Lumos

Increasing Awareness of Analytic Behavior During Visual Data Analysis

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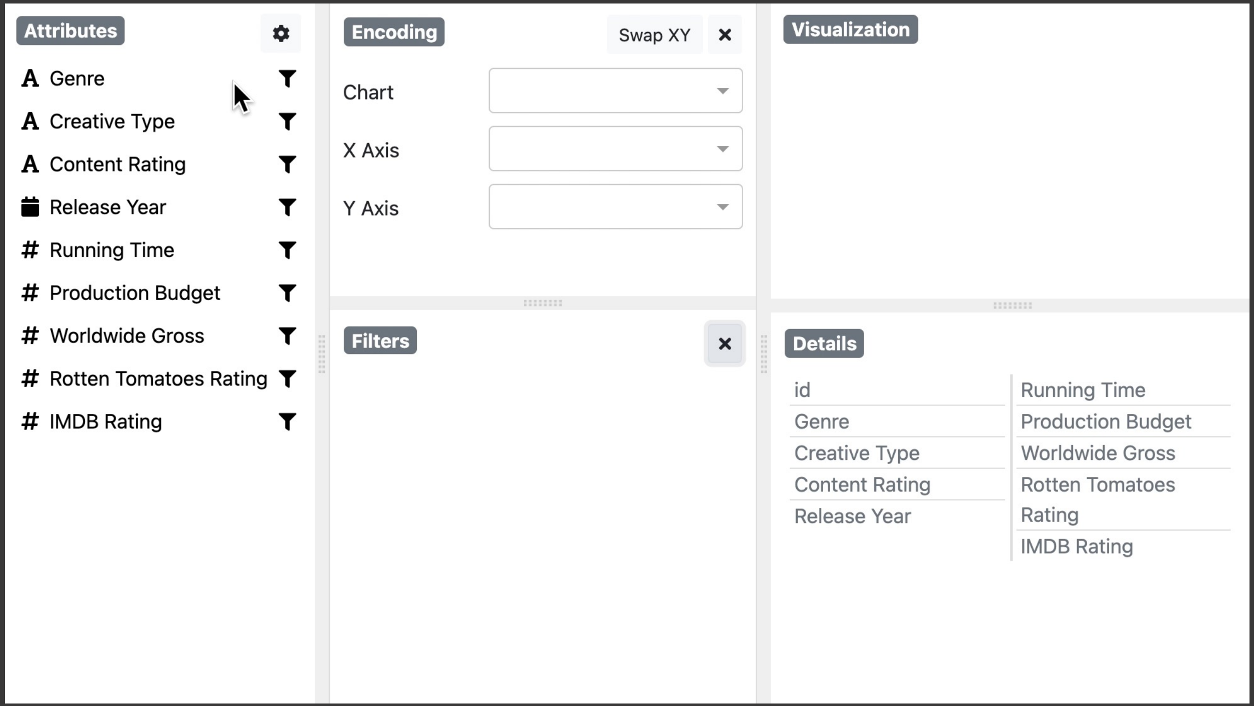
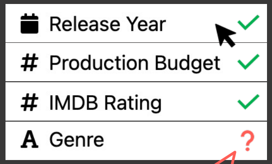
EMORY UNIVERSITY

Visual Data Analysis



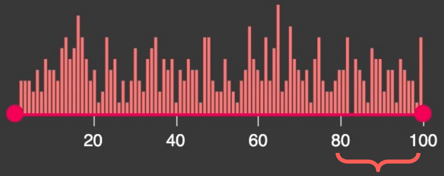
While this is great, things can go wrong...

Under emphasized certain data?



Did **NOT**
consider **Genre**

Over emphasized?



Only considered movies with
High **Rotten Tomatoes Ratings**.

Your analytic behavior was probably biased ...

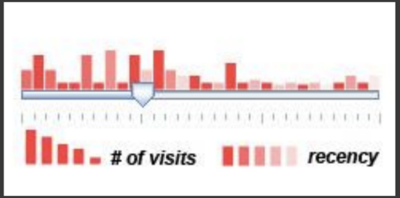
Biased Analytic Behavior: The deviation of the distribution of users' interactions with data from an expected baseline behavior.

Research Question

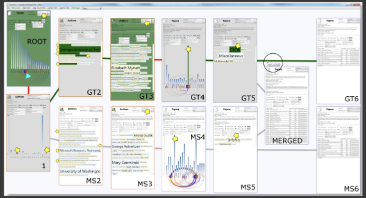
How can we **design systems** that
increase user awareness
of analytic behaviors?

