Detecting Influencers in Very Large Social Networks of Games

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Conference | Research Institutes | Research funding

Introduction

Digital Games

- A popular form of entertainment reaching millions of players;
- Universe of games is in constant ascendancy.
  - both production and consumption;
  - estimated U$ 150 billion for 2019[1].

Universe of Games

- eSports: professional competition;
- Streamers: players who produce online videos;
- **Game Influencers:** professional players and streamers.

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- Exist since the popularization of social media;
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- High influence in new trends.

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- What are the influencers' characteristics?

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  - **Evolution of "likes"**, a trend of peaks.

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The evolution of "likes" over time.

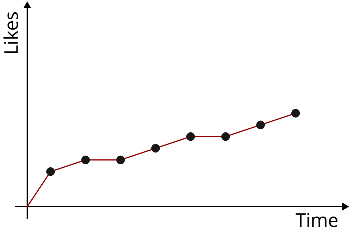

Figure: Normal player.

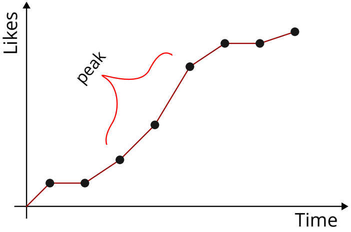

Figure: Game influencer.

Where are the influencers? In a **Platform of Games**.

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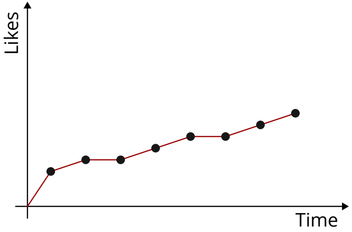

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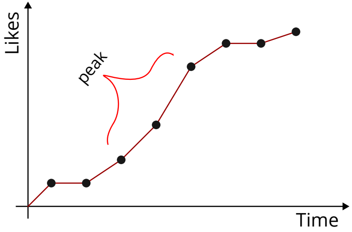

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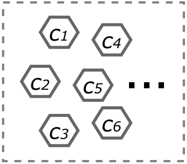
  - *e.g.*, develop
- **Social Networks of Games** (or simply SNG).

SNG can change over time...



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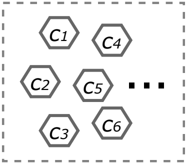

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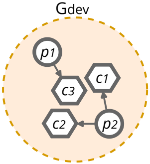

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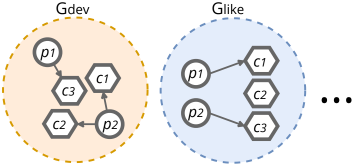

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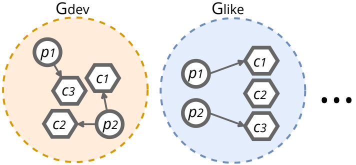

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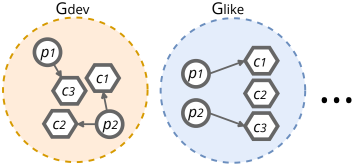

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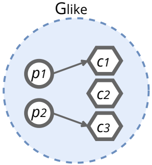

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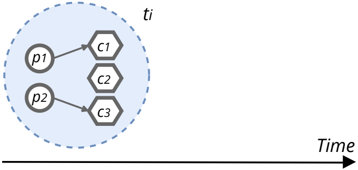

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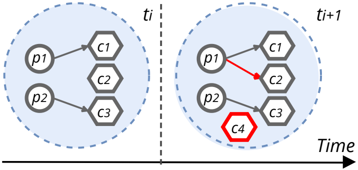

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Social Networks of Games (SNG)

A **Social Networks of Games**

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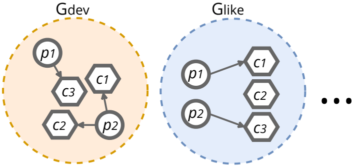

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Social Networks of Games (SNG)

Directed bipartite graph

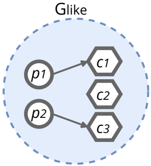
$G_{like} = \{V, E_{like}\}$

heterogeneous graph:

