Dynamic visualization of high-dimensional data via low-dimension projections and sectioning across 2D and 3D display devices

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Candidature Confirmation
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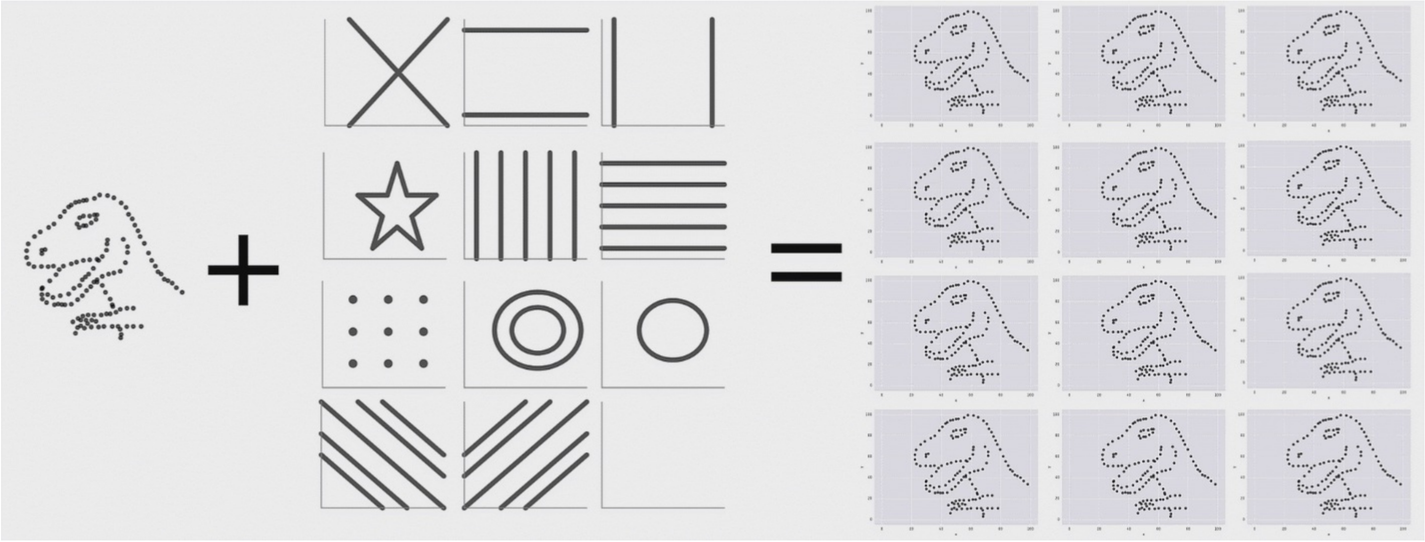
Slides – github.com/nspyrison/confirmation_talk

Motivation

Exploratory data analysis is important and ubiquitous, and it is important to keep visual interpretation:

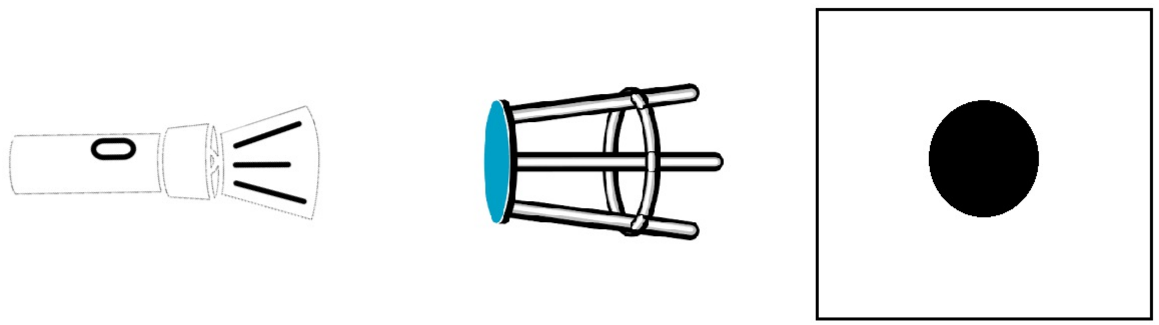


Datasaurus dozen; same means, standard deviations, and correlations, *(Matejka & Fitzmaurice, 2017)*

