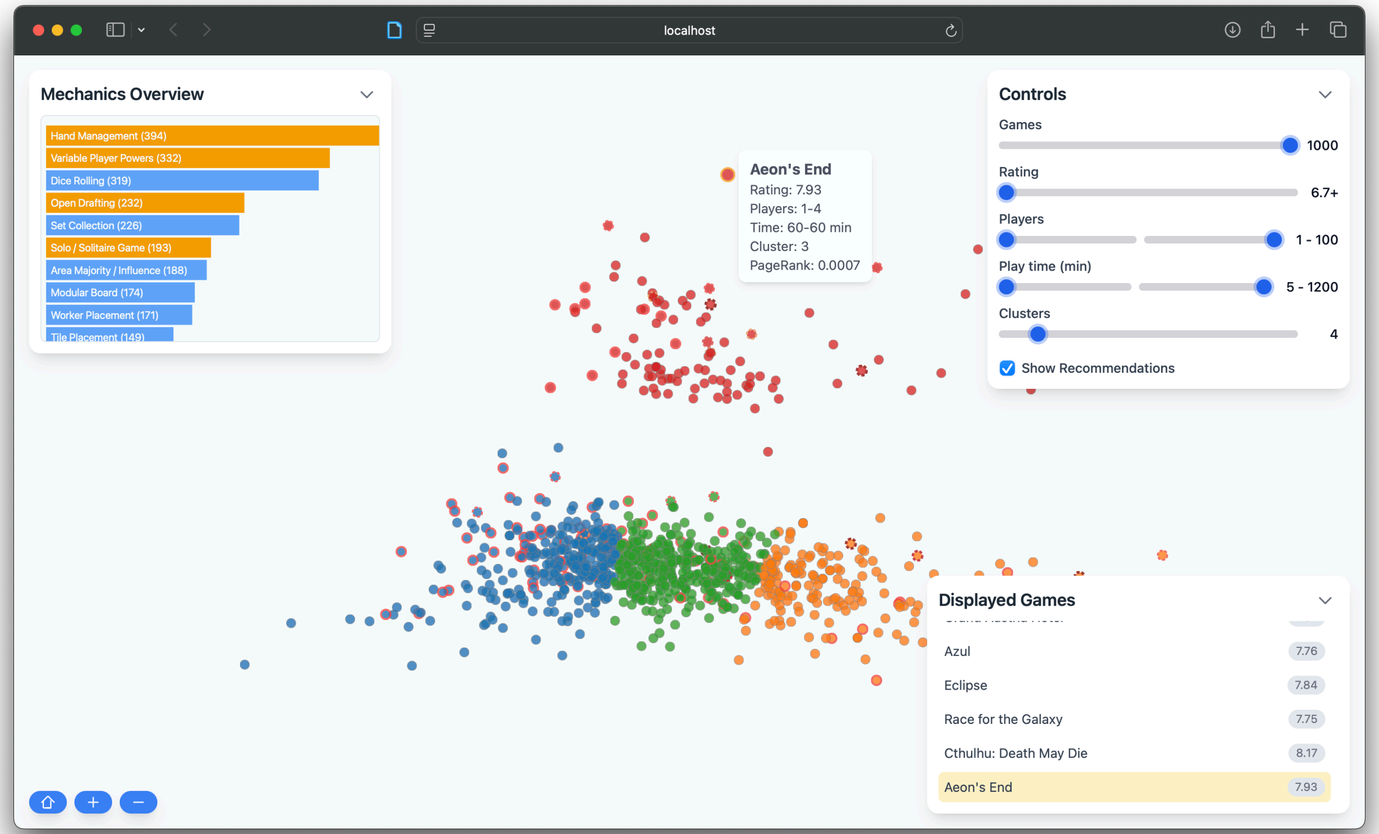
Visual Analytics Dashboard for Boardgames

Task 2: Group games that follow similar trends

Task 3: Investigate impact of mechanics on board game recommendations



Girish Mohan: Design (0.5 hrs), D3 visualization (3 hrs), Interactions (1 hr), Presentation (0.5 hrs).
Shashwata Sourav Roy Samya: Design (0.5 hrs), Preprocessing (3 hrs), Presentation (0.5 hrs).

