

# Dual Space Coupling Model Guided Overlap-Free Scatterplot

**Zeyu Li**, Ruizhi Shi, Yan Liu, Shizhuo Long, Ziheng Guo, Shichao Jia, and Jiawan, Zhang Tianjin University

# Agenda

- Motivation
- Previous work
- Dual-space coupling model
- Methods
- Evaluation
- Conclusion



#### **Motivation**

Example scatterplots created by different ways:



**projection results** of high-dimensional data **coordinates** from geographic space

**layout results** of large-scale graphs

**regular scatterplots** with two semantic axes



### **Motivation**

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four mixed classes

non-uniform

20% transparency

20% transparency

density

**In reality:**

**Looks like: In reality:**



#### **The overdraw problem severely damages visual tasks of scatterplots:**

- density perception
- cluster identification
- shape examination
- trend analysis
- outlier identification
- similar data visual inspection

#### **Data Space Methods**

data transformation  $\sqrt{}$ view transformation  $\mathbf{\times}$ 

#### **Visual Space Methods**

view transformation  $\blacktriangledown$ data transformation  $\mathbf{\times}$ 

#### **Hybrid Methods**

view transformation data transformation  $\sqrt{}$ 



#### **Data Space Methods**

data transformation view transformation

**1. Data sampling or aggregation**



- ineludible data loss
- cannot eliminate overlaps
- break one-to-one correspondence

#### **2. Jitter**



- cannot eliminate overlaps
- may disturb data features

#### **Visual Space Methods Hybrid Methods**

view transformation data transformation  $\mathbf{\times}$ 



**Data Space Methods** data transformation view transformation

**1. Data sampling or aggregation**



- ineludible data loss and bias
- cannot eliminate overlaps
- break one-to-one correspondence  $\begin{array}{ccc} 1 & 2. \text{Node dispersion} & & \\ \hline & & \end{array}$  3. Subspace mapping methods

#### **2. Jitter**

where  $\cdots \Rightarrow$ 

- cannot eliminate overlaps
- may disturb data features

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#### **Visual Space Methods Hybrid Methods**

view transformation data transformation

#### **1. Appearance adjustment**



- time-consuming
- color blending
- **2. Node dispersion**



- poor scalability
- severe distortion
- cannot eliminate overlaps

view transformation data transformation



• shape and density distortion in high density regions

**Data Space Methods** data transformation view transformation X

**1. Data sampling or aggregation**



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- may disturb data features
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**Visual Space Methods**  $\parallel$  **Hybrid Methods** view transformation data transformation **1. Appearance adjustment**



- time-consuming
- color blending
- **2. Node dispersion**



- poor scalability
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view transformation data transformation



- ineludible data loss
- break one-to-one correspondence
- **3. Subspace mapping methods**



• shape and density distortion in high density regions

# Dual-space coupling model - four criteria and a goal

 $DS = \{x, y\}$ data set in data space, each data point is scale-free and immaterial  $NS = \{x, y, r\}$ visual node set in visual space, each visual node has a measurable radius

**Four criteria** that the overdraw solution should consider:

*C1*. Mutual Exclusion of Data Points: ------------  $\forall d_1, d_2 \in DS$ ,  $d_1 \cap_D d_2 = \emptyset$ 

*C2*. Mutual Exclusion of Visual Nodes: ---------- $\forall n_1, n_2 \in NS$ ,  $n_1 \cap_V n_2 = \emptyset$ 

*C3***.** Data-Visual Space Bijection:

*C4***.** Data-Visual Space Distribution Consistency: -------------  $F_V(NS) \sim F_D(DS)$ 

The **goal** of a desired overdraw solution:

 $argmax(similarity(F_V(NS), F_D(DS))), s.t. C1, C2, C3$  $\ast$  C1 is not mandatory

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#### Dual-space coupling model - metrics of distribution consistency

#### Local features:

- KNN preservation
- Displacement minimization

#### Global features:

- Shape preservation
- Density preservation

#### An individual comprehensive metric:

• Overall similarity

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Related visual tasks:

- outlier identification
- similar data visual inspection

- density perception
- cluster identification
- shape examination
- trend analysis

average similarity observed from multiple angles

#### Dual-space coupling model - overview





# Methods - core idea and three key questions



**FM halftoning**



The **core idea** to reconstruct density distribution:

- simulate density by controlling the quantity of visual nodes in local area
- hypothesis: the filling rate of colored pixel  $\alpha$  perceived density

#### **Three key questions** raised by the core idea:

- Q1. How to generate a set of circles that record the data distribution intactly? **Essence: transcribe** the data distribution from data space to visual space
- Q2. How to layout the circles to present the recorded distribution without overlaps? **Essence: translate** the transcribed distribution into visual space
- Q3. How to ensure no overlap occurs during necessary radius configuration? **Essence: express** and **embellish** the distribution in visual space

# Methods - pipeline









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 $r_{\mathit{pack}}$ 



**phyllotaxis**

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# Methods - pipeline







**1. build polar coordinates** 



 $\mathbf{N}S' = \frac{\{(x, y, r_{pack}, r_{draw}, y, r_{new})\}}{density disangle}$ density, <mark>dis, angle</mark> ) }<sub>N'</sub>



layout the circles without overlaps to present the recorded distribution



**PolarPacking** *C2: mutual exclusion of visual nodes C4: distribution consistency* 











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# Methods - pipeline





















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Two examples of applying our  $\pmb{f}_{\pmb{r}_{draw}}$  to **improve the visual quality** of a scatterplot.

Solve *low contrast* issue faced by HDR datasets by moving the HD-control point to the left

Solve *outlier invisible* issue by raising the LD-control point

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- Competing Algorithms
	- node dispersion methods: *PFS′, PRISM, Gtree,* and *RWordle-L* Sampled3k
	- subspace-mapping methods: *HaGrid* and *DGrid* **——** Full datasets
- Datasets:50 real-world datasets, data scale ranges from 4k to 1M
	- 12 example datasets:





- Our method achieves the best or near the best scores on all metrics compared with the state-of-the-art algorithms.
- Our method takes great advantage on computational efficiency (average time cost: 1/4.6 of Hagrid, 1/47.6 of DGrid).
- Our method presents strong adaptability to high dynamic range(HDR) datasets.



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Impact of parameters on time cost:



Time Complexity:  $O(N'\sqrt{N'})$ 

 $N'$  is the number of nodes to be packed, including **data nodes**  and **dummy nodes**.

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#### Impact of parameters on metrics:

- Size has a larger impact than  $k$  and sampling rate, and all metrics get worse as it raises.
- Size controls the global resolution of the captured structures.
- Our method is fairly robust on parameters.





Our method can maintain data distribution and reveal details hidden by overdraw.



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Our method can overcome the crowded issue faced by state-of-the-art methods.





Our method can present rich and complete details at the micro scale.



# **Conclusion**

- We contribute a dual space coupling model to represent the complex relationship within and between data space and visual space analytically to solve the scatterplot overdraw problem.
- The proposed model introduces a new design space for promising overlap removal algorithm and interaction paradigm.
- We also develop an overlap-free scatterplot visualization method on the basis of the model, which shows competitive advantages compared with the state-of-theart methods.





