



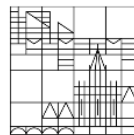
Quality Metrics for Information Visualization

M. Behrisch, M. Blumenschein, N. W. Kim, L. Shao,
M. El-Assady, J. Fuchs, D. Seebacher, A. Diehl, U. Brandes,
H. Pfister, T. Schreck, and D. Weiskopf, D. A. Keim

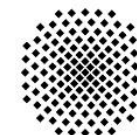


HARVARD
John A. Paulson
School of Engineering
and Applied Sciences

Universität
Konstanz



ETH zürich



Universität Stuttgart



Effectiveness

Usefulness

Appropriateness

Efficiency

Usability

Expressiveness

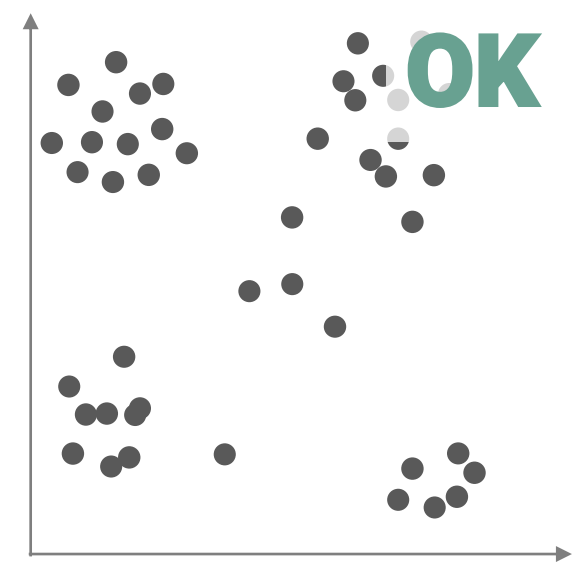
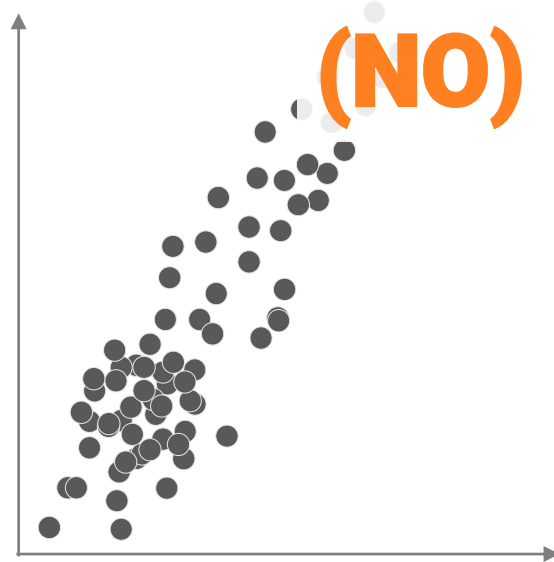
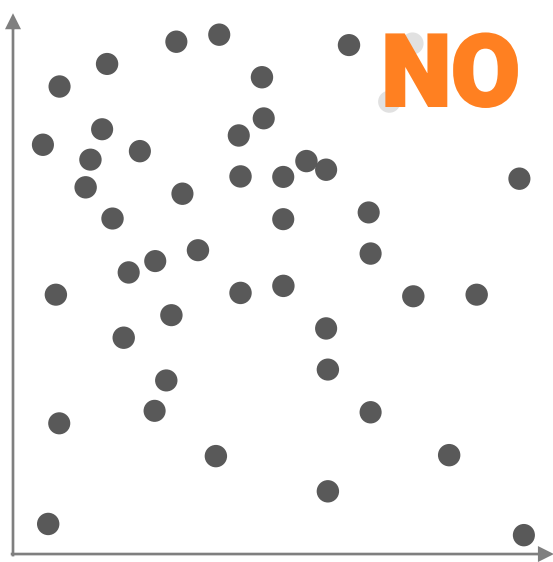
Expressiveness

Interpretability

Quality Metrics



Patterns in Information Visualizations



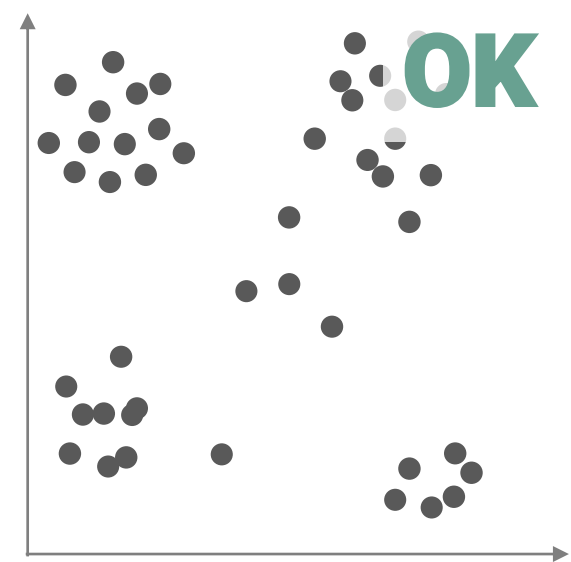
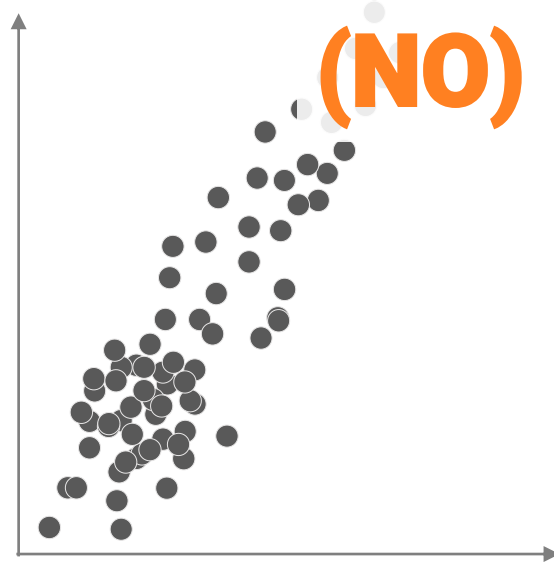
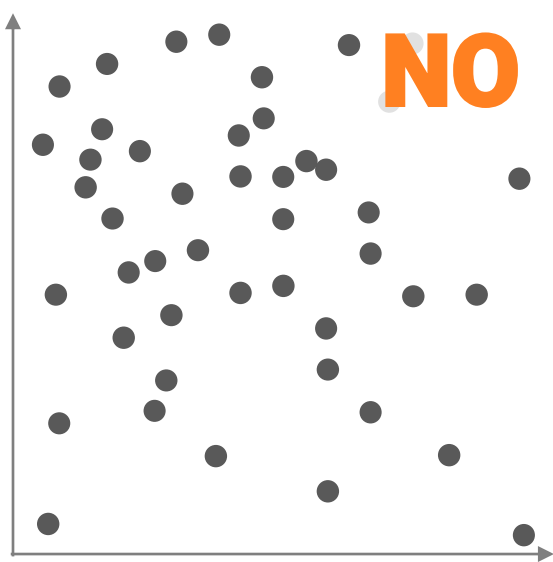
**Conceptual/
Pattern Space**



