

# Identifying Avatar Aliases in Starcraft 2

Unscrambling confusion matrices of behavioural classifiers

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LYON



MLSA@ECML/PKDD 2015, PORTO, PORTUGAL

Being or not a sport...



**League of Legends – NA LCS Summer Final  
Madison Square Garden in New York, NY (19 August 2015)**

## ... competitive gaming is raising drastically



- Video game is a lucrative industry
- People enjoy watching other playing (streaming via Twitch.tv)
- E-sports: professional *cyberathletes* with teams, commentators, sponsors, cash prizes, ... ; between sport and pure marketing



G. Cheung and J. Huang.

Starcraft from the stands: understanding the game spectator.

In *SIGCHI Conference on Human Factors in Computing Systems*. ACM, 2011, pp. 763–772.



M. Kaytoue, A. Silva, L. Cerf, W. Meira Jr. et C. Raïssi

Watch me playing, i am a professional: a first study on video game live streaming.

In *WWW 2012 (Companion Volume)*, pages 1181–1188. ACM, 2012.



T. L. Taylor

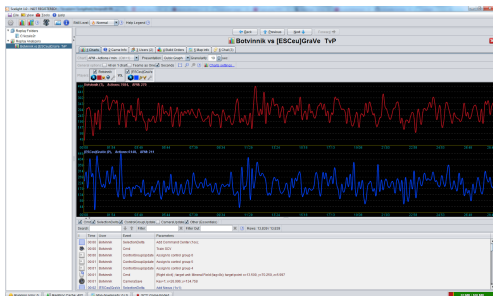
Raising the Stakes:E-Sports and the Professionalization of Computer Gaming.

In *MIT Press*, 2012.

# A lot of challenges

## Millions of games played on a daily basis

- Security issues
- Bugs, cheaters
- Balance issues
- Fun vs challenging agents
- Profiling & prediction
- Match preparation
- Playground for AI research



Arthur von Eschen

Machine Learning and Data Mining in Call of Duty (invited industrial talk).  
European Conference on Machine Learning and Knowledge Discovery in Databases,  
ECML/PKDD, Nancy, France, Sept. 2014)



S. Ontanon, G. Synnaeve, A. Uriarte, F. Richoux, D. Churchill, and M. Preuss,

A survey of real-time strategy game ai research and competition in starcraft.

Computational Intelligence and AI in Games, IEEE Transactions on, vol. 5, no. 4, pp. 293–311, 2013.)

## Players and teams observe game records of others

- Complete game logs are available
- Global ranking as well (such as ATP in tennis)

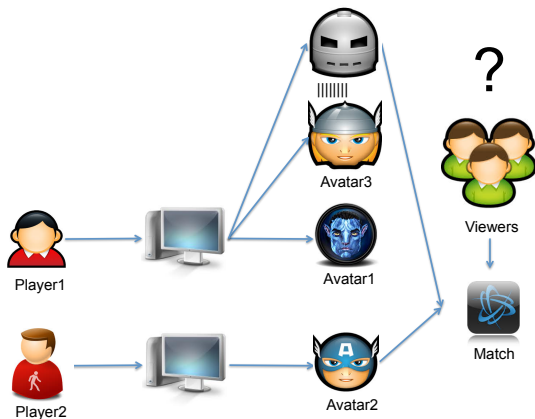
More and more players use several [un-]official accounts to hide their games and not being studied by the others

순위	플레이어
1번째	[플레이어 아이콘]
2번째	[플레이어 아이콘]
3번째	[플레이어 아이콘]
4번째	[플레이어 아이콘]
5번째	[토스는종말이] lifeisarisk
6번째	[플레이어 아이콘]
7번째	[플레이어 아이콘]
8번째	[플레이어 아이콘]
9번째	[플레이어 아이콘]
10번째	[플레이어 아이콘]
11번째	[플레이어 아이콘]
12번째	[플레이어 아이콘]
13번째	[플레이어 아이콘]
14번째	[플레이어 아이콘]
15번째	[플레이어 아이콘]
16번째	[imp] yoeFWLeenock

<http://leagueoflegends.wikia.com/wiki/Smurf>

[https://www.reddit.com/r/starcraft/comments/3gkfs0/sc2\\_who\\_is\\_that\\_smurf/](https://www.reddit.com/r/starcraft/comments/3gkfs0/sc2_who_is_that_smurf/)