Related Work

Graphical Traces of Analytic Provenance

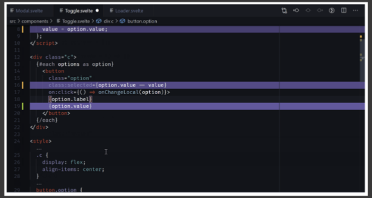


Willett et al. TVCG'07



Dunne et al. CHI'12

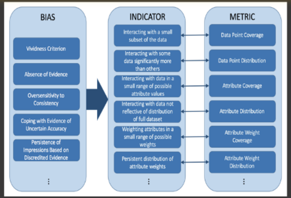
Sarvghad et al. GI'15



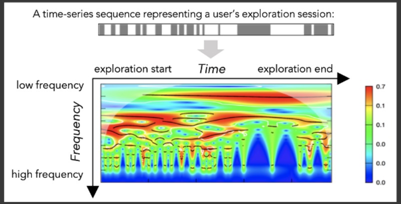
Footsteps for VSCode '21

Modeling User Behavior

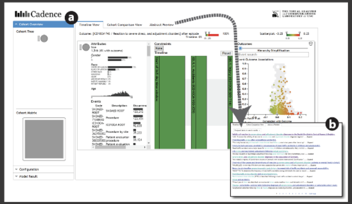
Gotz et al. IUI'16



Wall et al. VAST'17



Feng et al. VIS'18

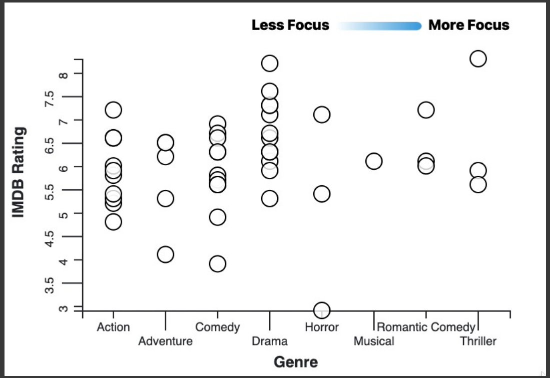


Zhou et al. CHI'21

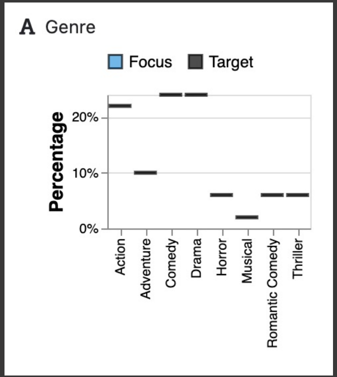
What did we do?

Interaction Traces - Visual feedback of the user's analytic behavior in the UI

In-situ
(at the place of interaction)



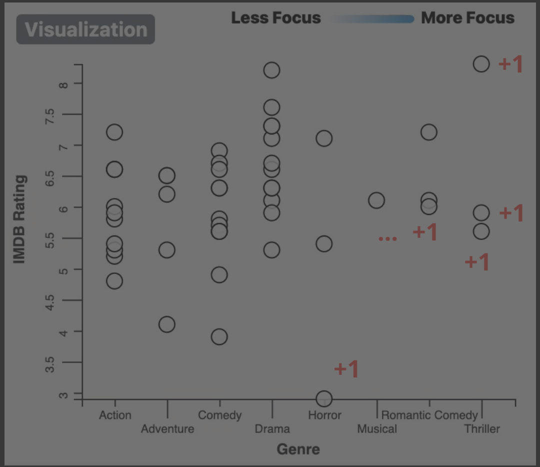
Ex-situ
(in an external view)

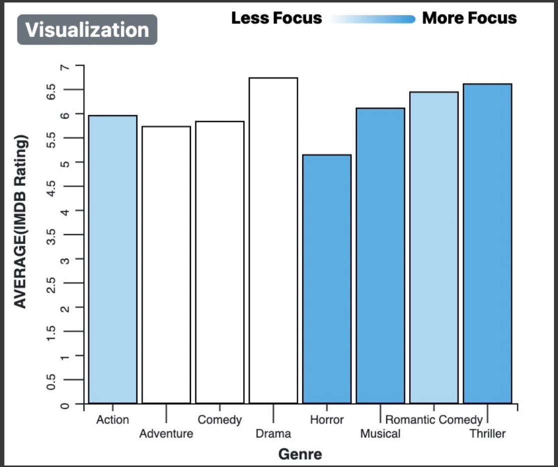


Interaction Traces: In-situ - Values

Unit Visualizations (e.g. Scatterplot)

Aggregated Visualizations (e.g., Bar chart, Line chart)



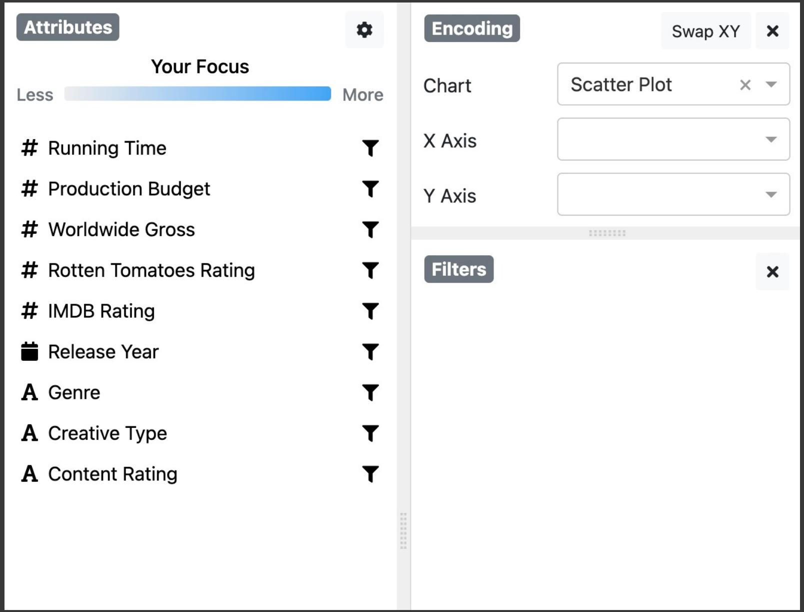


1 hover = 1 unit of focus for each data point.