$p, c \in V$

directed links:

$e = (p, c) | e \in E_{like}$



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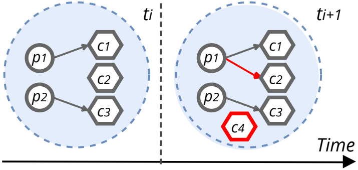

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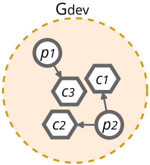

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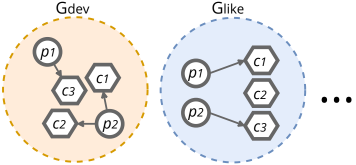

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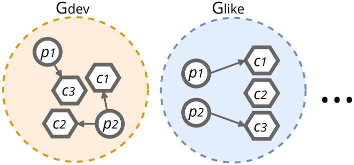

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How spot the influencers?

Influencer Detection

Influencer Detection in Social Network:

- There is no research on Social Networks of Games;
- We outline the *state-of-the-art*
  - Top-rank
    - Morone et al. (2016)
    - Wang et al. (2017)
  - Feature extraction
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Influencer Detection - *Top-rank*

Algorithms

- based-on centrality indices;
- developed to homogeneous network; *it's single type of node*
  - our problem is a heterogeneous network.
- developed to static network.
  - our problem is a dynamic network.

Example of Degree Centrality

- G_{dev}, rank by number of developed games.
- G_{like}, rank by number of likes given.
- Unfortunately, more elaborated techniques fail too.

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  - our problem has two or more networks.
- or heavily depend on specific node characteristics.
  - *e.g.*, in Chino et al. (2017), text of the comments.
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Conclusion

- These works **cannot** tackle our problem;
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Stream Modeling

Figure: G_{like} changing over time.

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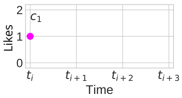

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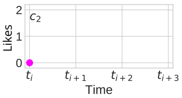

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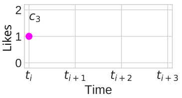

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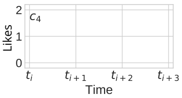

(d) c_4 stream

Figure: Stream Modeling on the toy G_{like}.

Figure: G_{like} changing over time.

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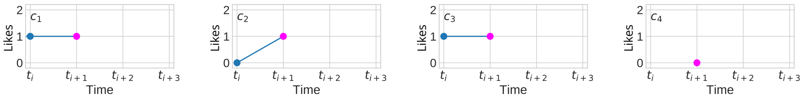

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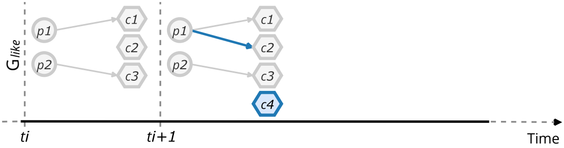

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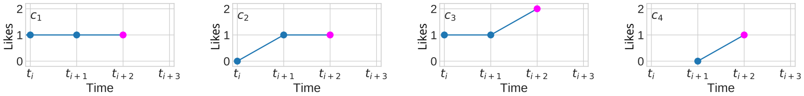

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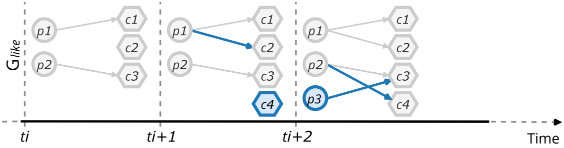

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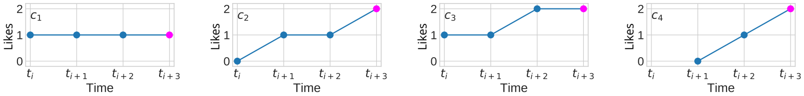

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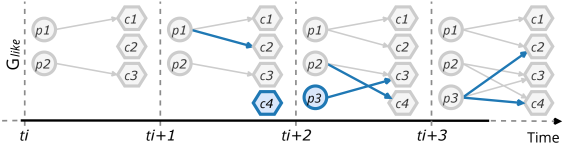

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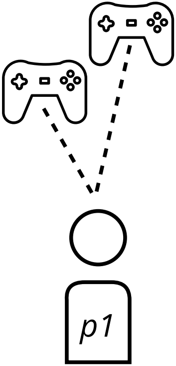
2. Extract features to be used by classification algorithms.
   a. Extract features from stream;
   b. Model the player.