Task



Patterns in Information Visualizations



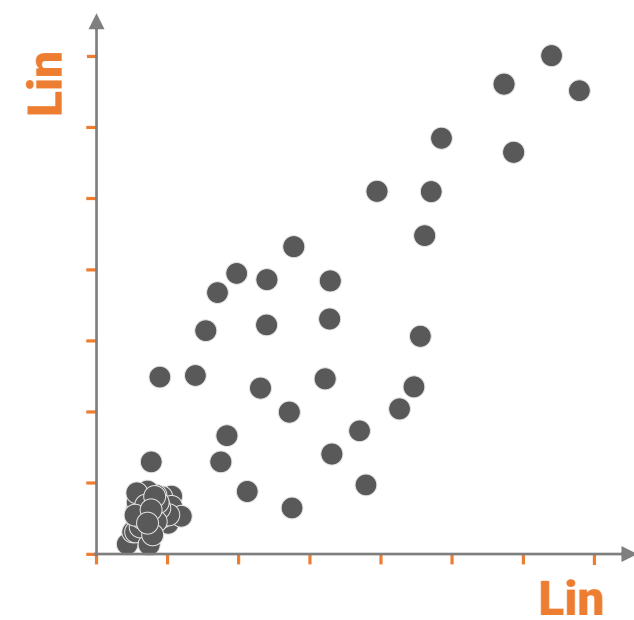
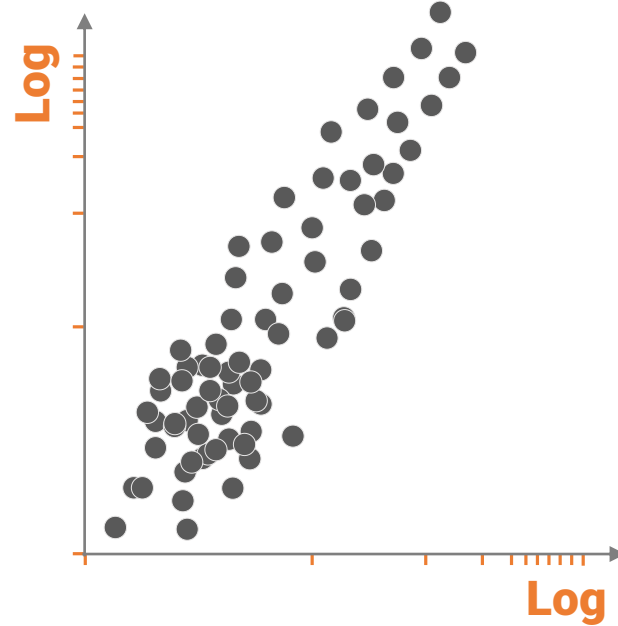
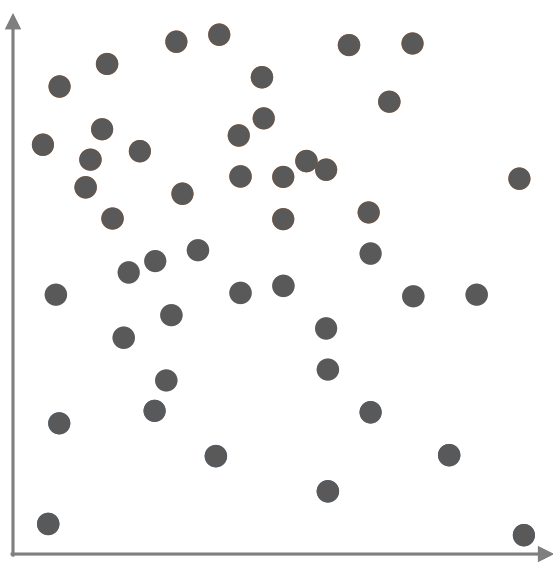
Conceptual/
Pattern Space



Task



Patterns in Information Visualizations



Visualization
Parameter ↔ **Dataset**
Characteristics

Visualization
Parameter ↔ **User**
Understandability



Quality **Metric**

Visualization
Parameters

Data

User

Task

$$q(\phi \mid D, U, T)$$

Optimization
Algorithm

Quality
Criterion



Structure and Goals of the Survey

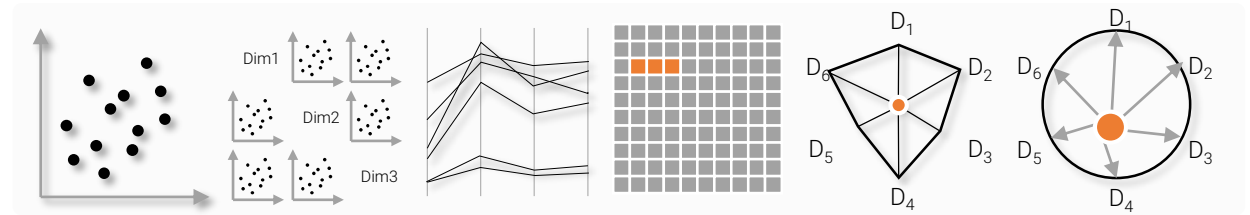
Research Goals

Reference Manual for QM

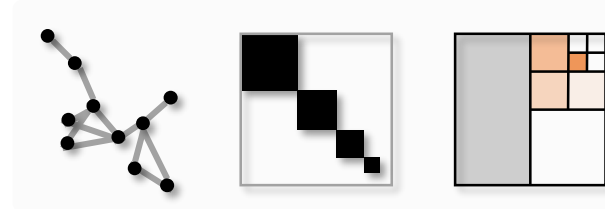
Establish Common **Vocabulary**

Open Challenges and **Future Research Directions**

Multi- and High-Dimensional



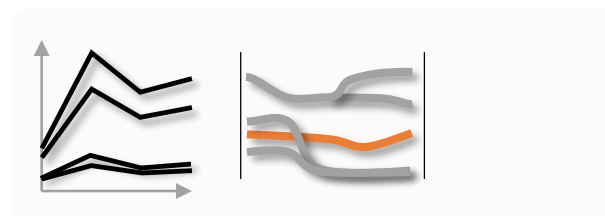
Relational Data



Geo-Spatial Data



Sequential/Temporal



Text Data



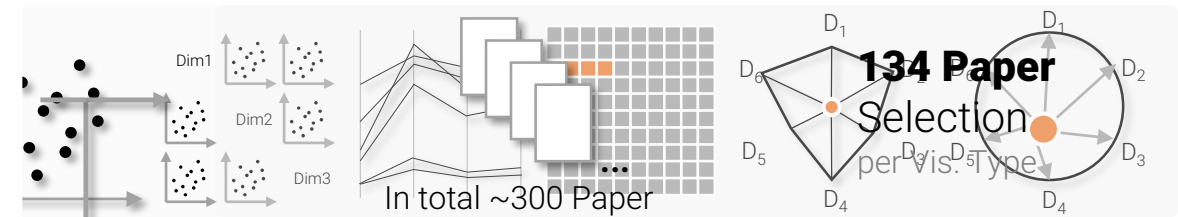


Structure and Goals of the Survey

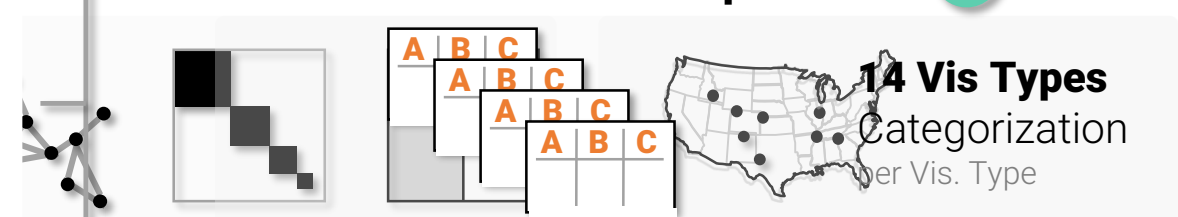
For each Vis Type

1. Visualization Description
2. Why do we need QMs?
- 3. Typical Analysis Tasks**
4. Summary of Approaches
- 5. Evaluations Methods**
6. Open Research Questions

