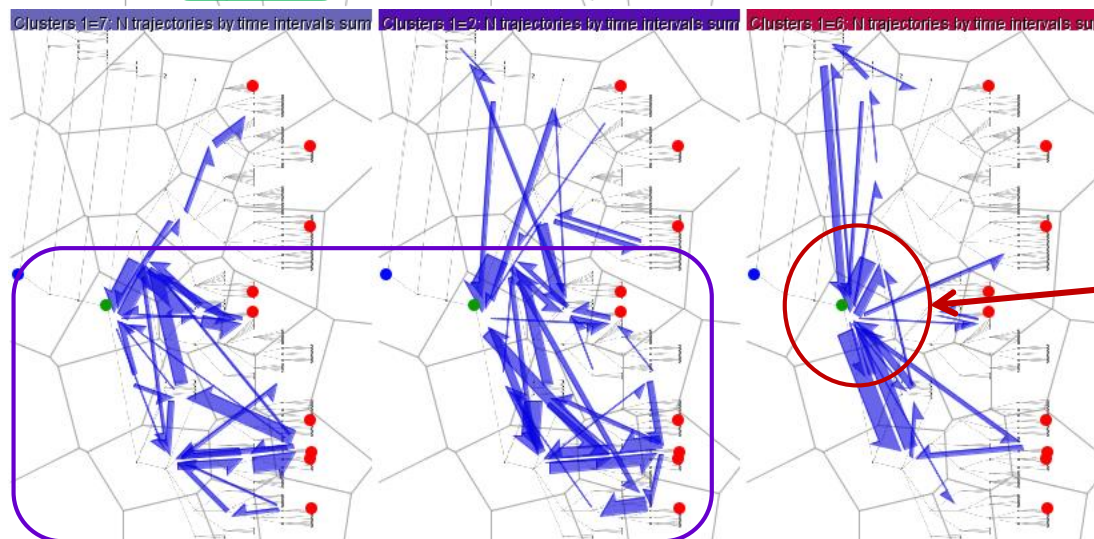
Eye Movement Patterns Over Time



We can infer types of users' viewing activities

Loss of time!

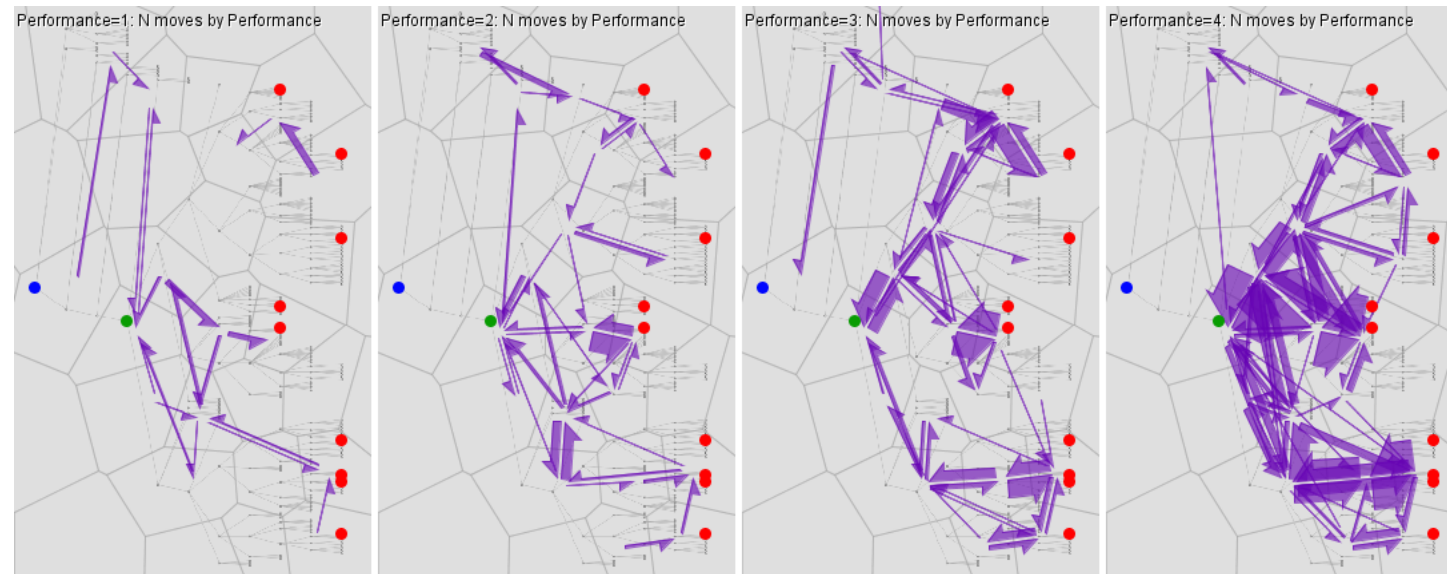
Time intervals clustered according to similarity of the aggregated eye movements