Feature Extraction



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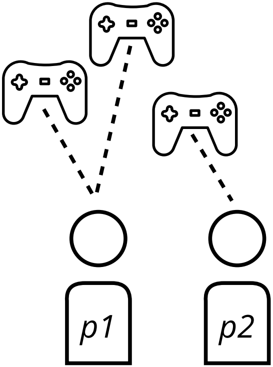

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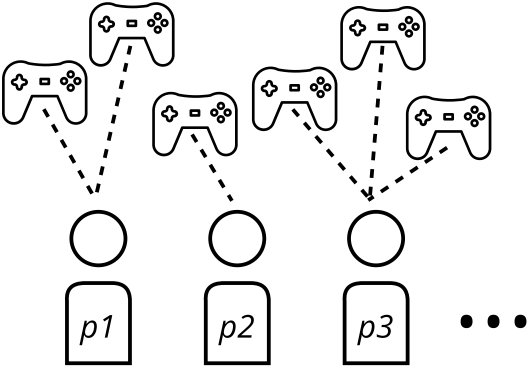

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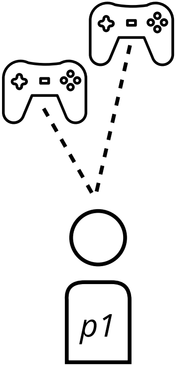

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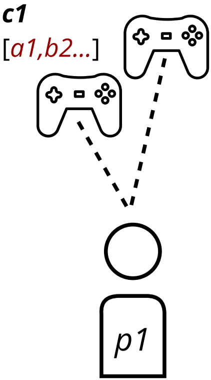

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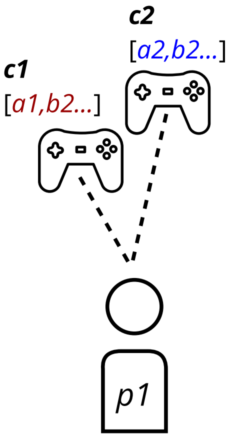

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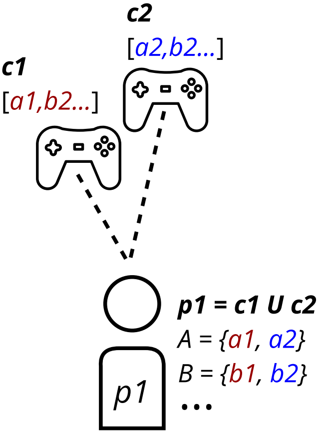

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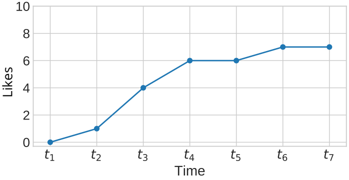
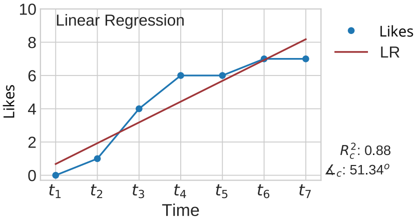


Figure: Stream example.