Visualizing multivariate spaces

- Visualization multivariate spaces becomes complex; dimension reduction
- One static projection does not portray all of the variation
- Dynamic rotations do conveys more variation and more accurate structure

Shadow puppet analogy (linear projection from 3- to 2D):



Dynamic linear projections, tours

Available on CRAN, tourr R package, *(Wickham et al. 2011)*

- Random choice - *grand tour* random forest walk in p-space *(Asimov 1985)*
- Data-driven - *guided tour* projection pursuit, optimize an objective function on the projection *(Hurley & Buja 1990)*
- Many other geometric displays, this talk uses scatterplots

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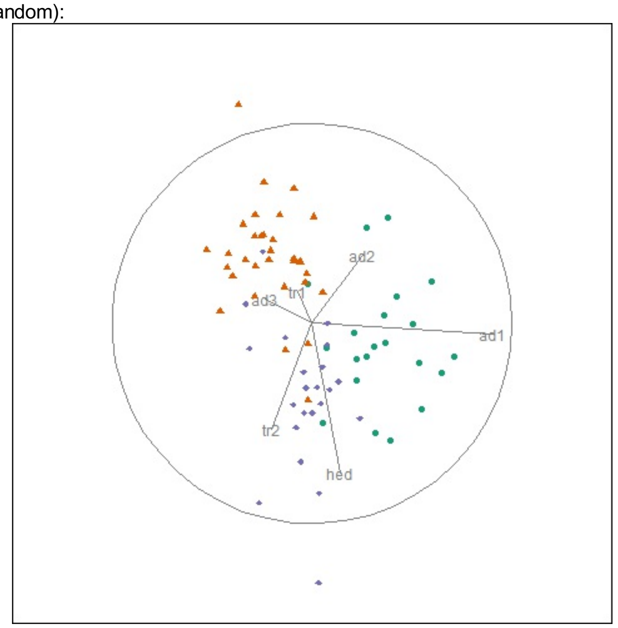
grand tour (random):



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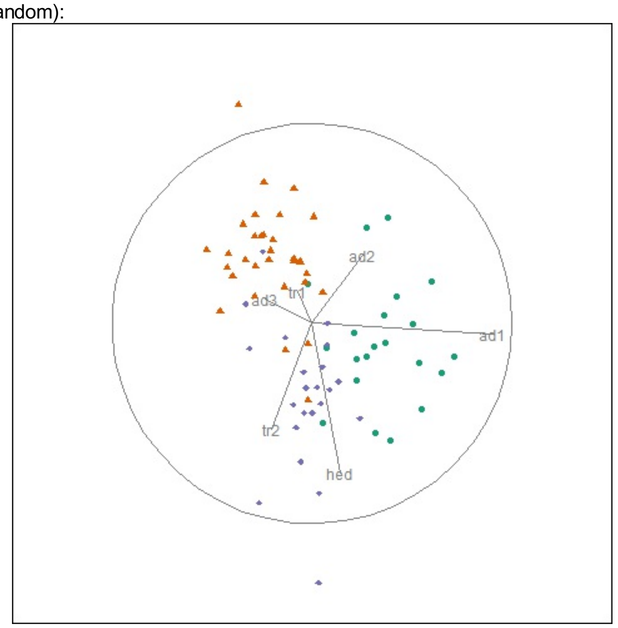
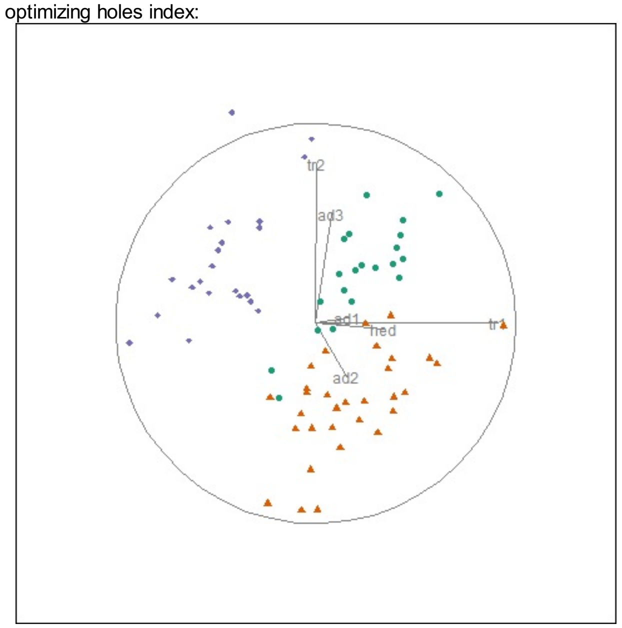
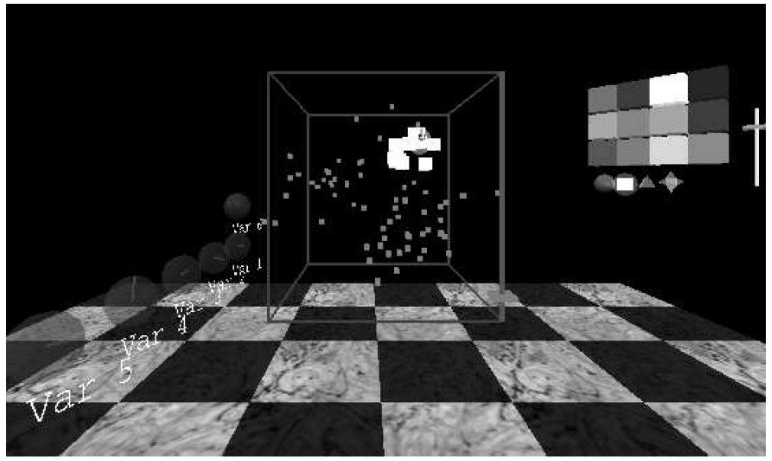