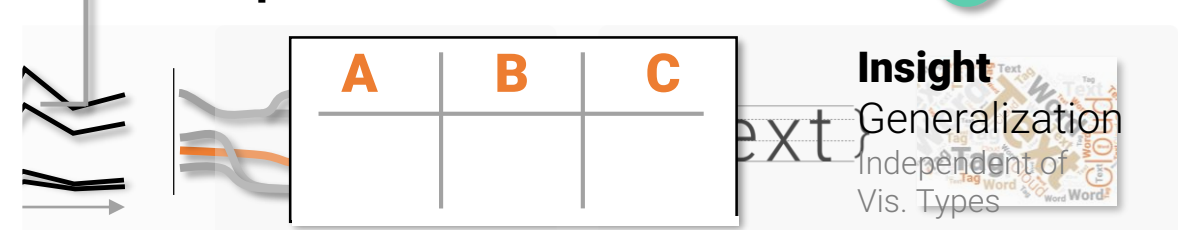
ti- and High-Dimensional



ational Data



quential/Temporal





Quality **Metric**

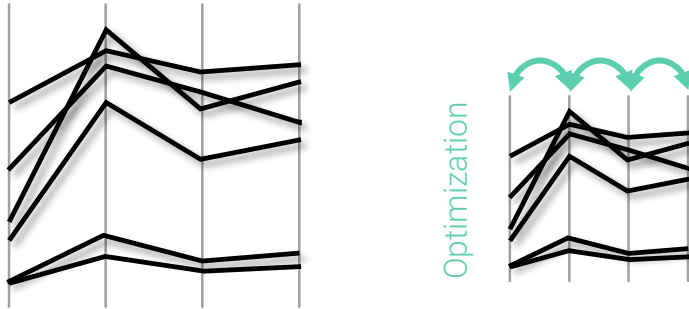
$$\arg \min_{\phi \in \Phi} \max q(\phi \mid D, U, T)$$

Clutter Removal vs **Pattern** Retrieval

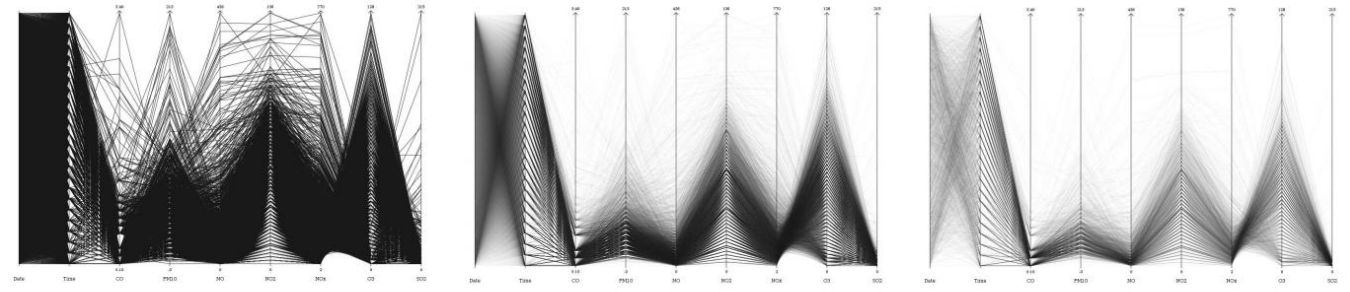
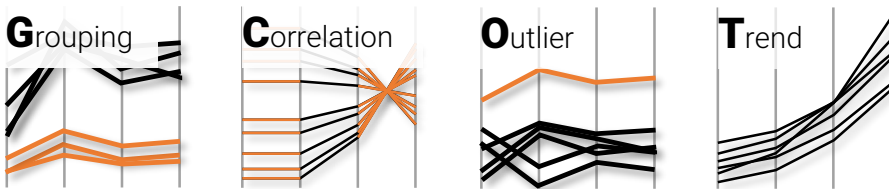


Auto-Sampling – Clutter Removal

Parallel Coordinates



Patterns and Tasks



(a) Initial plot showing 8392 datapoints.

(b) Opacity reduced to 4%.

(c) Opacity reduced to 4% and 75% of the data removed.

Overplotted%

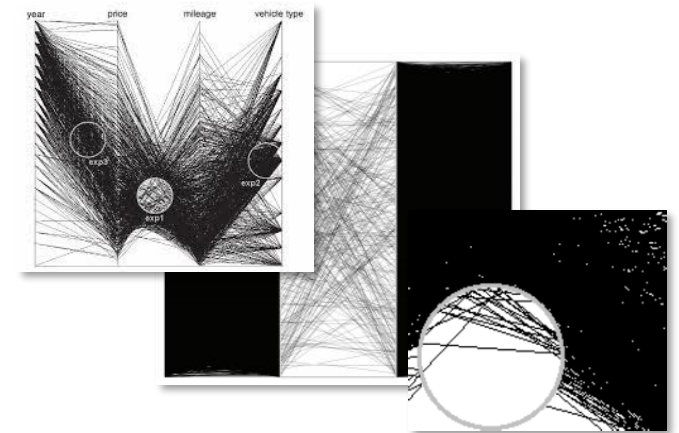
Percentage of **pixels** containing more than one plotted point

Overcrowded%

Percentage of **plotted points** hidden behind a **pixel**

Hidden%

Percentage of **plotted points** that are **hidden** due to being overplotted

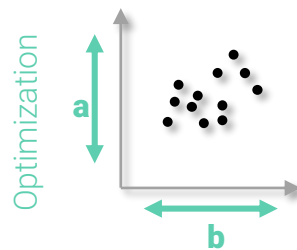
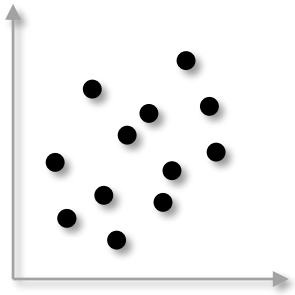


[Ellis2006]

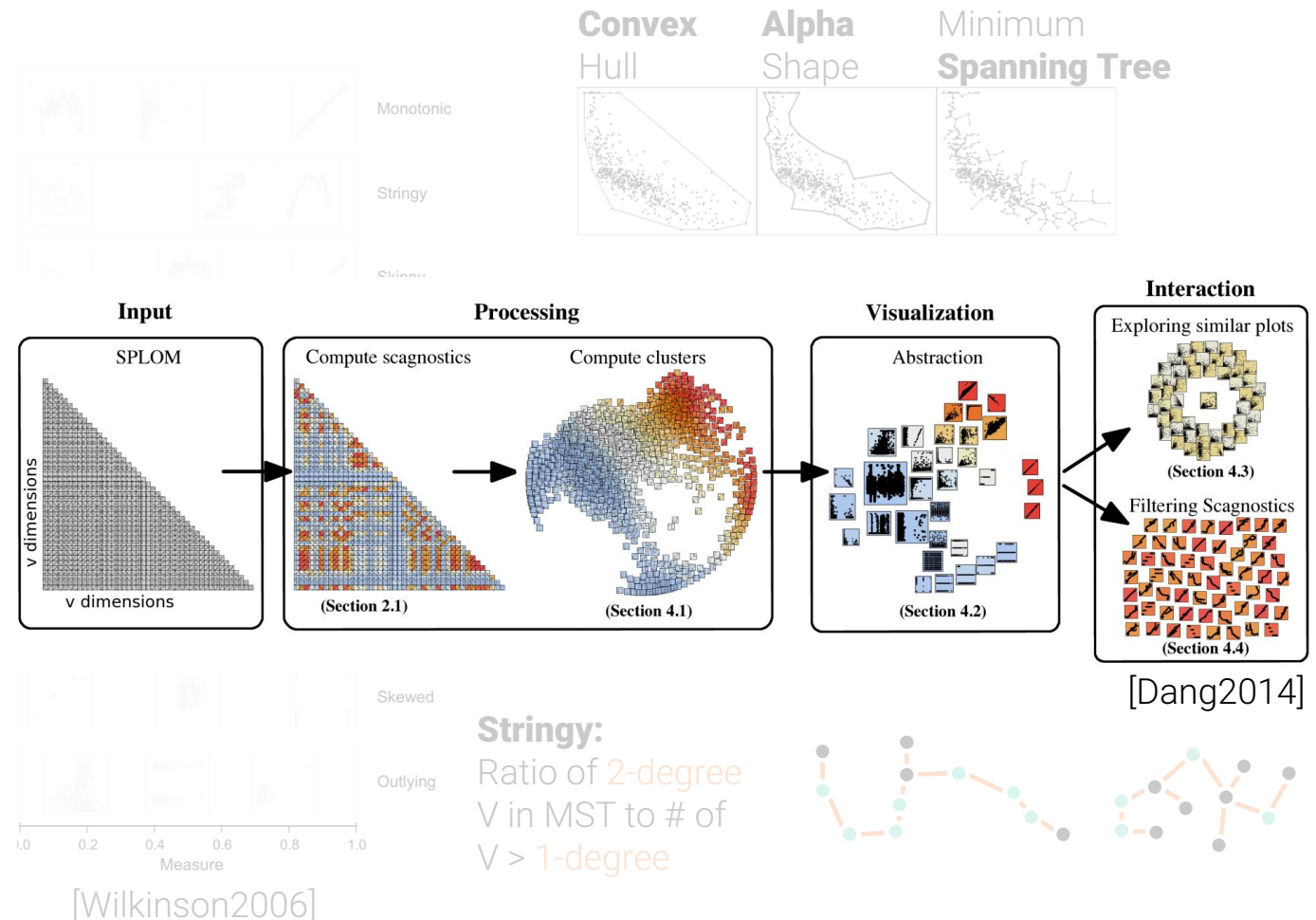
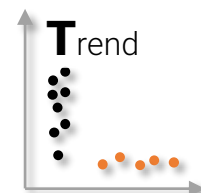
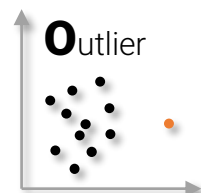
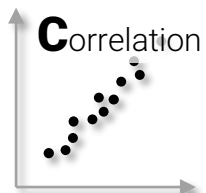
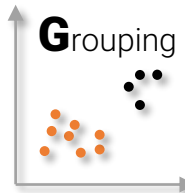