1 hover = 1/N units of focus for each datapoint
(N = number of data points belonging to the aggregation)

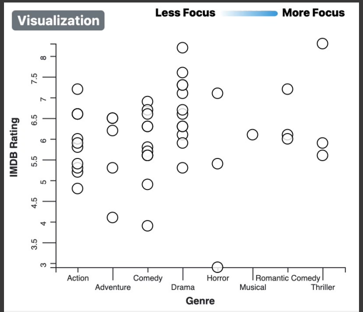
Greater # units of focus = darker shade of blue

Interaction Traces: In-situ - Attributes

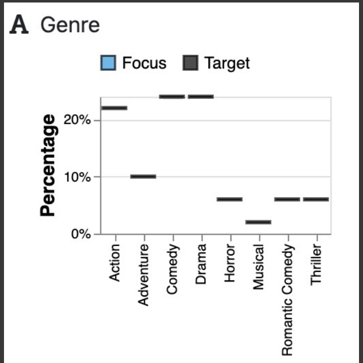


- 1 Encoding change = 1 unit of focus
- 1 Filter change = 1 unit of focus
- Greater # units of focus = darker shade of blue
- Sort attributes based on focus!

Interaction Traces: Ex-situ

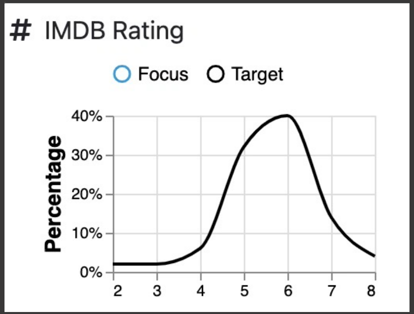


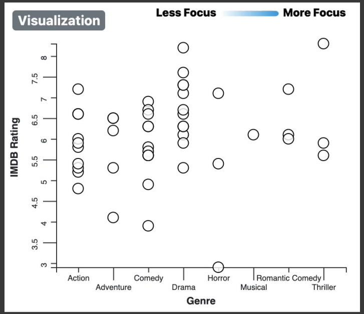
Categorical Attributes



- Black strips show the % count of values in the underlying data.
- Blue bars show the % count of values based on user's interactions.
- Red card means **greater** deviation between users' interactions and the target distribution.
- User has ***not*** interacted with ***Adventure***, ***Comedy***, and ***Drama*** movies at all!

Interaction Traces: Ex-situ

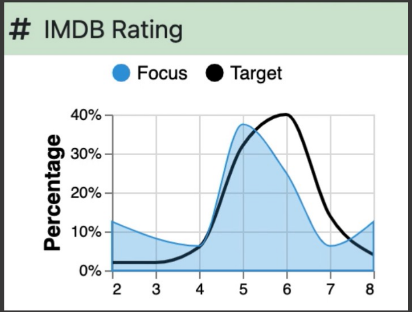


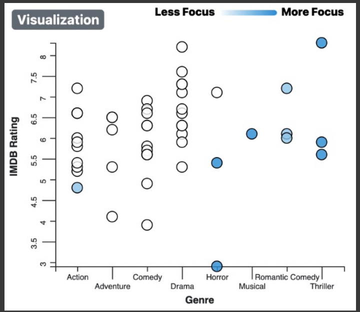


Quantitative Attributes

- Black curve shows the % distribution of values in the underlying data.
- Blue area curve shows the % distribution of values based on the user's interactions.
- Green card means **lesser** deviation between users' interactions and the target distribution.
- The shapes of the two distributions are similar!