guided tour - optimizing holes index:



3D and immersive 3D data visualization

Data visualization has lagged behind in adopting 3D and immersive technologies, despite promising finds



(Nelson et al. 1998)

tours: head-tracked VR vs standard monitor

better cluster and shape identification, slower brushing

3D visuals generally convey more information with more speed, but manipulation is slower when compared with orthogonal 2D, though 3D with 2D gives the best perception *[Lee 1986, Wickens 1994, Tory 2006]*

Embedded multivariate data in immersive 3D report improved accuracy and faster response time, but a slower manipulation speed and less comfort *[Gracia 2016, Wagner 2018, Nelson 1998, counterexample: Sedlmair 2013]*

Modern VR equipment has improved quality, increased audience, and reduced the costs of VR, it is timely to research dynamic projections in VR

Research objectives

1) How can user-controlled steering (UCS) be generalized to work within graphic-specific environments for 2D projections?

2) Does 2D UCS tours provide benefits over alternatives?

3) How do we extend UCS to 3D?

4) Does UCS in 3D displays provide benefits over 2D displays?

RO 1) How can UCS be generalized to work within graphic-specific environments for 2D projections?

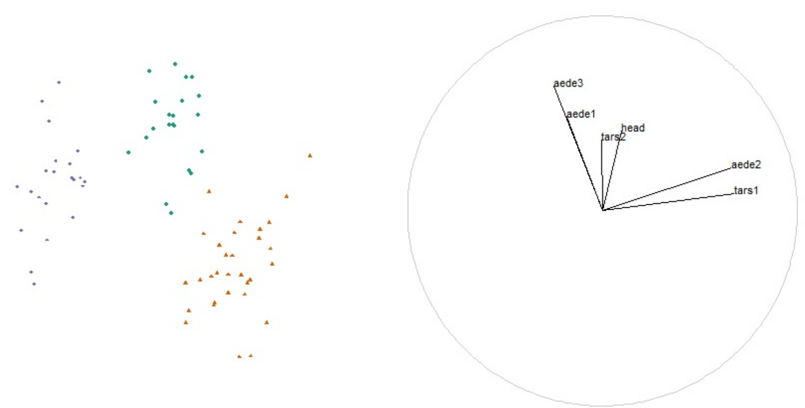
- Manual choice - *manual tour* user-controlled manipulation of a selected variable *(Cook & Buja 1997)*
  - Used to explore the sensitivity of the structure to the variables contributing to the projection

Algorithm design, work in progress & paper to be submitted to the R Journal:

- Algorithm generalizing for consumption by graphics environments
- R implementation via the package `spinifex`, available on github.com/nspyrison/spinifex `devtools::install_github("nspyrison/spinifex")`
  - manual tours in R, extending the `tourr` package
  - platform to pass tours to animation-specific environments
- application to contemporary high energy physics

RO1 Step 1) Choose a variable of interest

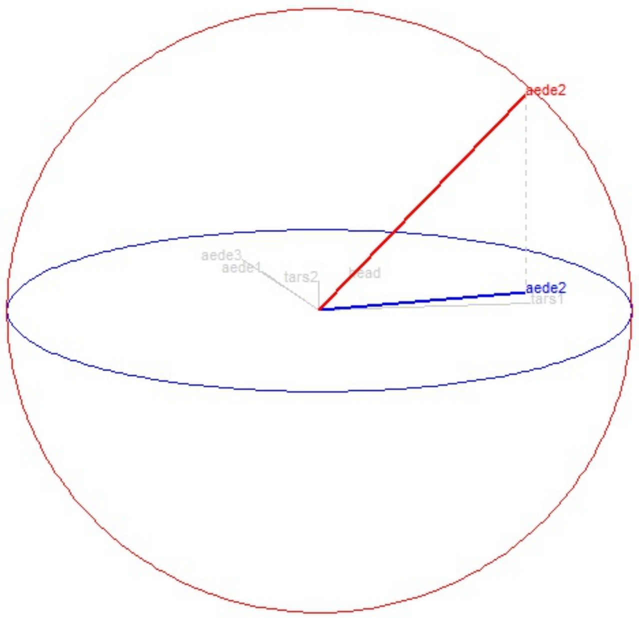
Starting with the last projection of the previous holes-indexed guided tour:



	x	y
tars1	0.6770	0.0886
tars2	-0.0027	0.3637
head	0.0951	0.4114
aede1	-0.1830	0.4830
aede2	0.6619	0.2234
aede3	-0.2469	0.6383

Choose a manipulation variable: aede2

RO1 Step 2) Create a manipulation space



Orthonormalize a dimension with a full contribution to the manipulation variable

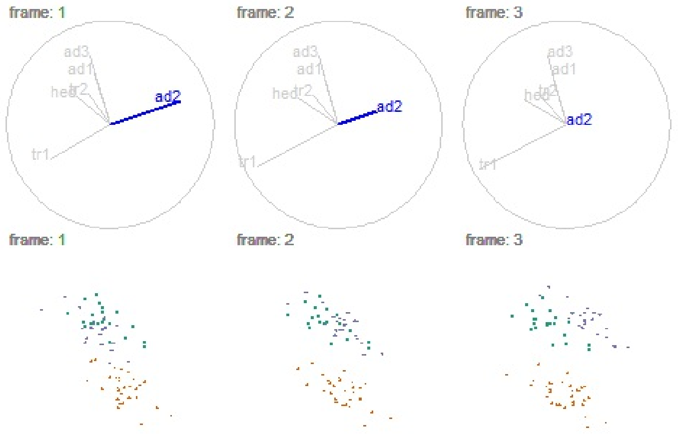
This provides a means to rotate the basis out of the projection plane (for example, lifting paper off the table rather than being confined to the surface)

Create a sequence of values for the 'out-of-plane' angle that will change the projection coefficients of the manipulation variable

RO1 Step 3) Generate the rotation

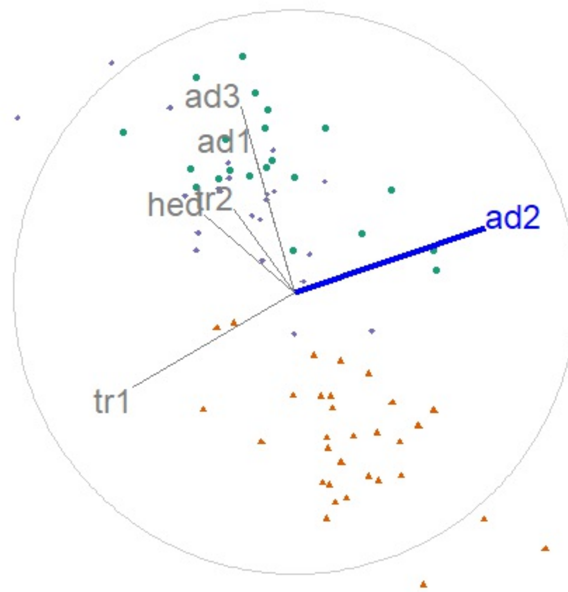
Over the sequence of angles: rotate the manipulation space for each element