# The problem



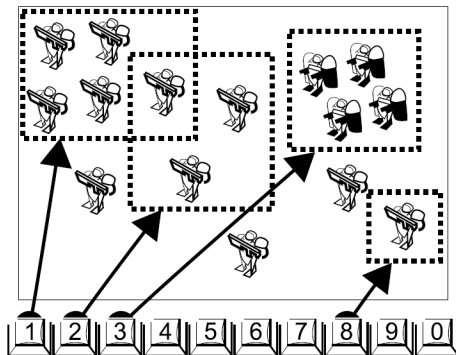
**Can we identify if two avatars belong to the same player?**

We have huge amounts of behavioural data!

- 1 Context
- 2 Predictive models from behavioural data**
- 3 Unscrambling models to identify aliases
- 4 Experimental validation
- 5 Conclusion

## The RTS game StarCraft 2: to improve strategy execution, players

- assign control groups to units and buildings,
- bind them to keyboard hotkeys (1, 2, ..., 9, 0),
- use them intensively along with the mouse.



Source: Yan et al., SIGCHI2015

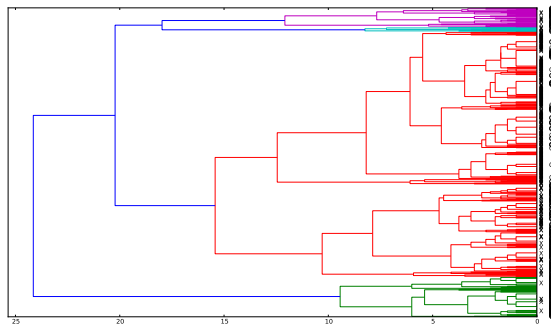
Avatar	Game trace	Outcome
Ror0	s,s,hotkey4a,s,hotkey3a,s,hotkey3s, ...	Lose
TAiLS	Base,hotkey1a,s,hotkey1s,s,hotkey1s, ...	Win



# Keyboard usage patterns

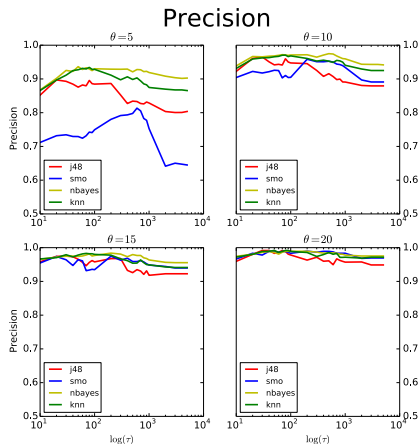
## Hypothesis

A player cannot hide behavioural patterns when changing avatars



**Dendrogram of a hierarchical clustering from 708 traces from 354 games: each color denotes a unique avatar**

# Predictive models with high accuracy



## Hotkeys hide unique patterns

- 20 first seconds of the game are enough
- 20 games are enough

We found a similar result, but considering on purpose dataset without avatar aliases, since precision drastically drops



Eddie Q. Yan, Jeff Huang, Gifford K. Cheung.

Masters of Control: Behavioral Patterns of Simultaneous Unit Group Manipulation in StarCraft2. In *CHI 2015, Crossings, Seoul, Korea 37–11*, 2015.

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## A prediction model $\rho : T \rightarrow L$ is learned

- $T$  a set of **traces**
- $L$  a set of trace **labels** (the avatars)
- $T_l$  the set of traces generated by avatar  $l \in L$

## The model is evaluated (e.g. cross-validation)

- $\rho(t) \in L$  return the model prediction for the trace  $t \in T$
- **Confusion matrix**  $\tilde{C}^\rho = [c_{i,j} / |T_{l_i}|]$  with  
 $c_{i,j} = |\{t \in T_{l_i} \text{ s.t. } \rho(t) = l_j\}|$

	$l_1$	$l_2$	$l_3$	$l_4$	$l_5$
$l_1$	0.6	0.4	0	0	0
$l_2$	0.4	0.55	0.05	0	0
$l_3$	0	0	0.8	0.15	0.05
$l_4$	0	0.05	0	0.7	0.25
$l_5$	0	0	0	0.5	0.5