The Data

- Two files: ***bgg_Gameitems.csv*** & ***recommendations-2021-12-31.csv***

- ***bgg_Gameitems.csv*** shape:
  113,904 rows, 37 columns

  recommendations-2021-12-31.csv shape:
  1000 rows, 37 columns

- ***bgg_Gameitems.csv*** key observations:
  Several ID-columns (**bga_id**, **dbpedia_id**, etc.) were 100% null.
  Metadata flags like **cooperative**, **implementation**, **integration** also >90% null

- ***recommendations-2021-12-31.csv*** key observations:
  28 recommendation columns; after **6**, null rate jumps to ~33%.
  Other fields (**Name**, **URL**, **Thumbnail**) are complete.

The Data Cleaning & Processing

- For **bgg_Gameitems.csv**:

  Dropped extremely sparse columns **(>90% null)**

  Removed redundant player-count variants
  Originally three sets of min/max player counts: **raw**, **recommended** and **best.**
  For most analyses, the raw counts suffice. Columns pruning leaves only **min_players** & **max_players.**

  Dropped the original **rank** column
  Final reduction from **37 → 19 columns**

  Parsing list-style fields
  mechanic, **family**, **categories** now a true Python **list[str]**

  Filled up null numeric fields with respective column's **median values**
  Filled up null categorical fields with **Unknown**

  Downcasting & **type refinement**
  year, ***play times***, ***ages***, ***ratings***, ***votes***: casted from **float64** to **float32**
  name, ***publisher***, ***game_type***, ***artist***: converted to pandas **category** dtype

  Re-ranked games by **bayesian estimate, secondarily** by **vote count**

The Data Cleaning & Processing

- For **recommendations-2021-12-31.csv**:

  Dropped sparse recommendation columns (>33% null): ***recommendation7*** to ***recommendation28***
  Collapsed the remaining recommendation columns into a single list-column ***fans_liked***

  Dropped *URL* and ***Thumbnail*** columns as they bloats the file and duplicates data we already have

  Lowercased and **renamed** columns for consistency
  (e.g. **ID → bgg_id**, **Average → avg_rating**, etc.).

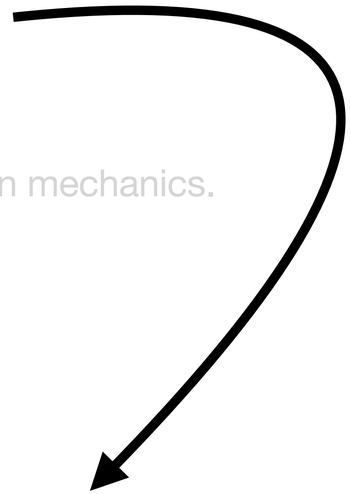
  Downcasting & **type refinement**
  Year and ***rank*** to **int16*; num_votes*** to **int32**
  avg_rating & ***bayes_rating*** to **float32**; **parsed *fans_liked*** into Python **list[int].**

The Data Cleaning & Processing

- **Merged** both dataframes which carries over **full metadata plus top-6 recommendations**
- **Renamed** any columns that appear twice in both datasets with a suffix ***_rec***
- **Constructed** JSON records and **exported** it to further visualization

Why these tasks?

- Task 2:
  “Which games have similar trends?"
  📌 An analyst can explore trends within clusters and understand what defines a cluster.
- Task 3:
  “Why a board game is recommended from another?"
  📌 An analyst can compare the similarity of recommended games and correlate based on mechanics.



Goal: *Explore*

Means: *Identify*

Target: *Trends*

Attribute: Mechanics

Cardinality: *All*

The user wants to (explore) and (identify) (trends) in board game (mechanics) for (all) games.