- Project the data
- Plot the first two variables of the rotated basis and projection



Display as an animation

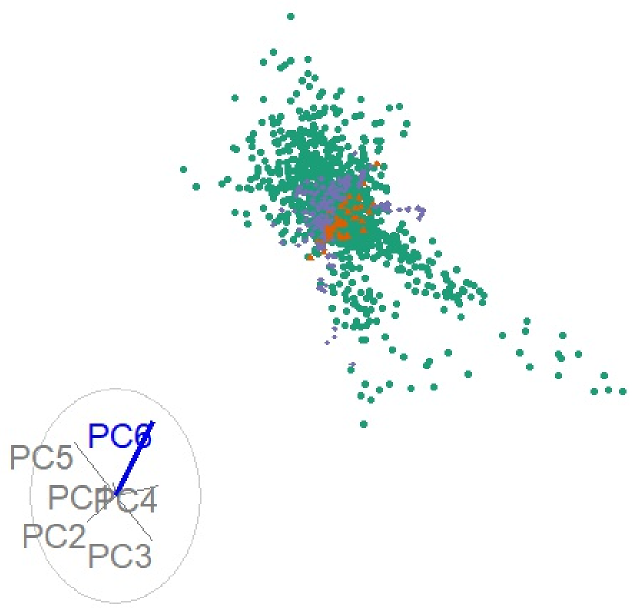
aede2 is important for distinguishing between the green and purple clusters



As an html widget

Application -- high energy physics

Hadronic collision experiment data, $\mathbf{X} \in \mathbb{R}^{56}$, *(Wang, et al. 2018)*, studied with guided tours *(Cook, et al. 2018)*



Given:

- Data summarized in 6 principal components, ~48% of the variation
- Starting basis from previously published figures

Conclusion, PC6 is important in explaining the structural features in the data:

- When the contribution of PC6 is full, the plane of green points extends into the line of sight
- When the contribution is zeroed, the line of purple points is approaching a head-on view

As an html widget, UCS on each of the 6 components

RO 2) What benefits does UCS provide over alternatives?

Future performance comparison measured across contemporary benchmark datasets

- Principal Component Analysis (PCA)
  - A linear transformation that produces linear combinations of the variables in descending order of variation explained
- Multi-Dimensional Scaling (MDS)
  - Non-leaner dimension reduction that compares the pairwise distance between observations
- T-distributed Stochastic Neighbor Embedding (tSNE)
  - Static non-linear transformation preserves local proximity and reduces relative entropy
- User-controlled steering (USC), manual tour
  - Dynamic linear projections controlling the contribution of a selected variable

Measures: variation, variable transparency, clustering, structure

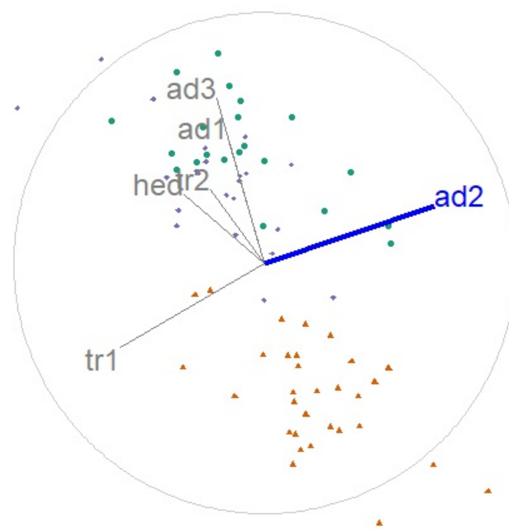
Design space: data sets, techniques, and measures of comparison