Scagnostics – Pattern Retrieval

Scatter Plots



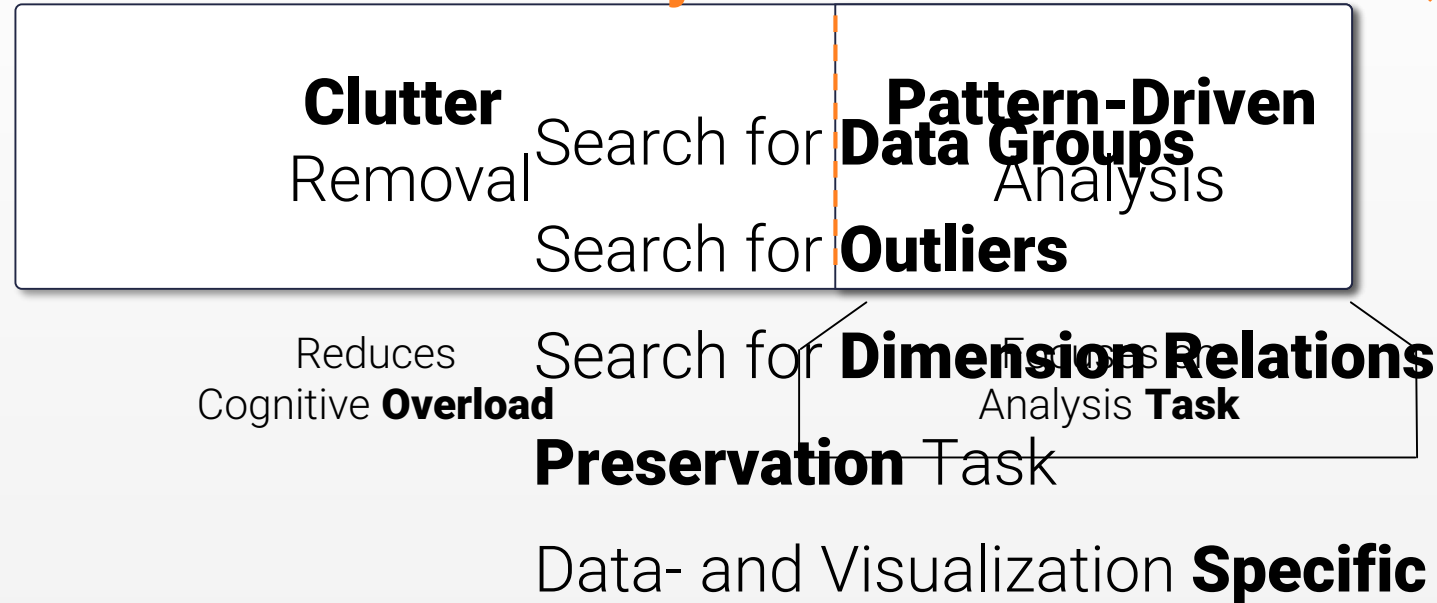
Patterns and Tasks



Quality **Metric**

$$\arg \min_{\phi \in \Phi} \max q(\phi \mid D, U, T)$$

Analysis Scenarios/Tasks for QM





Quality **Metric**

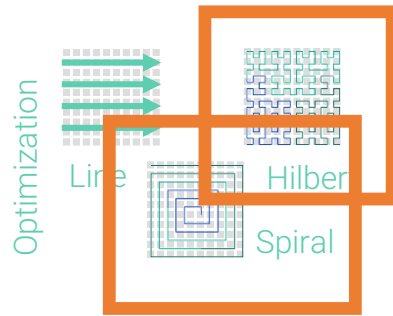
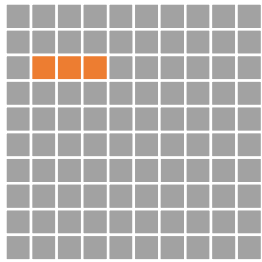
$$\arg \min_{\phi \in \Phi} \max q(\phi \mid D, U, T)$$