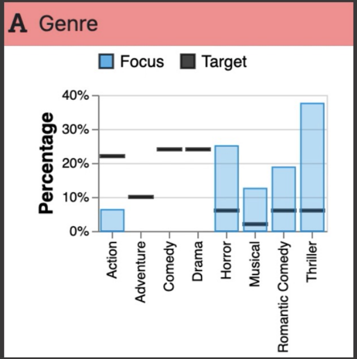
Interaction Traces: Ex-situ





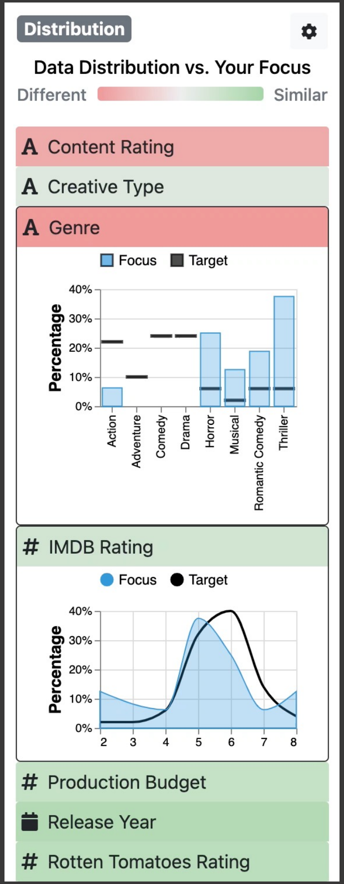
Quantitative Attributes

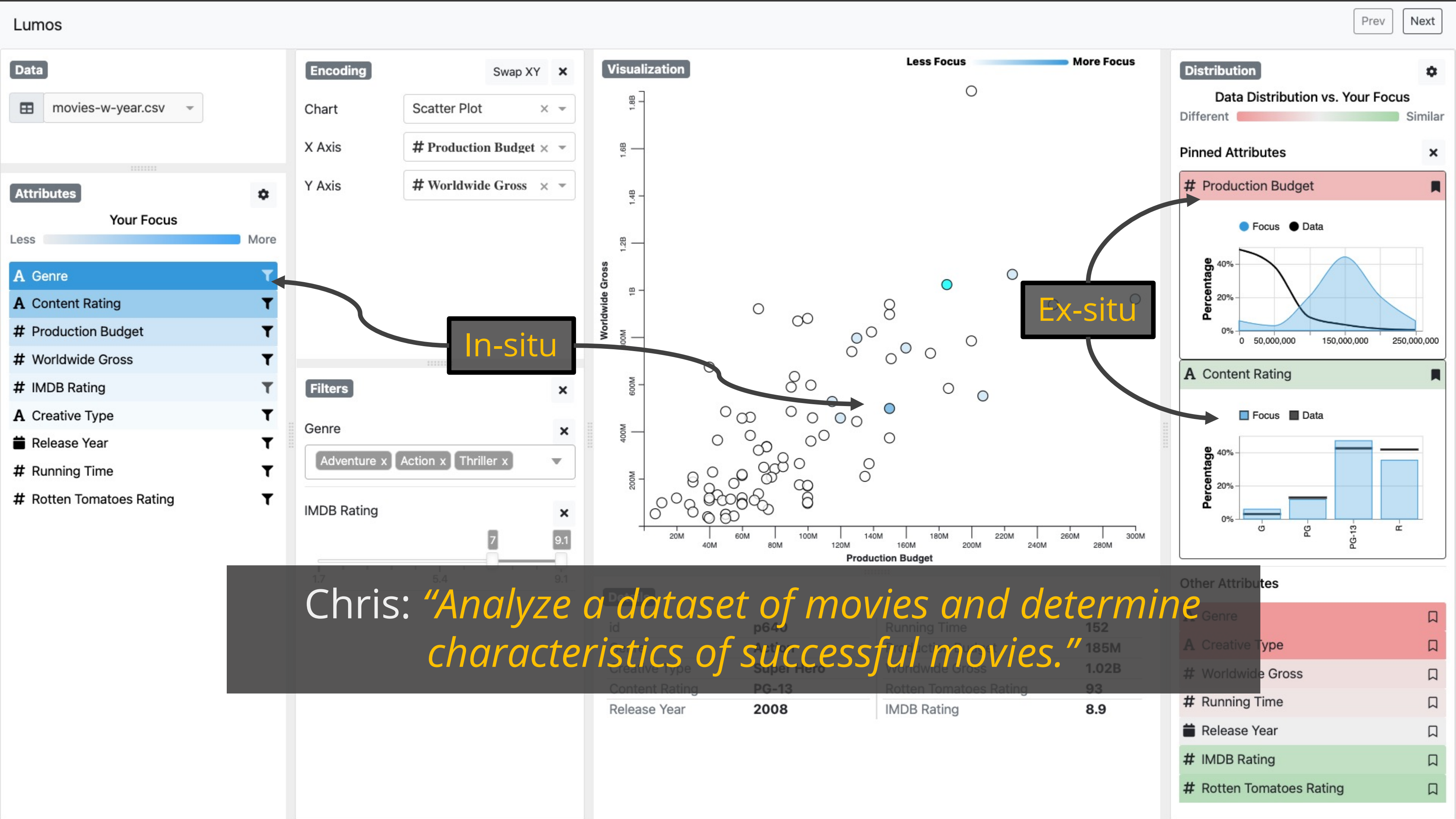
Categorical Attributes



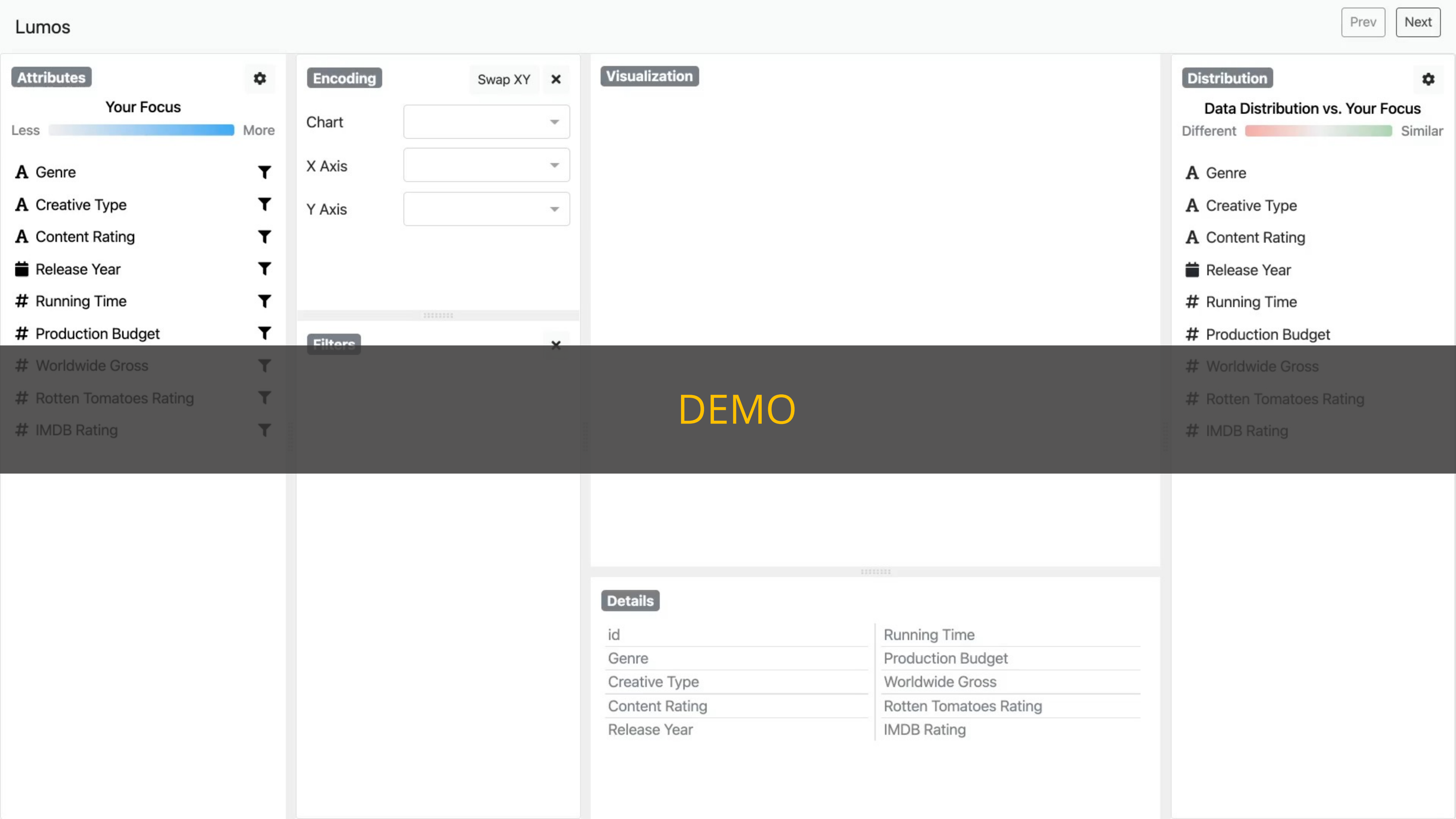
Interaction Traces: Ex-situ

- Distribution curves for all Attributes.
- Interactions with **Content Rating** were deviated from the data.
- Interactions with **Rotten Tomatoes Rating** were proportional to the data.





Lumos
Prev
Next
Data
movies-w-year.csv
Attributes
Your Focus
Less
More
Genre
Content Rating
Production Budget
Worldwide Gross
IMDB Rating
Creative Type
Release Year
Running Time
Rotten Tomatoes Rating
Encoding
Swap XY
Chart
Scatter Plot
X Axis
Production Budget
Y Axis
Worldwide Gross
Filters
Genre
Adventure x
Action x
Thriller x
IMDB Rating
7
9.1
Visualization
Less Focus
More Focus
Worldwide Gross
Production Budget
In-situ
Ex-situ
Distribution