Idea: two avatars of the same player should draw a high confusion

	$l_1$	$l_2$	$l_3$	$l_4$	$l_5$
$l_1$	<b>0.6</b>	<b>0.4</b>	0	0	0
$l_2$	<b>0.4</b>	<b>0.55</b>	0.05	0	0
$l_3$	0	0	<b>0.8</b>	0.15	0.05
$l_4$	0	0.05	0	<b>0.7</b>	<b>0.25</b>
$l_5$	0	0	0	<b>0.5</b>	<b>0.5</b>

We are searching for pairs of labels that concentrate the fusion (arbitrary sets are left for later)

- $\tilde{C}_{ij}^p \simeq \tilde{C}_{ji}^p \simeq \tilde{C}_{ii}^p \simeq \tilde{C}_{jj}^p$
- $\tilde{C}_{ij}^p + \tilde{C}_{ji}^p + \tilde{C}_{ii}^p + \tilde{C}_{jj}^p \simeq 2$

	...	$l_i$	$l_j$	...
...	...			
$l_i$	...	$C_{i,i}$	$C_{i,j}$	...
$l_j$	...	$C_{j,i}$	$C_{j,j}$	...
...	...			

# Method (1/2): extract fuzzy concepts

## Formal Concept Analysis (FCA) with a fuzzy set intersection

- Each label (row) is considered as a fuzzy set
- Labels and their (fuzzy) intersections  $\sqcap$  form a semi-lattice
- Closed sets are extracted and scored (monotone constraint possible)



M. Kaytoue, V. Codocedo, A. Buzmakov, J. Baixeries, S.O. Kuznetsov, A. Napoli:  
Pattern Structures and Concept Lattices for Data Mining and Knowledge Processing.  
ECML/PKDD 2015, Nectar track

## Example

	$l_1$	$l_2$	$l_3$	$l_4$	$l_5$
$l_1$	0.6	0.4	0	0	0
$l_2$	0.4	0.55	0.05	0	0
$l_3$	0	0	0.8	0.15	0.05
$l_4$	0	0.05	0	0.7	0.25
$l_5$	0	0	0	0.5	0.5

$$\delta(l_1) = \{l_1^{0.6}, l_2^{0.4}, l_3^0, l_4^0, l_5^0\}$$

$$\delta(l_2) = \{l_1^{0.4}, l_2^{0.55}, l_3^{0.05}, l_4^0, l_5^0\}$$

$$d = \delta(l_1) \sqcap \delta(l_2) = \{l_1^{0.4}, l_2^{0.4}, l_3^0, l_4^0, l_5^0\}$$

$$\text{support}(d) = \{l_1, l_2\}$$

$$s(d) = \sum_{j=1}^{|L|} d^j = 0.8$$

**The pair  $(l_1, l_2)$  is an avatar alias candidate**

## Method (2/2): rank and filter pairs

### Candidate pairs are scored

- A cosine similarity is used, the highest the better

$$\text{cluster\_score}(a_i, a_j) = \text{cosine}(\langle \tilde{C}_{ii}^\rho, \tilde{C}_{ij}^\rho \rangle, \langle \tilde{C}_{jj}^\rho, \tilde{C}_{ji}^\rho \rangle)$$

	...	$l_i$	$l_j$	...
...	...			
$l_i$	...	$C_{i,i}$	$C_{i,j}$	...
$l_j$	...	$C_{j,i}$	$C_{j,j}$	...
...	...			

- Why?

	$a_i$	$a_j$
$a_i$	1	0
$a_j$	1	0

$$\text{cosine}(\langle 1, 0 \rangle, \langle 0, 1 \rangle) = 0$$

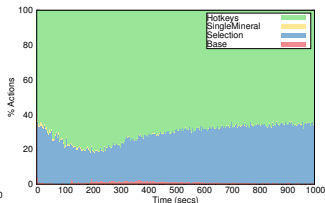
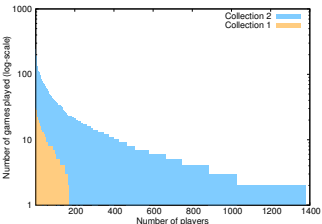
Candidates are ranked; the list is cut with a threshold if necessary