Linear Regression (LR)

Least Squares:
$f(t_i) = \alpha + \beta \cdot t_i$

- Model: $m_c = (\alpha, \beta)$
  $\alpha = 0.57$
  $\beta = 1.25$
- Measure: R_c^2
  $R_c^2 = 0.88$
- Angle: $\measuredangle_c$
  $\measuredangle_c = 51.34^o$



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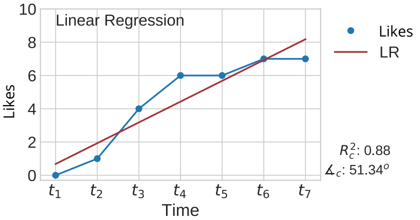
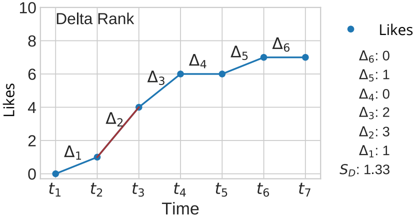


Delta Rank (DR)

$$\Delta = like_{i+1} - like_i$$
$$D_c = \{\Delta_1, \Delta_2, \ldots\}$$

- Set: D_c
  $D_c = \{1, 3, 2, 0, 1, 0\}$
- Entropy: S_{D_c}
  $S_{D_c} = 1.33$



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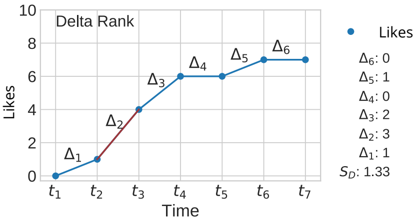


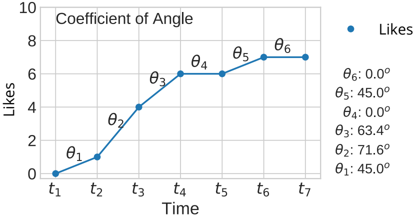
Coefficient of Angle (CA)

$$\theta = \arctan\left(\frac{like_{i+1} - like_i}{t_{i+1} - t_i}\right)$$

$$T_c = \{\theta_1, \theta_2, \ldots\}$$

- Set: T_c

  $T_c = \{45.0^0, 71.6^0, 63.4^0, 0, 45.0^0, 0\}$



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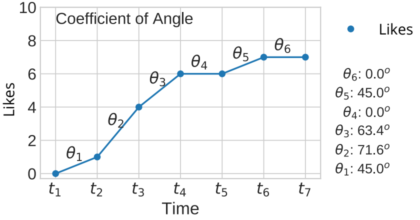

Feature Extraction

Table: Feature Extractors.

	Based on	Game's Features	Player Modeling
LR	Linear Regression	m_c, R^2_c, $\measuredangle_c$	$m_p = \{m_{c1}, m_{c2}, \dots\}$, $R^2 = \{R^2_{c1}, R^2_{c2}, \dots\}$, $\measuredangle = \{\measuredangle_{c1}, \measuredangle_{c2}, \dots\}$
DR	Difference	D_c, S_{D_c}	$D_p = D_{c1} \cup D_{c2} \cup \dots$, $S_p = \{S_{D_{c1}}, S_{D_{c2}}, \dots\}$
CA	Angle	T_c	$T_p = T_{c1} \cup_{c2} \cup \dots$

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CA	Angle	T_c	$T_p = T_{c1} \cup_{c2} \cup \dots$
F_{ALL}	Combination	$\dots$	$\dots$

Dataset

Super Mario Maker[2]

- Crawled daily by a 3-months period.

  +884k players and +75k game maps
  which received +380k likes.

Dataset

- Canadian (CAN) players - train/test
  - *Manually* labeled the top-100 players by the number of "likes", 41 influencers.
  - **consensus**: *influencers* who published in popular websites of the game community;
- French (FRA) players - generality test

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Features Extractors

- **Task**: Analyze each feature extractor;
  - LR, DR, CA, individually
  - F_{ALL}, combination
- Evaluated 28 classification algorithms;
  - standard input parameter
- Top-100 CAN players with a 5-fold cross-validation.

Features Extractors

Table: Top-3 best classifiers for each extractor.