Data Distribution vs. Your Focus
Different
Similar
Pinned Attributes
Production Budget
Focus
Data
Percentage
Content Rating
Focus
Data
Percentage
Other Attributes
Genre
Creative Type
Worldwide Gross
Running Time
Release Year
IMDB Rating
Rotten Tomatoes Rating
Release Year
2008
IMDB Rating
8.9
Chris: “Analyze a dataset of movies and determine characteristics of successful movies.”


Lumos
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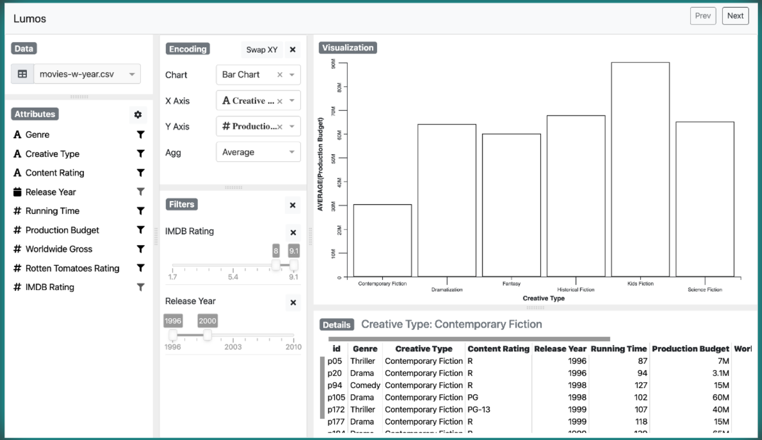
Worldwide Gross
Rotten Tomatoes Rating
IMDB Rating
Encoding
Swap XY
Chart
X Axis
Y Axis
Filters
Visualization
DEMO
Details
id
Genre
Creative Type
Content Rating
Release Year
Running Time
Production Budget
Worldwide Gross
Rotten Tomatoes Rating
IMDB Rating
Distribution
Data Distribution vs. Your Focus
Different
Similar
Genre
Creative Type
Content Rating
Release Year
Running Time
Production Budget
Worldwide Gross
Rotten Tomatoes Rating
IMDB Rating