Explicit and **Implicit** QM

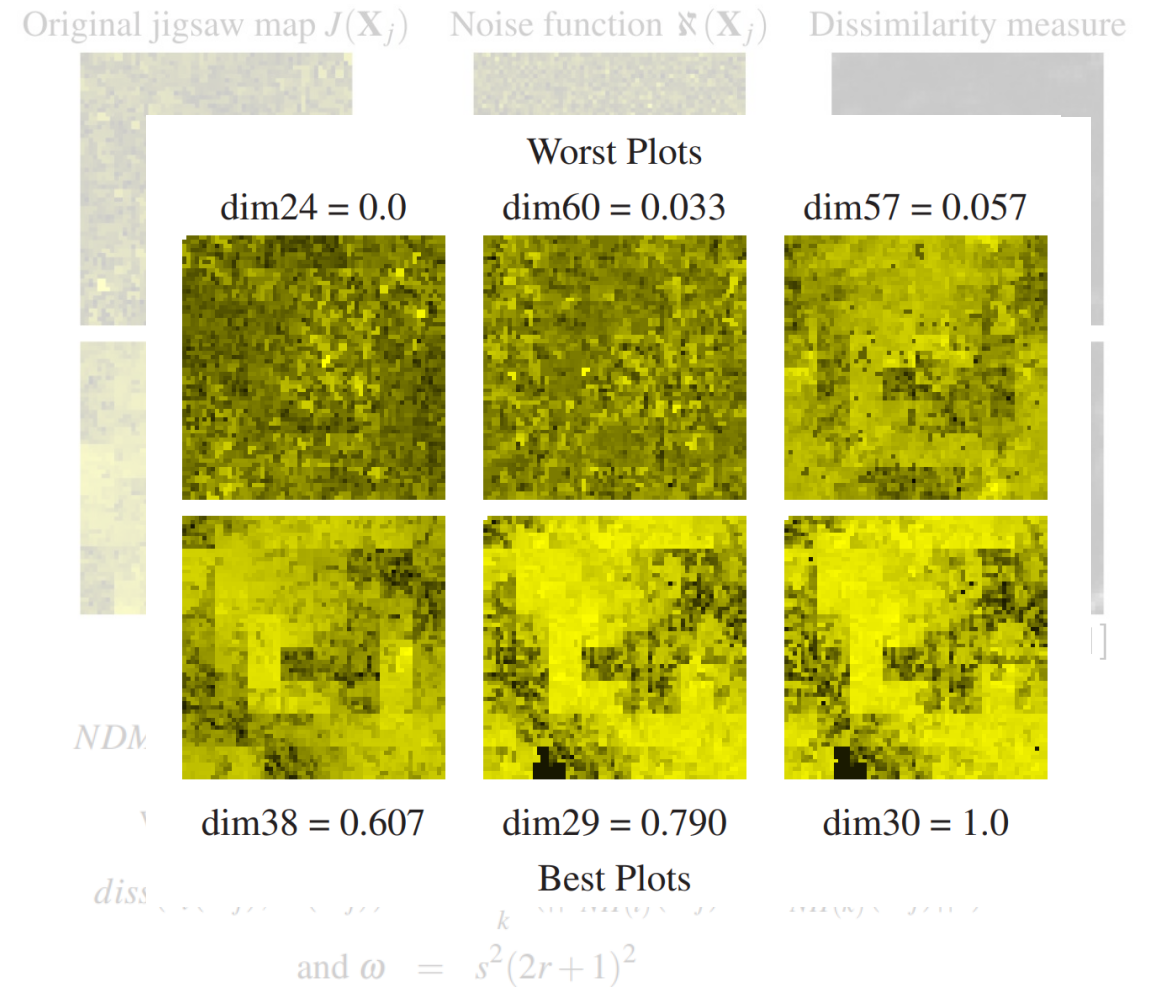
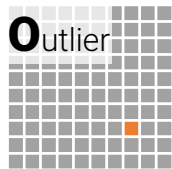


Noise Dissimilarity – Explicit QM

Pixel-based Techniques



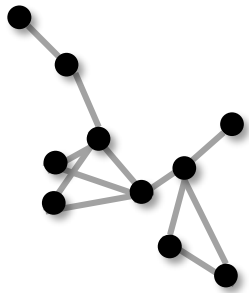
Patterns and Tasks



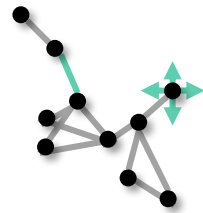


Force Directed Layout – Implicit QM

Node-Link Diagrams



Optimization



Patterns and Tasks

Grouping



Item



Connectivity

Group



Connectivity

Path



Connectivity



Cluster Overlap +
Star Constraint

Cluster Overlap +
Circle + Star Constraint [2018]



Quality **Metric**

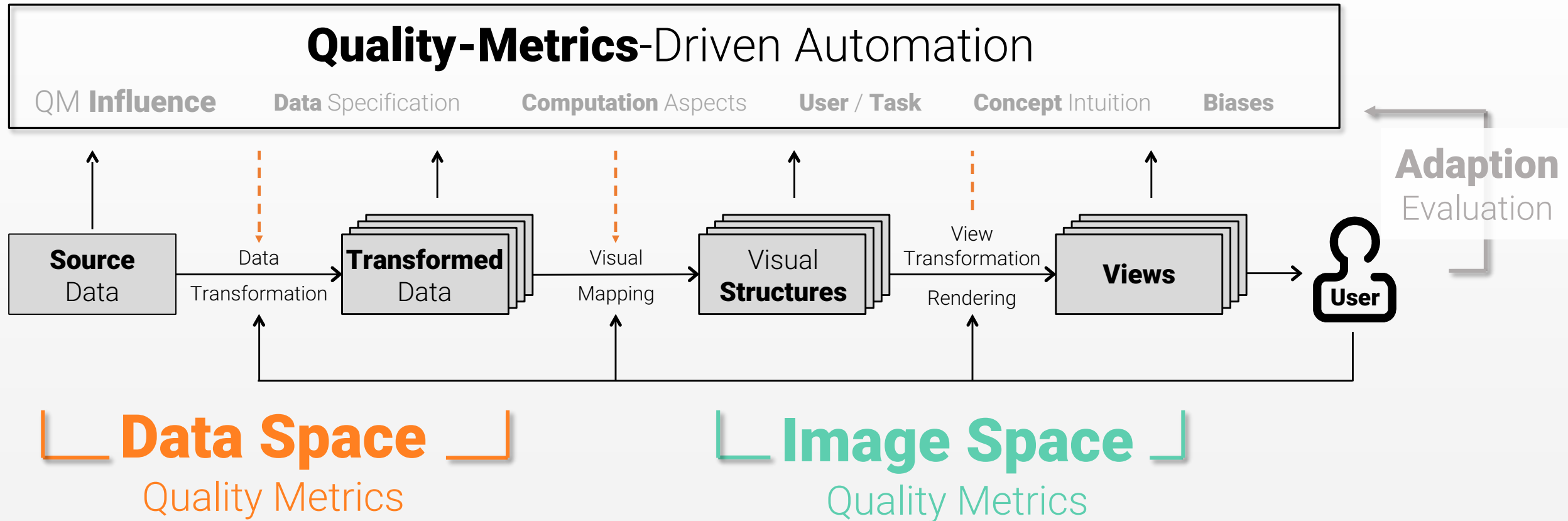
$$\arg \min_{\phi \in \Phi} \max q(\phi \mid D, U, T)$$

Data Space VS **Image Space**

Quality **Metric**

$$\arg \min_{\phi \in \Phi} \max q(\phi \mid D, U, T)$$

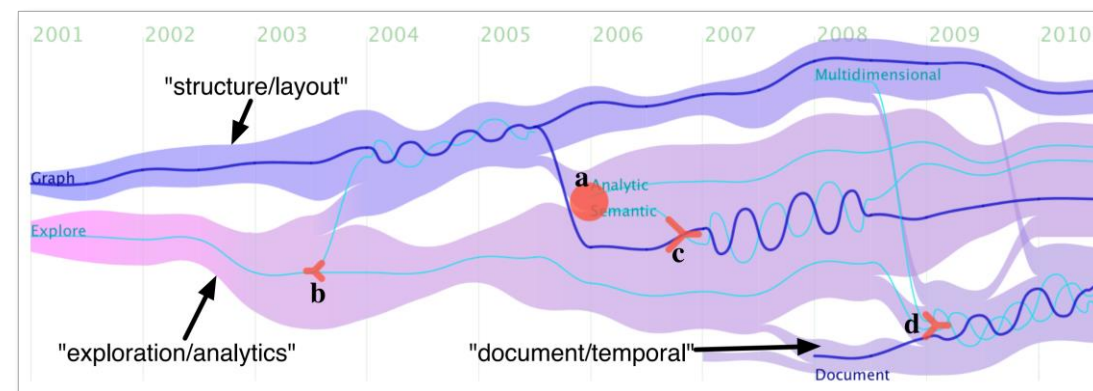
Quality-Metrics-Driven Automation





TextFlow – Data Space QM

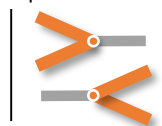
Stacked Charts



[Cui2011]