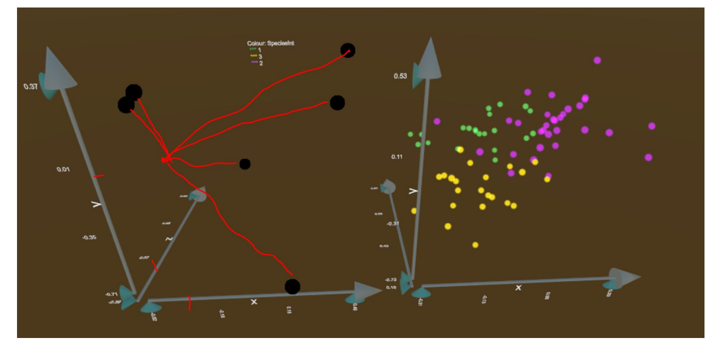
RO 3) How do we extend UCS to 3D?

future algorithm design

Extend UCS algorithm to 3D projections and integrate with Immersive Analytics Tool Kit, IATK, *(Cordeil 2019)* for common user interface across display devices

Develop for 3D scatterplots and then extend to multi-dimensional function surfaces

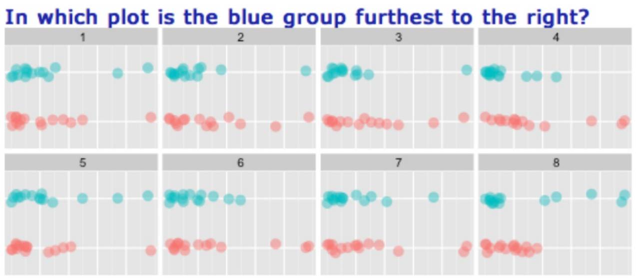




RO 4) Does UCS in 3D displays provide benefits over 2D displays?

future usability study -- lineup design *(Hofmann et al. 2012)*

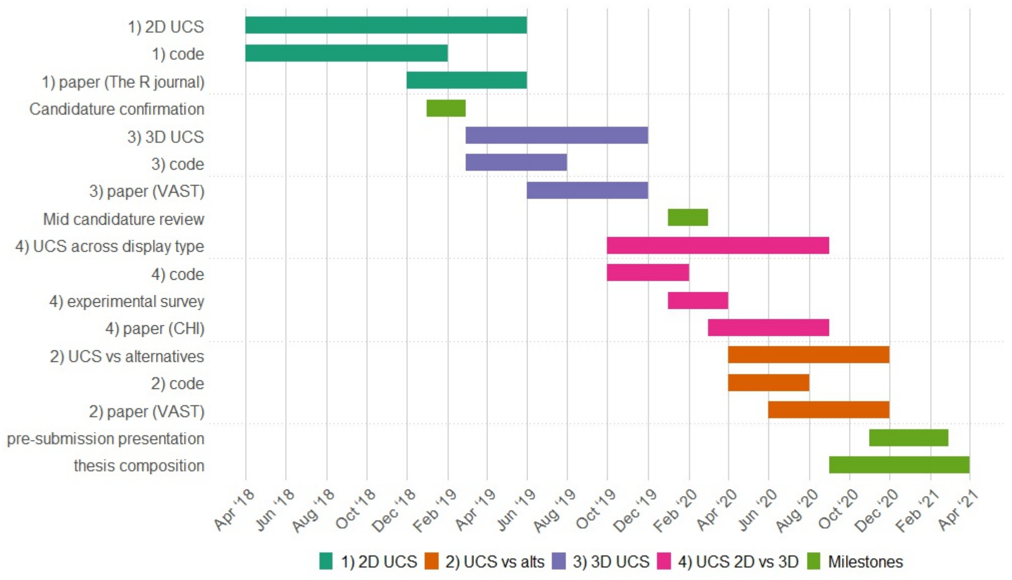
- Visual variant of statistical p-test
- Pick the real data against data generated from the null hypothesis
- Quantitative comparison across display type



Design space:

- Display type: 2D monitor, 3D monitor, head-mount, physical immersion
- Task type: structure, UCS, clustering, dimensionality
- Measures: accuracy, speed, confidence, preference, demographic information, VR and data visualization expertise

Research timeline



Thanks!

Slides created in R using rmarkdown and xaringan

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Questions?

R Core Team, 2018

Xie et al. 2018

Xie, 2018

References (1/2)

In order of appearance:

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