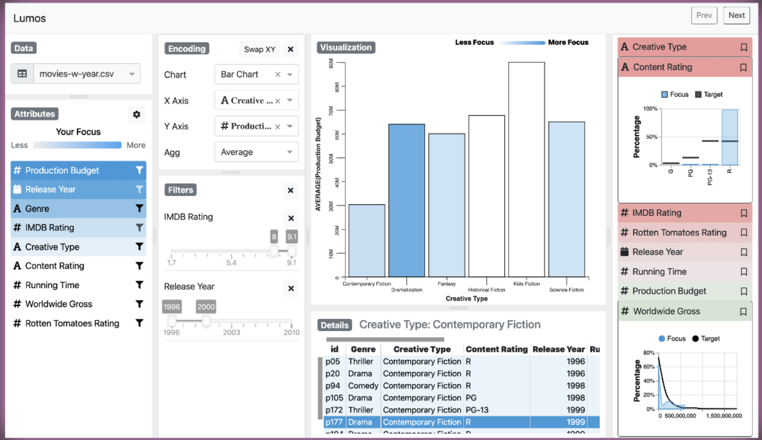
Between-Subjects Qualitative User Study

- 24 participants (1 hour each)
  - students, researchers, and industry professionals from a computing field
  - randomly divided into *two* groups:

Control [C]: <u>*without*</u> interaction traces



Awareness [A]: <u>*with*</u> interaction traces



Task

“Analyse a dataset of movies to recommend the characteristics of movies that a movie production company (e.g., Netflix) should make next.”

Lumos

Increased awareness of users' analytic behavior in real-time.

Promoted reflection upon and acknowledgement of their intentions.

Influenced subsequent interactions.

Increased user awareness … or the desire for it

"I see that I have spent a lot of time on Release Year, so I'll now see something else"

P05$_A$

*"I don't think **Release Year** should matter too much, hence I am not interacting with it"*

P04$_A$

*"Geez, I haven't looked at **Drama** at all (on seeing inside the **Genre** Distribution Card)"*

P07$_A$

"I hope I have interacted with all [attributes]"

P14$_C$

…used hand gestures to recollect and count the attributes they interacted with

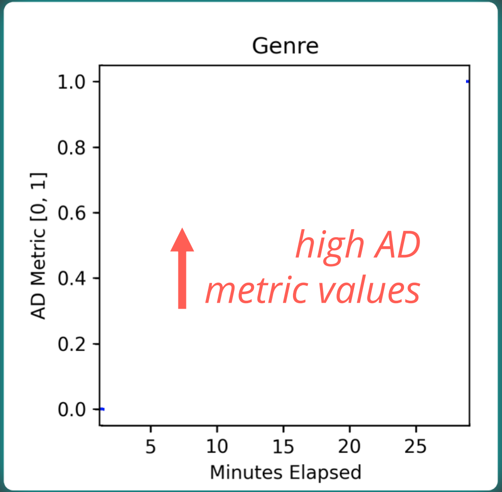
P13$_C$

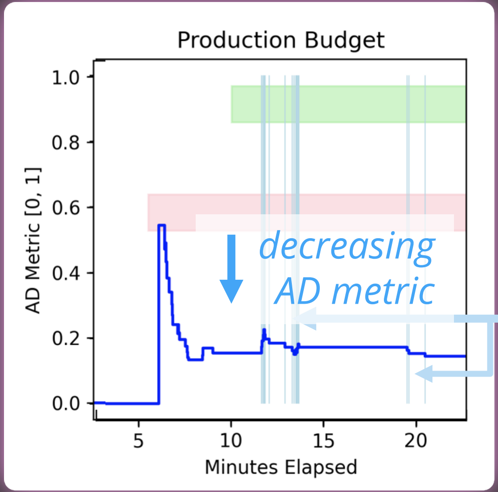
Influenced subsequent interactions

AD [Attribute Distribution, Wall et al. *"Warning, bias may occur…"*, VAST 2017]

0 → 1
Bias

P16$_C$





Assigned as an Encoding

Distribution Panel Card inspected

Interacted with datapoints

P01$_A$

Biased analytic behavior toward **Genre**.

Bias mitigating analytic behavior for **Production Budget**.

In-situ traces

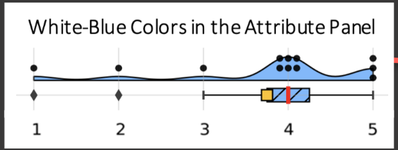
"I was initially confused but then over use I got used to them and found them useful in tracking visited points"