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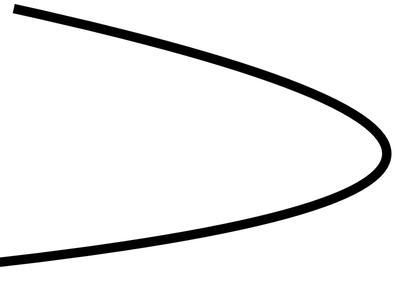

Goal: *Describe*

Means: *Locate*

Target: Correlate

Attribute: Score + Recommendation + Features

Cardinality: All

The user wants to (describe) and (locate) (correlations) that impact boardgames recommendations for (all) games.

How are these helpful?

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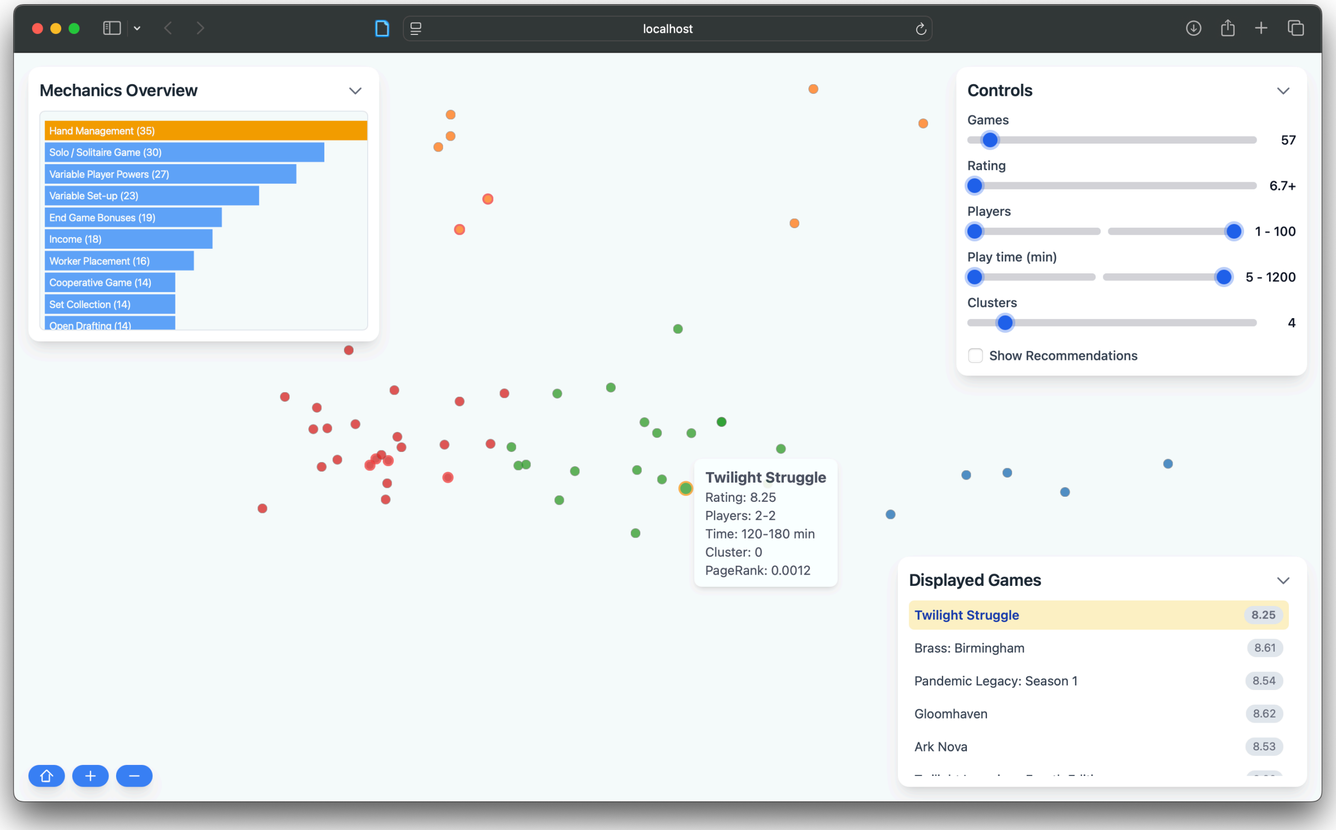