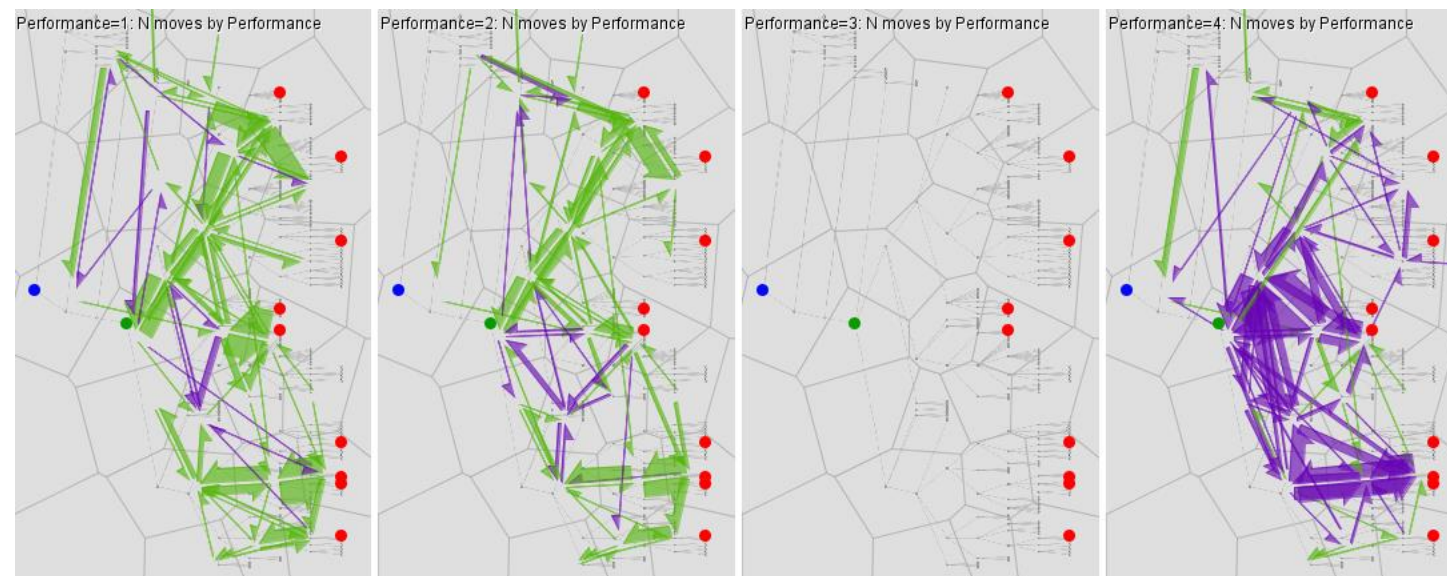
Target!

Comparison of Fast and Slow Users

4 user groups according to task completion time (trajectory duration)



Differences to group 3



From Laboratory to the Real World

- Properties of stimuli
 - Static 2D
 - Traditional InfoVis studies
 - Dynamic
 - videos, animations
 - Interactive
 - Web pages, GUIs, Visual Analytics systems
 - 3D scene, free exploration
 - Car driving, shopping, sports events

From Laboratory to the Real World

- Additional data sources
 - Electroencephalography (EEG)
 - Pupil dilation
 - Galvanic skin response (GSR)
 - Motion tracking
 - Functional magnetic resonance imaging (fMRI)
 - Verbal data
 - Mouse and keyboard interactions
 - Personal data from social networks
 - ...

➔ Big Eye-Movement Data Visual Analytics

From Laboratory to the Real World

- 3 future scenarios
 - Car driving
 - Sports event
 - Shopping

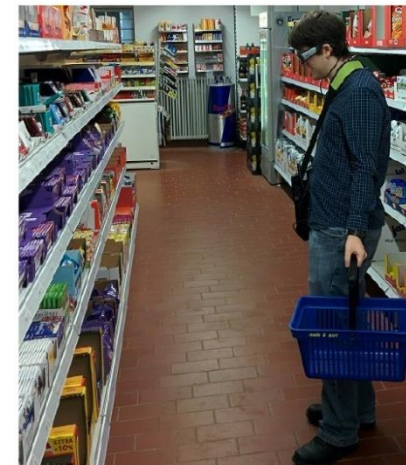


Fig. 4. User wearing eye tracking glasses in a supermarket shopping task.

Future Challenges

THE PAST, PRESENT, AND FUTURE OF EYE TRACKING WITH RESPECT TO HARDWARE, COSTS, STIMULI, USERS, RECORDED DATA AND METRICS, AND EVALUATION METHODS.

	Past	Present	Future
Hardware & Costs	Stationary Eye Tracking Devices (Self made)	Professional Glasses (>\$30 000) Low-cost Remote Eye Trackers (\$99)	Smart Phones and Personal Eye Tracking Glasses
Stimuli	2D static stimuli (images)	2D/3D dynamic stimuli (virtual reality, video)	unconstrained real-world scenarios
Users	<10	10 to 500	>1,000,000
Recorded Data and Metrics	fixation and saccades	video, high-resolution gaze data (smooth pursuits)	numerous additional data sources
Evaluation Methods	Visual inspection	Statistics & Visualization	Big Data Visual Analytics

References

- [Andrienko et al. 12] G. L. Andrienko, N. V. Andrienko, M. Burch, D. Weiskopf: Visual analytics methodology for eye movement studies. IEEE Transactions on Visualization and Computer Graphics 18(12): 2889-2898, 2012
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- [KurzHALS et al. 14a] K. KurzHALS, B. D. Fisher, M. Burch, D. Weiskopf: Evaluating visual analytics with eye tracking. BELIV 2014: 61-69
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