Patterns and Tasks

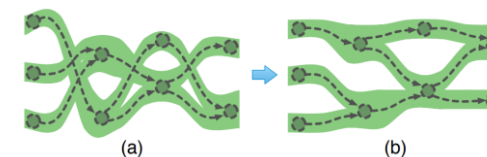
Split / **M**erge



Parallel

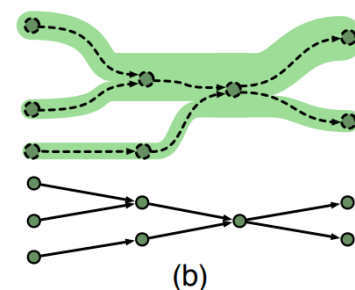


Trend



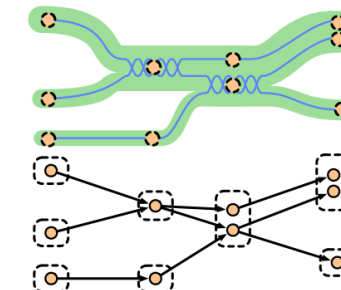
(a)

(b)

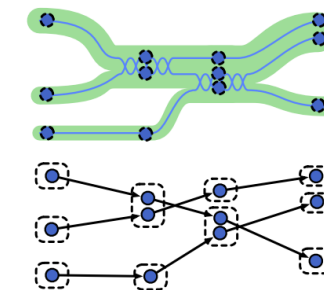


(b)

Topic Flow



Topic Bundles

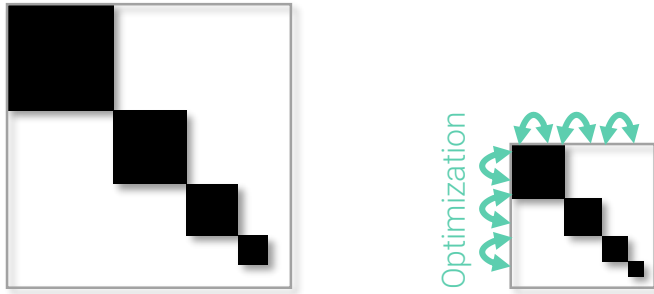


Thread



Magnostics – Image Space QM

Matrix



Patterns and Tasks

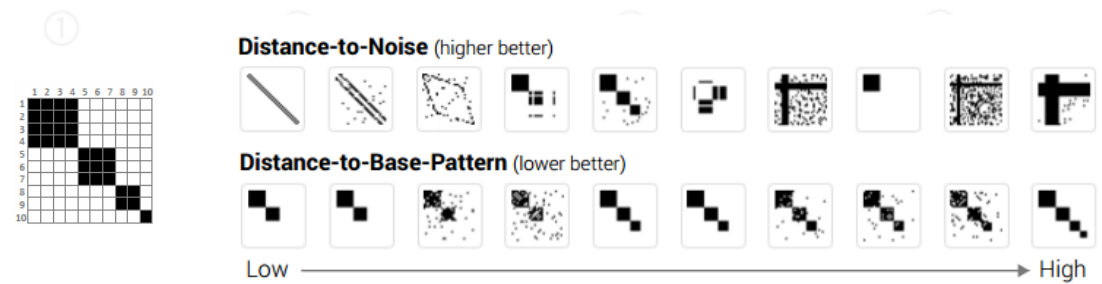
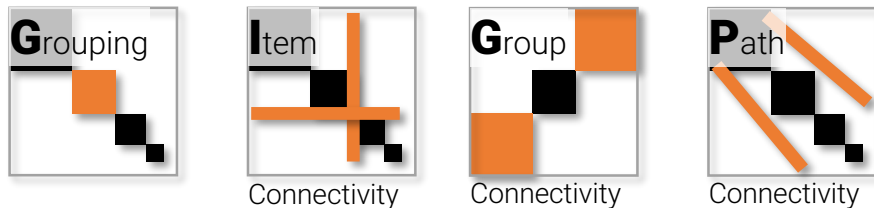


Figure 1.10 Examples for our Block Descriptor, specifically engineered to retrieve blocks around the matrix diagonal.

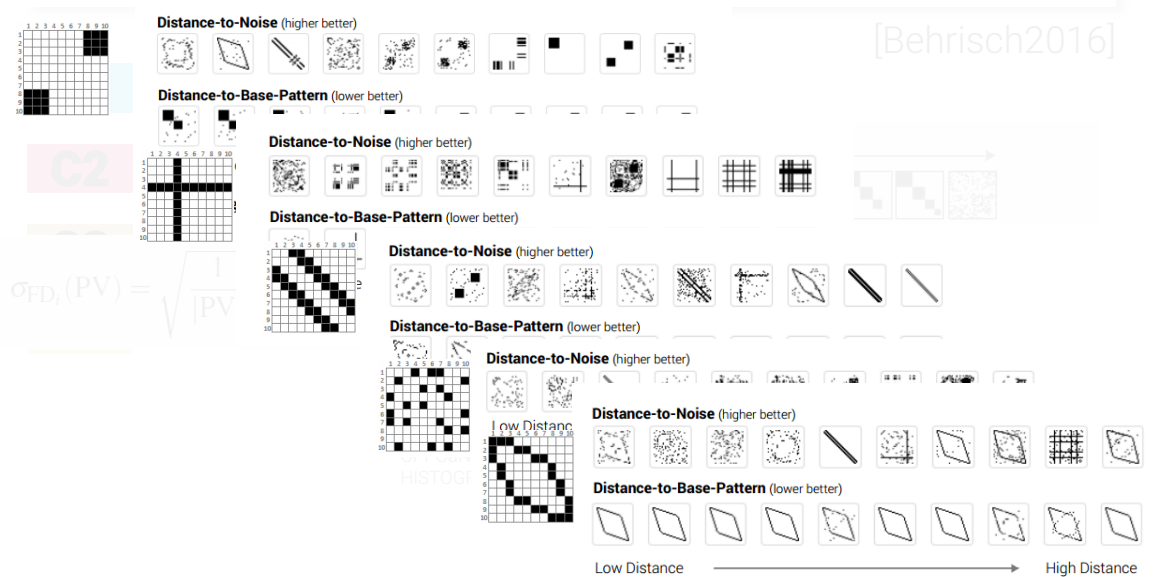
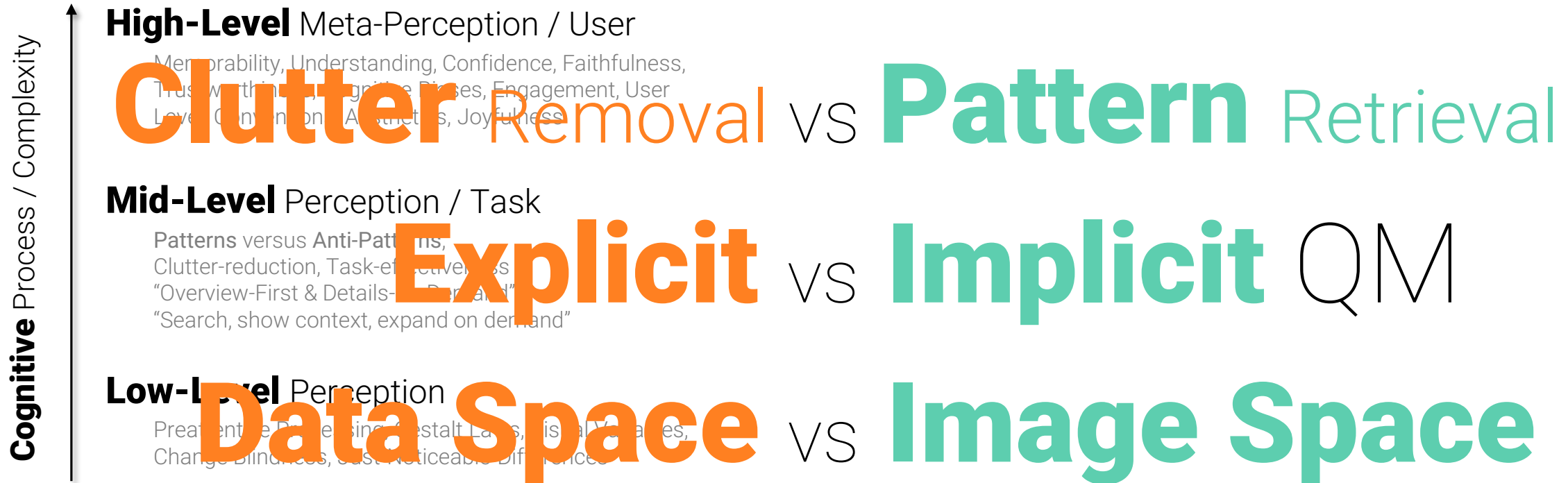


Figure 1.14 Examples for the CEDD Descriptor.