	Classifier	Accuracy	Precision	Recall	F1-score
LR	Decision Tree	0.670 (±0.08)	0.621 (±0.11)	0.645 (±0.10)	0.595 (±0.10)
	Bernoulli NB	0.665 (±0.11)	0.432 (±0.15)	0.600 (±0.10)	0.489 (±0.13)
	Quadratic Disc.	0.665 (±0.11)	0.432 (±0.15)	0.600 (±0.10)	0.489 (±0.13)
DR	Decision Tree	0.690 (±0.07)	0.680 (±0.09)	0.658 (±0.07)	0.632 (±0.07)
	Extra Tree	0.670 (±0.07)	0.616 (±0.10)	0.653 (±0.08)	0.607 (±0.09)
	Gradient Boost.	0.670 (±0.06)	0.593 (±0.10)	0.613 (±0.06)	0.579 (±0.08)
CA	Gradient Boost.	0.740 (±0.07)	0.745 (±0.07)	**0.766** (±0.08)	0.722 (±0.07)
	Bagging	0.696 (±0.09)	0.648 (±0.10)	0.675 (±0.11)	0.640 (±0.10)
	Extra Tree	0.680 (±0.07)	0.650 (±0.09)	0.687 (±0.09)	0.644 (±0.08)
F_{ALL}	Logistic Reg.	**0.808** (±0.11)	**0.808** (±0.11)	0.733 (±0.16)	**0.745** (±0.14)
	Ridge CV	0.775 (±0.11)	0.733 (±0.13)	0.675 (±0.16)	0.685 (±0.14)
	Linear SVC	0.750 (±0.11)	0.750 (±0.11)	0.683 (±0.15)	0.688 (±0.14)

Parameter Tuning

- **Task**: Improve the top-3 classifiers (F_{ALL}).
  - Logistic Reg.
  - Ridge CV
  - Linear SVC
- Grid search through the hyperparameter space.
  - More than 2,500 tests;
  - Logistic Reg., 6 parameters ($C, dual, fit\_intercept, max\_iter, penalty, solver$)
  - Ridge CV, 4 parameters ($alphas, cv, fit\_intercept, store\_cv\_values$)
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Parameter Tuning

Table: Tuning the top-3 classifiers.

	Classifier	Accuracy	Precision	Recall	F1-score
Default F_{ALL}	Logistic Reg.	0.808 (±0.11)	0.808 (±0.11)	0.733 (±0.16)	0.745 (±0.14)
	Ridge CV	0.775 (±0.11)	0.733 (±0.13)	0.675 (±0.16)	0.685 (±0.14)
	Linear SVC	0.750 (±0.11)	0.750 (±0.11)	0.683 (±0.15)	0.688 (±0.14)
Tuning F_{ALL}	Logistic Reg.	**0.871** (±0.07)	**0.903** (±0.05)	**0.859** (±0.08)	**0.857** (±0.08)
	Ridge CV	0.806 (±0.22)	0.790 (±0.27)	0.823 (±0.21)	0.785 (±0.26)
	Linear SVC	0.839 (±0.09)	0.860 (±0.10)	0.831 (±0.10)	0.827 (±0.10)

Generality Test

- **Task**: Evaluated the generality of the feature extractor.
- Best Configuration
  - Extractor: F_{ALL}
  - Classifier: Logistic Reg. (*tuning*)
  - Train: Top-100 CAN players
- Find influencers in top-100 FRA players.

Generality Test

Influencer Detection

- Labeled 27 players as game influencers, *automatically*
- in which 21 were *manually* confirmed as true influencers.
- Precision: **77.8%**
- **Result:** A trained algorithm in one country was able to infer influencers in another nationality.

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Conclusion

- Novel framework to detect game influencers;
- Data stream modeling from Social Networks of Games;
- Three feature extraction techniques;
  - which model the evolution of "likes"
  - and extract player's features.
- Mapped the problem to a classification task;
  - Evaluated the extractors;
  - Parameter tuning;
  - Generality test.
    - which indicate that our proposal is generic to model the behaviour of influencers from different nationalities.
- **Future work:** Analyze other types of Social Networks.
  - *e.g.*, find influencers in Facebook.

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Thank you for your attention!

Questions?

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