$P06_A$

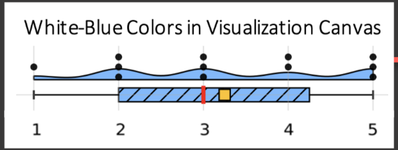
Median Utility Scores

5 = High, 1 = Low

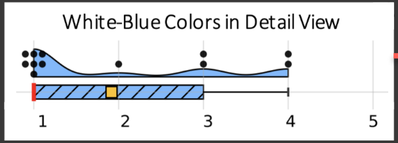
4 / 5

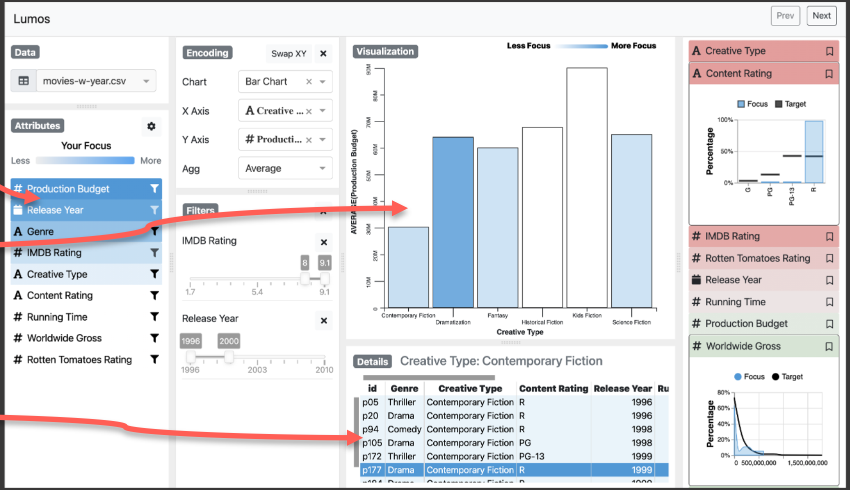


3 / 5



1 / 5





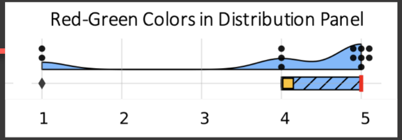
Ex-situ traces

> *"The Distribution Panel was a great idea to show users what their focus was"*

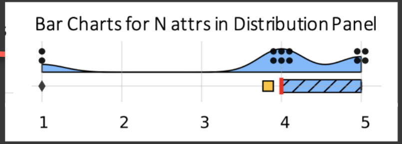
P09$_A$

Median Utility Scores

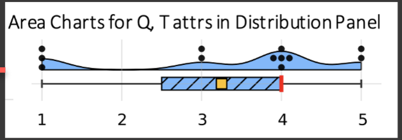
5 = High, 1 = Low



5 / 5

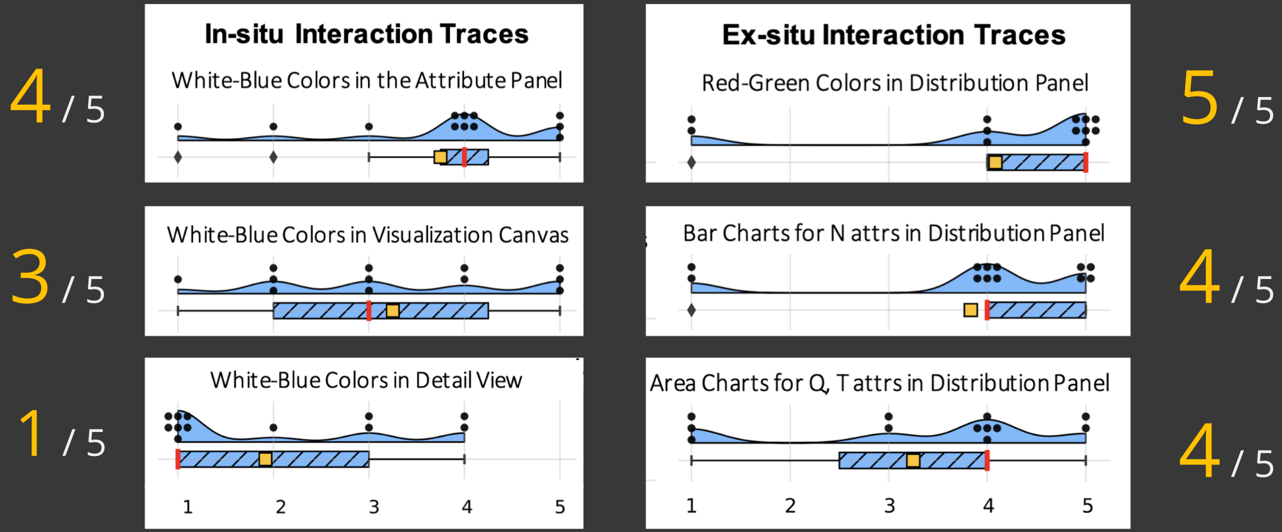


4 / 5



4 / 5

Ex-situ traces had more utility than in-situ



Why?

In-situ traces could be distracting at the place of interaction.

They also blocked out the color encoding channel.

Implications

- Color as an encoding channel

"Interacting [with points] and seeing colors change was fun"

Fun — $P08_A$

"I am getting drawn to the [already] visited points"

$P05_A$ — Distraction

"I confused the blue colors with an [attribute] encoding"

Confusion — $P02_A$

"making [Lumos] color-blind safe would be really important"

$P12_A$ — Accessibility

- If not color, other visual variables (e.g., stroke)?