Quality Metrics Landscape





Quality Metrics Landscape

Cognitive Process / Complexity

High-Level Meta-Perception / User

Memorability, Understanding, Confidence, Faithfulness, Trustworthiness, Cognitive Biases, Engagement, User Level, Conventions, Aesthetics, Joyfulness

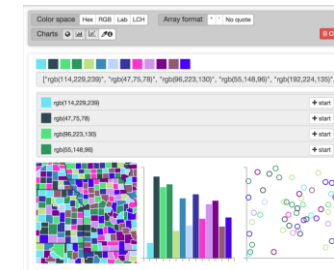
Mid-Level Perception / Task

Patterns versus Anti-Patterns,
Clutter-reduction, Task-effectiveness
“Overview-First & Details-on-Demand”,
“Search, show context, expand on demand”

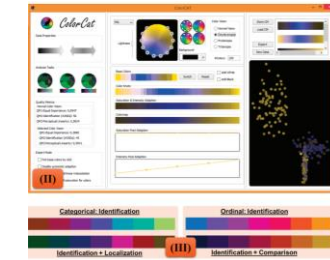
Low-Level Perception

Preattentive Processing, Gestalt Laws, **Visual Variables**,
Change Blindness, Just-Noticeable-Differences

Color Research

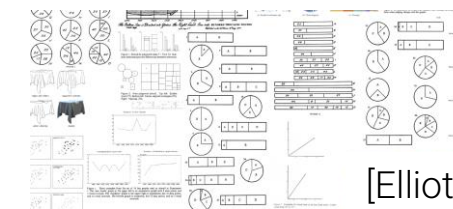


[Gramazio2016]



[Mittelstädt2015]

39 studies about human perception in 30 minutes



[Elliott2016]



Quality Metrics Landscape

Cognitive Process / Complexity

High-Level Meta-Perception / User

Memorability, Understanding, Confidence, Faithfulness, Trustworthiness, **Cognitive Biases**, Engagement, User Level, Conventions, **Aesthetics**, **Joyfulness**

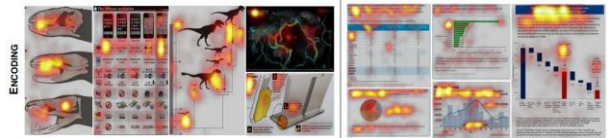
Mid-Level Perception / Task

Patterns versus Anti-Patterns,
Clutter-reduction, Task-effectiveness
“Overview-First & Details-on-Demand”,
“Search, show context, expand on demand”

Low-Level Perception

Preattentive Processing, Gestalt Laws, Visual Variables,
Change Blindness, Just-Noticeable-Differences

Memorability

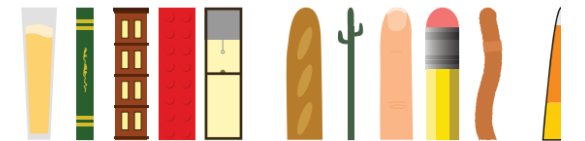


[Borkin2015]

DECISIVe 2017

Dealing with Cognitive Biases in Visualisations : a VIS 2017 workshop

Aesthetics Joyfulness



(a) Rectangular bars

(b) Rounded-top bars

[Skau2017]



Quality Metrics Landscape

Cognitive Process / Complexity ↑

High-Level Meta-Perception / User

Memorability, Understanding, Confidence, Faithfulness, Trustworthiness, Cognitive Biases, Engagement, User Level, Conventions, Aesthetics, Joyfulness

Mid-Level Perception / Task

Patterns versus **Anti-Patterns**,
Clutter-reduction, Task-effectiveness
“Overview-First & Details-on-Demand”,
“Search, show context, expand on demand”

Low-Level Perception

Preattentive Processing, Gestalt Laws, Visual Variables, Change Blindness, Just-Noticeable-Differences

Mid-Level Perceptual Quality Metrics

Clutter
Removal

Reduces
Cognitive **Overload**

Pattern-Driven
Analysis

Focuses on
Analysis **Task**

Computation
Aspects

User / Task

Data Spec.

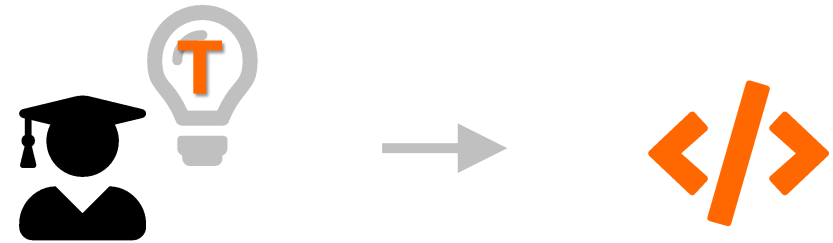
Concept
Intuition

Quality Metric
Influence



Discussion and Findings

Which **QM** favors
which **visual pattern**?



Quality **Metric**

$$\arg \min_{\phi \in \Phi} \max q(\phi \mid D, U, T)$$

- > Implicit, domain-inspired, pot. subjective expectation
- > What if pattern is not known apriori? Which QM?
- > Majority of QMs do not describe visual pattern

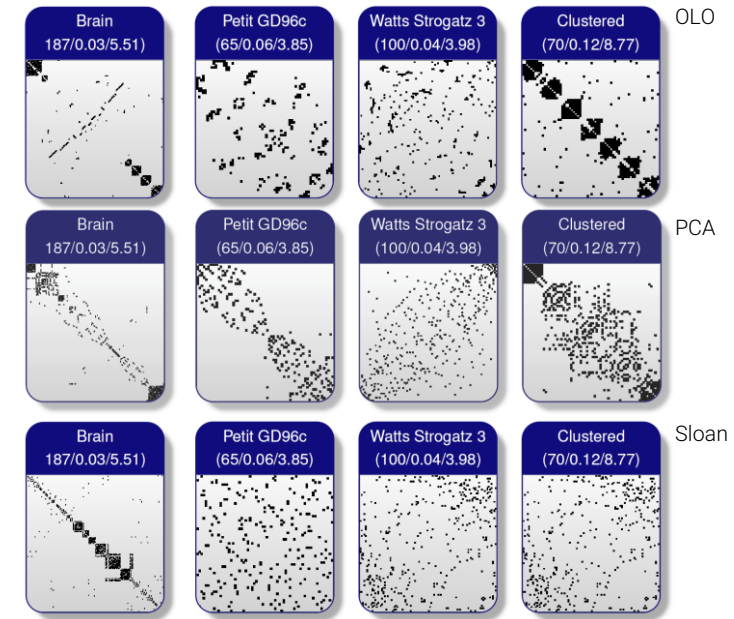


Discussion and Findings

What are **extreme cases** that a QM can deal with?