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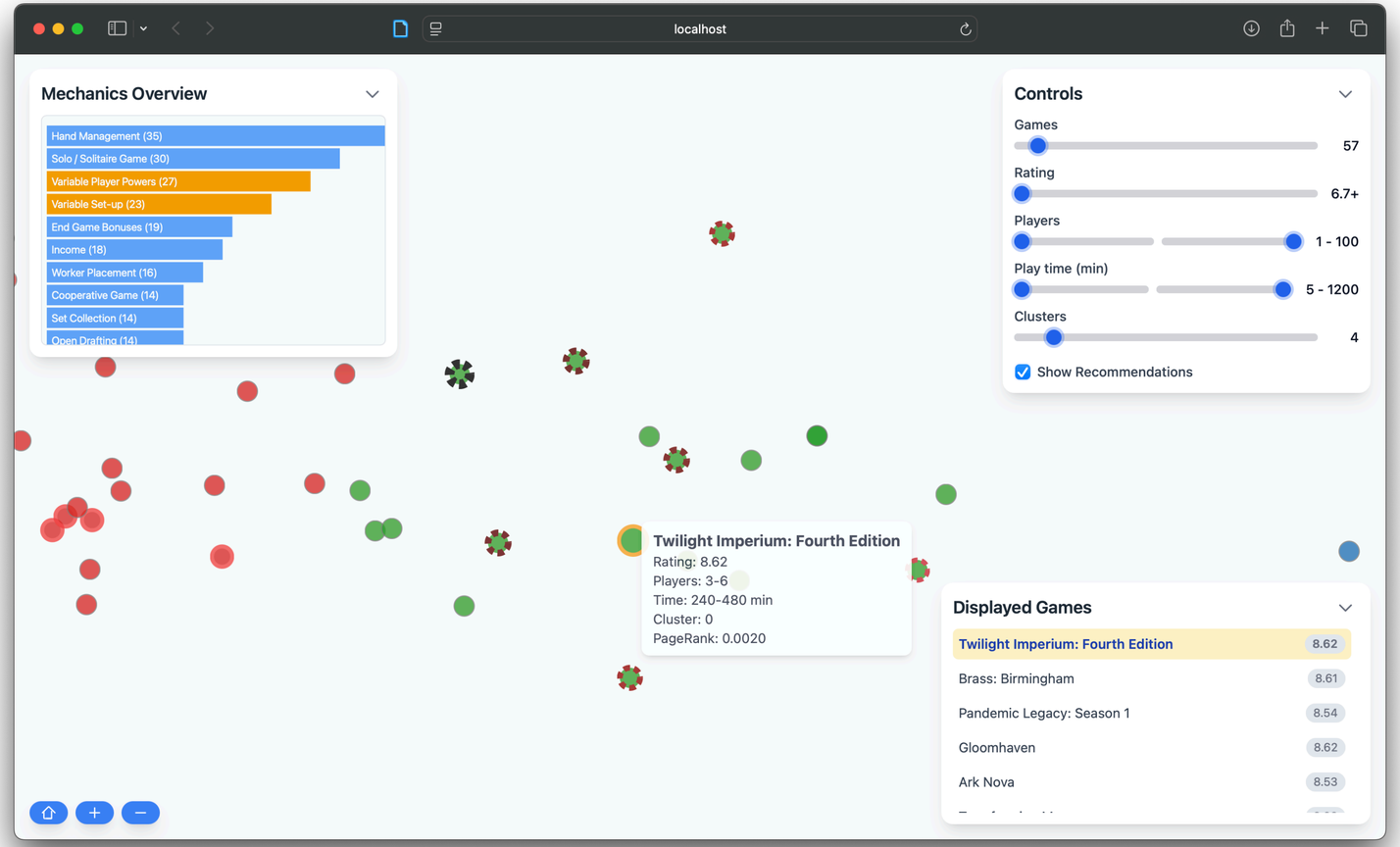

Demo

http://localhost:3000

What could be improved?

- Projection based on more features
- Panels clutter scatterplot
- More interactions