Lessons Learned

- Encourage users to get lost in their analysis, but use awareness features to remind them

- Awareness of one's own activity is helpful but guidance towards best ways to mitigate may be better

> *"didn't know exactly what to do about the [red-green] cards"*

$P05_A$

> *"I wish there were a button to automatically apply a reverse filter [instead of me having to manually apply it]"*

$P01_A$

Also at VIS’2021…

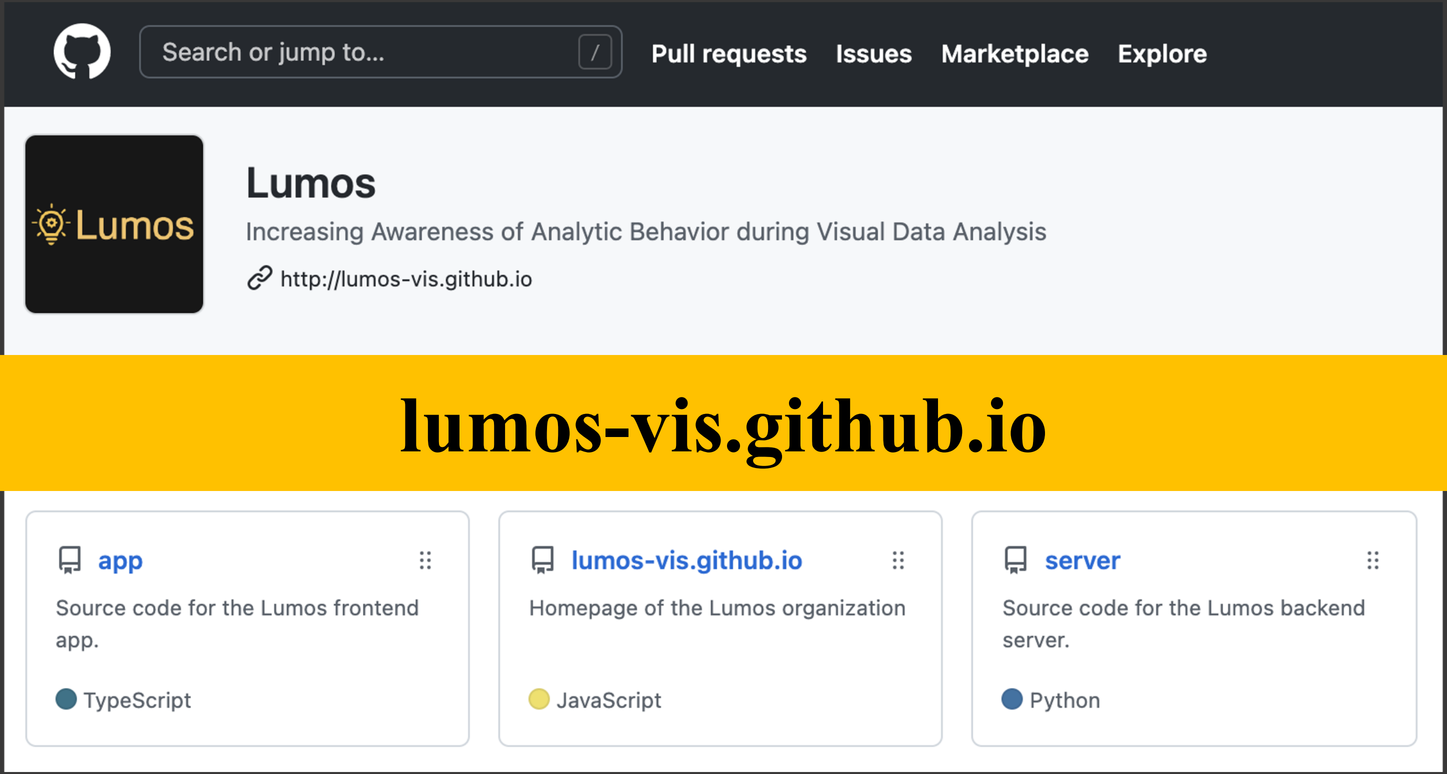
Left, Right, and Gender: Exploring Interaction Traces to Mitigate Human Biases

Emily Wall*, Arpit Narechania*, Adam Coscia, Jamal Paden, and Alex Endert

Abstract—Human biases impact the way people analyze data and make decisions. Recent work has shown that some visualization designs can better support cognitive processes and mitigate cognitive biases (i.e., errors that occur due to the use of mental “shortcuts”). In this work, we explore how visualizing a user’s interaction history (i.e., which data points and attributes a user has interacted with) can be used to mitigate potential biases that drive decision making by promoting conscious reflection of one’s analysis process. Given an interactive scatterplot-based visualization tool, we showed interaction history in *real-time* while exploring data (by coloring points in the scatterplot that the user has interacted with), and in a *summative* format after a decision has been made (by comparing the distribution of user interactions to the underlying distribution of the data). We conducted a series of in-lab experiments and a crowd-sourced experiment to evaluate the effectiveness of interaction history interventions toward mitigating bias. We contextualized this work in a political scenario in which participants were instructed to choose a committee of 10 fictitious politicians to review a recent bill passed in the U.S. state of Georgia banning abortion after 6 weeks, where things like gender bias or political party bias may drive one’s analysis process. We demonstrate the generalizability of this approach by evaluating a second decision making scenario related to movies. Our results are inconclusive for the effectiveness of interaction history (henceforth referred to as *interaction traces*) toward mitigating biased decision making. However, we find some mixed support that interaction traces, particularly in a summative format, can increase awareness of potential unconscious biases.

Index Terms—Human bias, bias mitigation, decision making, visual data analysis

Lumos is released as open-source software!



lumos-vis.github.io

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