Quality **Metric**

$$\arg \min_{\phi \in \Phi} \max q(\phi \mid D, U, T)$$



- > Noise (in-)variances and robustness toward skewed distributions
- > Bad QM must mean no pattern

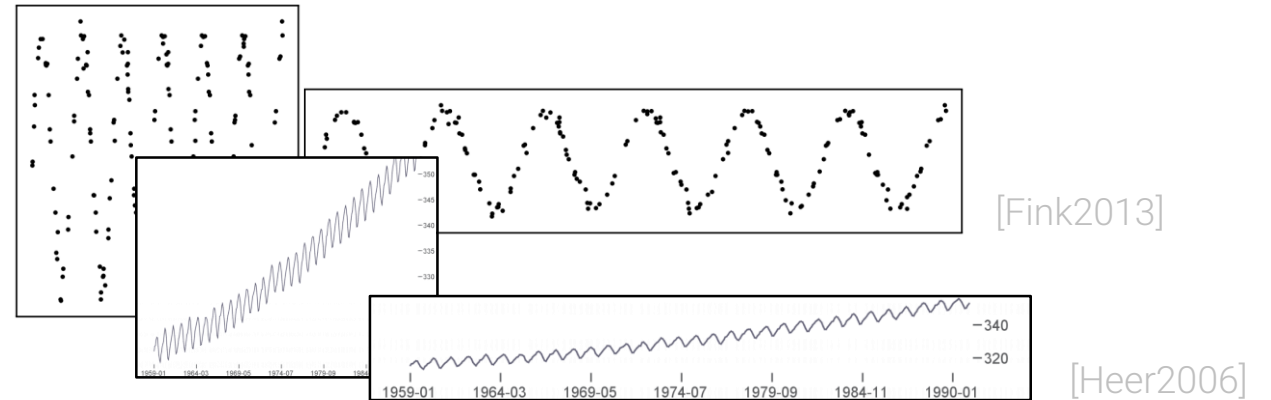


Discussion and Findings

Is QM research
transferable among
visualization types?

Quality **Metric**

$$\arg \min_{\phi \in \Phi} \max q(\phi \mid D, U, T)$$



- > Some vis subdomains share similar concepts
- > Set of base patterns in both visualizations

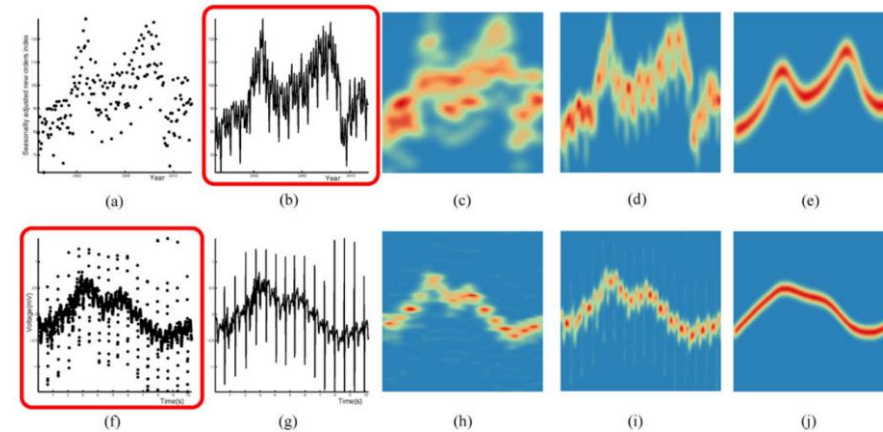


Discussion and Findings

Are QMs equally
descriptive?

Quality **Metric**

$$\arg \min_{\phi \in \Phi} \max q(\phi \mid D, U, T)$$



[Wang2018]

- > QM for recommendation of visualization technique
- > But, only standard patterns (not domain dependent)

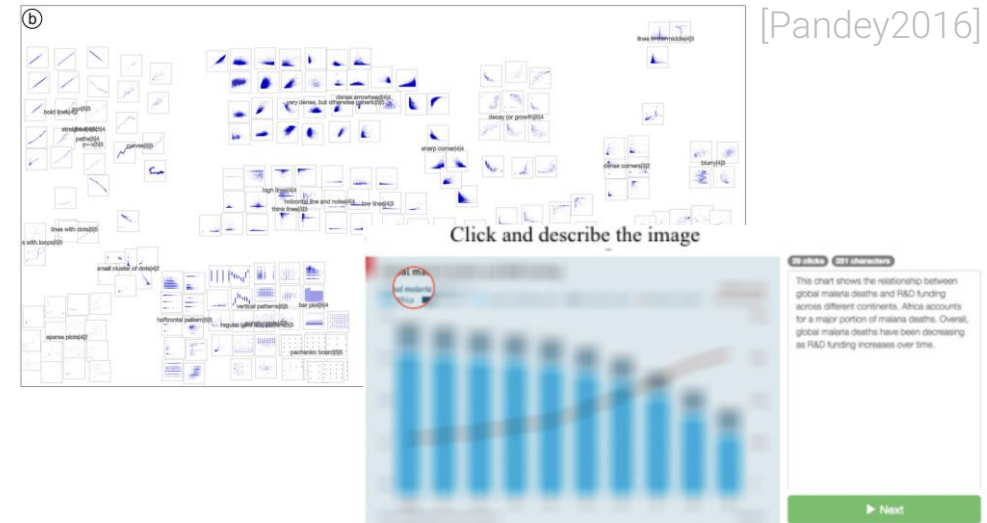


Discussion and Findings

Evaluation of Quality Metrics

Quality **Metric**

$$\arg \min_{\phi \in \Phi} \max q(\phi \mid D, U, T)$$



- > Heuristic, quantitative, pattern-focused QM research not backed up (enough) by perception QM studies
- > Design recommendations solely base their recommendations on studies



Research Directions

Multi-Criteria & Task-Adapted QM.

Mixture of patterns;
Tasks change in exploratory settings



▶ Intelligently navigate pattern space.

Machine Learning.

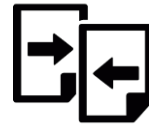
Deep learning possible, iff (1) suff. large training set;
(2) appropriate architecture



▶ Deep-Learning based QM.

Interactive & Human-Supported Quality Steering.

Algorithms can benefit from the user's input
to produce high quality results.



▶ Visual Support and Visual Analytics is needed.

Closing the Gap to Higher-level Perceptual QM.

Central goal is still reduce cognitive overload.



▶ QM can help to build understanding and trust.



Take Home Messages

Task and Pattern-based Quality Metrics.

Choose the right QM! More evaluation is necessary.

Visual Exploration Interfaces.

Needed to make use of QMs in the wild.

Visual Analytics will change the field (once again).

Opening the Black-Box will lead to novel algorithms.



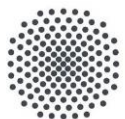
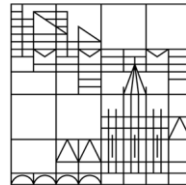


Thank YOU



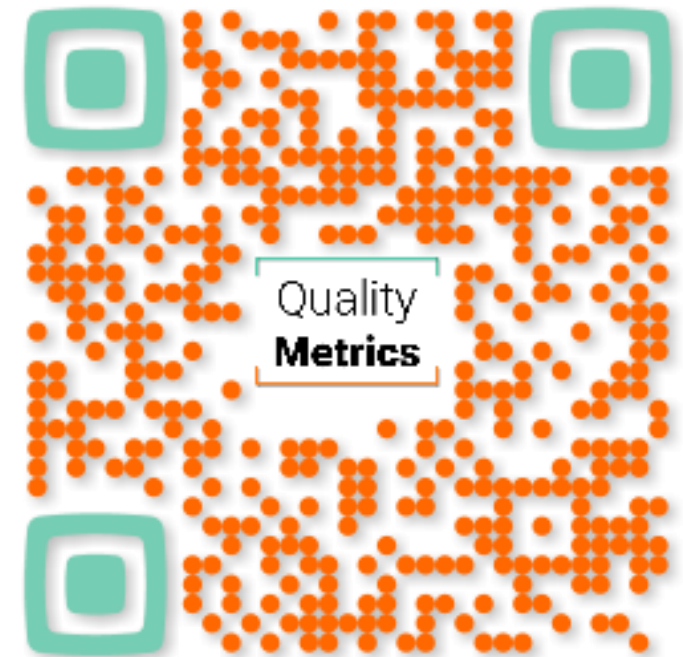
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