Reverse Recommendation of VTubers for Game Marketing

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Introduction

Problem: Traditional influencer marketing targets audience **size**, not **actual fit**.

- Subscriber count ignores streamer interests and social context
- Sponsored streams without genuine interest quickly lose impact
- Developers waste budgets by sending keys and sponsorships blindly

Question: Which creators are most likely to play a new game with genuine interest?

Idea: Invert the recommendation paradigm.
Instead of recommending games to players, we recommend players to developers.

Method

1. Acquire stream data via Holodex API
2. Clean and filter stream data
3. Generate list of games/topics and populate with tags from ontology
4. Build graph associating VTubers with their tag preferences (weighted)
5. Build social subgraph of collaborations (weighted)
6. Input tags for a hypothetical new game
7. Analyse graph and rank VTubers for marketing outreach

Scope & Data Source

Domain: VTubers (Hololive Production)

- ~120 VTubers
- ~120,000 historical streams

Data Source: Holodex API (JSON)

Data: (per stream)

- Stream topic/game
- Date
- Duration
- Collaboration partners / co-streamers

Tag Ontology: 20 tags

Tag Examples:

- multiplayer
- competitive
- fps

Tag Assignment: manual

Filtering: Non-game streams (art, cooking, etc.) are discarded.

Graph Construction

We build a bipartite social graph:
VTuber → played → Game
VTuber → collaborated with → VTuber

Edge weights:

- Recency (old streams matter less)
- Frequency (repeated play strengthens preference)
- Duration (long streams strengthen preference)

Node properties:

- Games annotated with content tags

Graph Analysis

Core Method:
Weighted bipartite projection with neighborhood-based influence propagation.

Supporting Analyses:

- Community Detection (Leiden) on collaboration graph
  - Reveals genre-oriented creator clusters
- Weighted degree centrality
  - Reflects overall activity and collaboration intensity
- Eigenvector centrality for social influence assessment
  - Measures a VTuber's connection to other socially important VTubers

Case Study #1

Input tags: fps, multiplayer, competitive

Rank	VTuber	Score	Content	Social	Degree	Eigen	Community	Tag_OR	Tag_AND
1	Nakiri Ayame	1	1	0.413	0.137	0.143	1	55.90%	55.90%
2	Robocosan	0.821	0.743	0.593	0.261	0.249	1	26.50%	19.20%
3	Tokoyami Towa	0.81	0.651	0.504	0.499	0.533	1	16.40%	15.60%
4	Shishiro Botan	0.744	0.539	0.491	0.725	0.749	1	9.40%	4.80%
5	Natsuiro Matsuri	0.599	0.583	0.404	0.19	0.149	0	13.40%	10.90%

Predictions include:

- VTubers with professional tournament backgrounds
- Creators known for streaming similar content
- Social clusters who regularly stream together

Case Study #2

Input tags: mystery, story, language_learning, education

Rank	VTuber	Score	Content	Social	Degree	Eigen	Community	Tag_OR	Tag_AND
1	Oozora Subaru	1	0.858	0.835	0.569	0.613	1	6.20%	0.00%
2	Shirakami Fubuki	0.912	0.655	0.756	1	1	1	1.10%	0.00%
3	Usada Pekora	0.894	0.82	0.88	0.528	0.379	0	2.90%	0.00%
4	Pavolia Reine	0.838	1	0.664	0.123	0.018	3	14.10%	0.00%
5	Kikirara Vivi	0.779	0.657	0.992	0.546	0.439	0	0.80%	0.00%

Output:

- A short, high-confidence outreach list.