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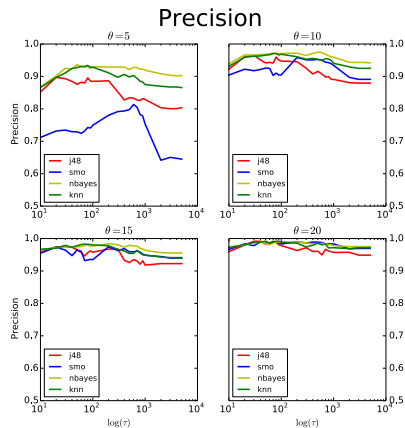
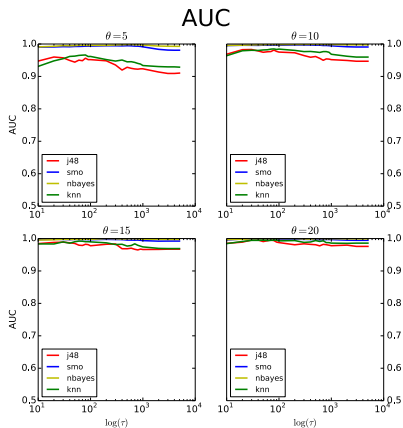


## Datasets

- Collection 1 - 2014 World Championship Series: 955 one-versus-one high level games and 171 unique players
- Collection 2 - *Spawning Tool* Website crawl July 2014: 10,108 one-versus-one games and 3,805 players



# Chosen features allow powerful prediction



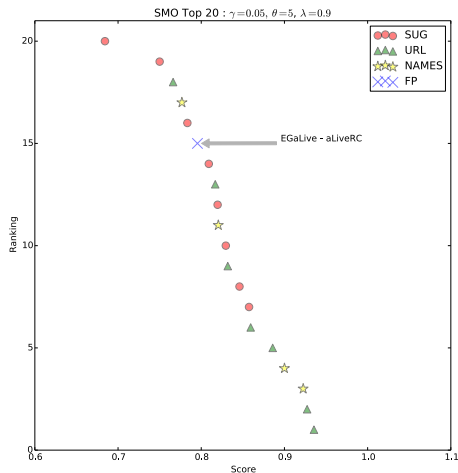
# Building a ground truth and evaluating aliases retrieval

Idea: each class is split into several; can we retrieve them?

Parameters: $\gamma = 0.2, \theta = 20, \lambda = 0.9, \tau = 90$						
<b>Surrogates</b>						
Classifier	F1	MAP	Recall	AUC	Precision	P@10
<i>j48</i>	0.468	0.824	0.805	0.904	0.33	1.0
<i>naivebayes</i>	0.226	0.740	0.390	0.915	0.16	0.8
<i>smo</i>	0.312	0.971	0.536	0.993	0.22	1.0
<i>knn</i>	0.567	0.822	0.976	0.882	0.4	0.9
<b>Surrogates &amp; URLs</b>						
Classifier	F1	MAP	Recall	AUC	Precision	P@10
<i>j48</i>	0.588	0.907	0.606	0.866	0.57	1.0
<i>naivebayes</i>	0.443	0.857	0.457	0.864	0.43	1.0
<i>smo</i>	0.257	0.912	0.266	0.945	0.25	1.0
<i>knn</i>	0.670	0.937	0.691	0.874	0.65	1.0
<b>Surrogates &amp; URLs &amp; Names</b>						
Classifier	F1	MAP	Recall	AUC	Precision	P@10
<i>j48</i>	0.689	0.983	0.606	0.935	0.8	1.0
<i>naivebayes</i>	0.560	0.943	0.492	0.906	0.65	1.0
<i>smo</i>	0.258	0.949	0.227	0.960	0.3	1.0
<i>knn</i>	0.758	0.967	0.667	0.792	0.88	1.0

# About false positive

- Some FP are not (same unique id hidden for the experiments)
- Some FP with high score are actually the avatars we are looking for!



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## Take away facts

- Games traces hide individual patterns
- In StarCraft 2, via customizable keyboard usage
- When avatar aliases are present, one needs to unscramble the confusion matrix
- We proposed a method rooted in formal concept analysis with promising results
- More details to be found (Cavadenti et al., DSAA15)



O. Cavadenti, V. Codocedo, J.-F. Boulicaut, M. Kaytoue

When Cyberathletes Conceal Their Game: Clustering Confusion Matrices to Identify Avatar Aliases.  
IEEE International Conference on Data Science and Advanced Analytics, Paris, France, October 2015

- Next: other games ; other methods

**Thanks for listening!**