Results & Discussion

Key Results:

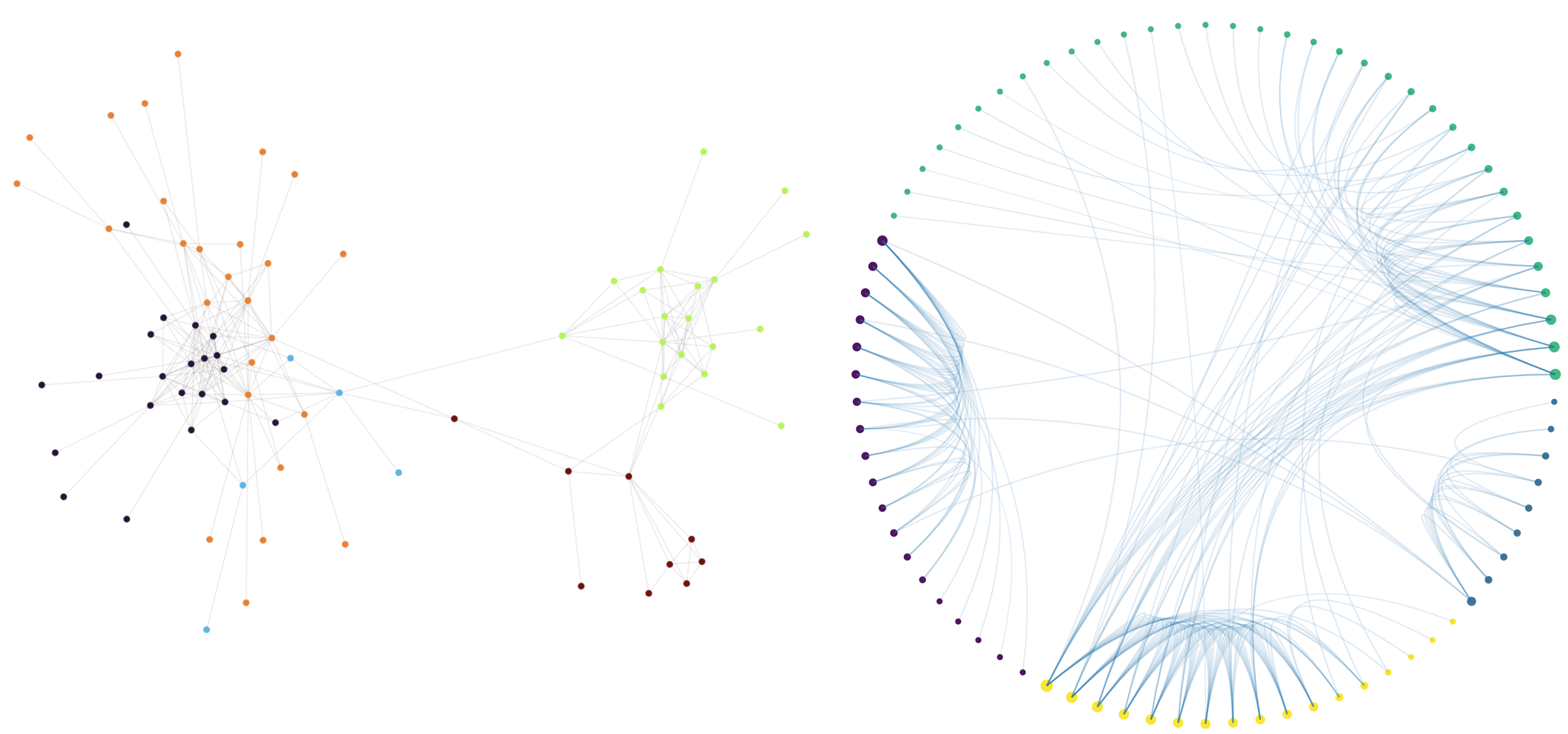
- Moves beyond subscriber-count targeting
- Captures interest, passion, and social influence
- Produces clear, ranked candidates for outreach
- Applicable both before and after a game is released

Impact:
For developers:

- Higher ROI on limited marketing budgets
- More authentic creator partnerships

For creators:

- Fewer irrelevant sponsorships
- More content aligned with personal interests



Figures: collaboration subgraph.

Conclusion & Future Work

Influence is not just views. It is relevance plus network effects. Our knowledge-graph approach transforms historical streaming data into a practical decision-making tool for modern game marketing.

Next steps:

- Automate tag assignment
- Apply natural language processing to stream transcripts and viewer chat to detect sentiment