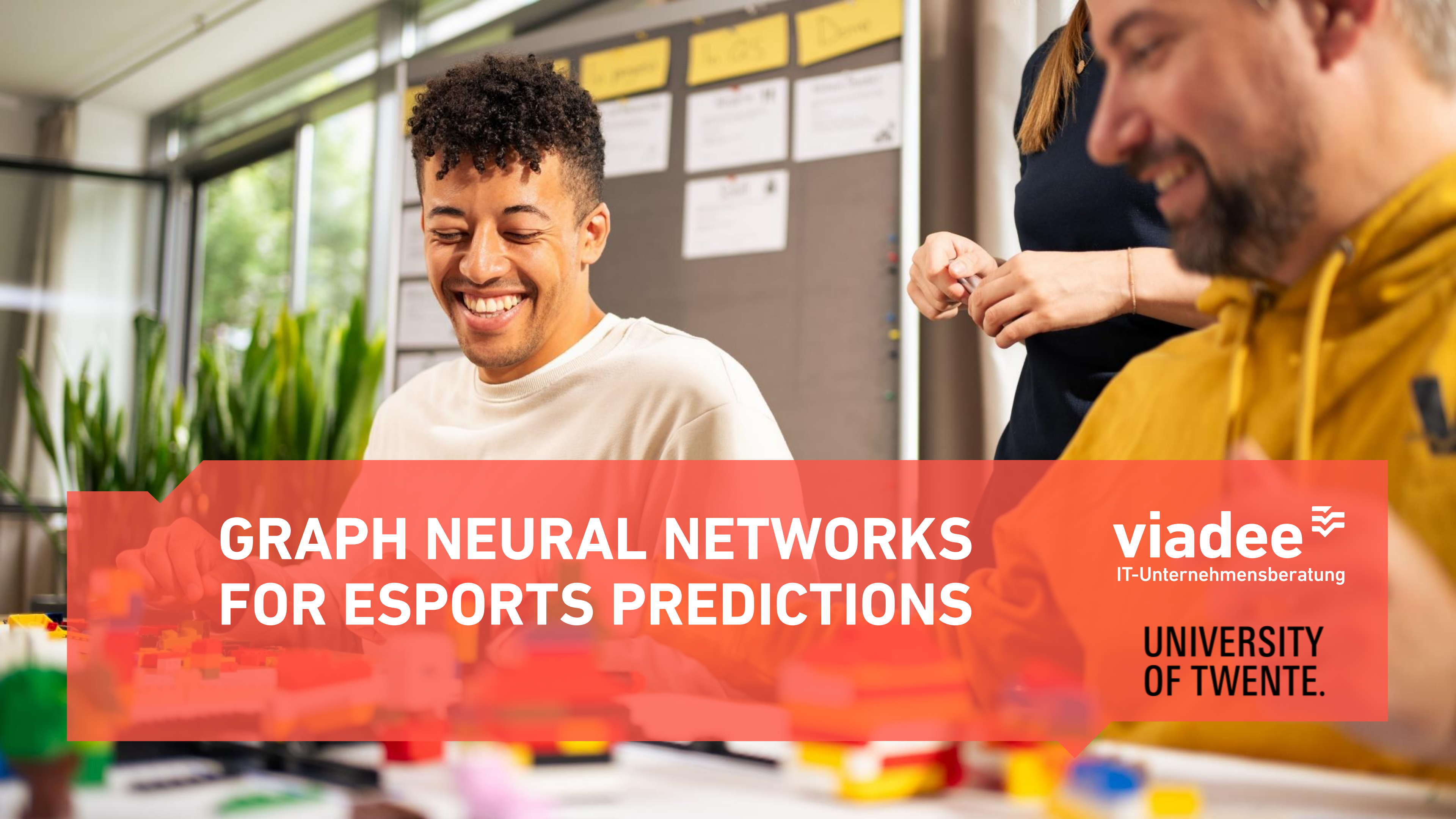

GRAPH NEURAL NETWORKS FOR ESPORTS PREDICTIONS

viadee
IT-Unternehmensberatung

UNIVERSITY OF TWENTE.

Image: Sky Sports

PIVOT: A Parsimonious End-to-End Learning Framework for Valuing Player Actions in Handball Using Tracking Data

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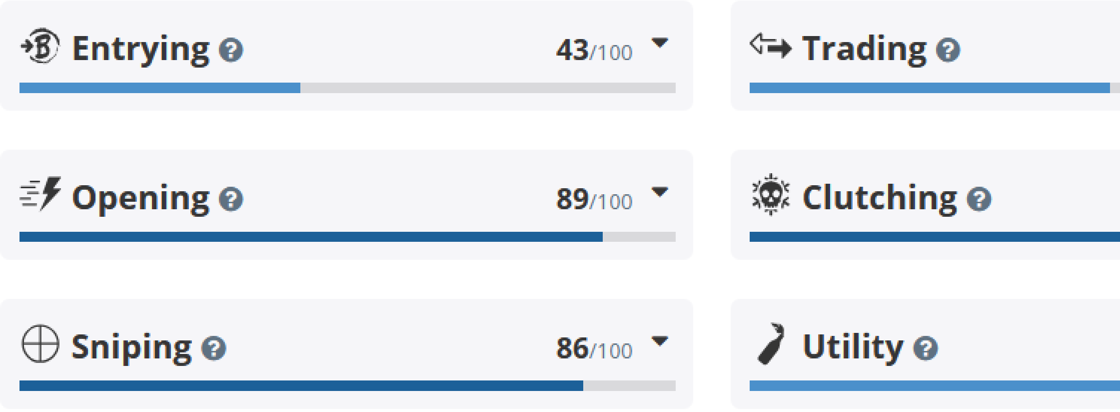
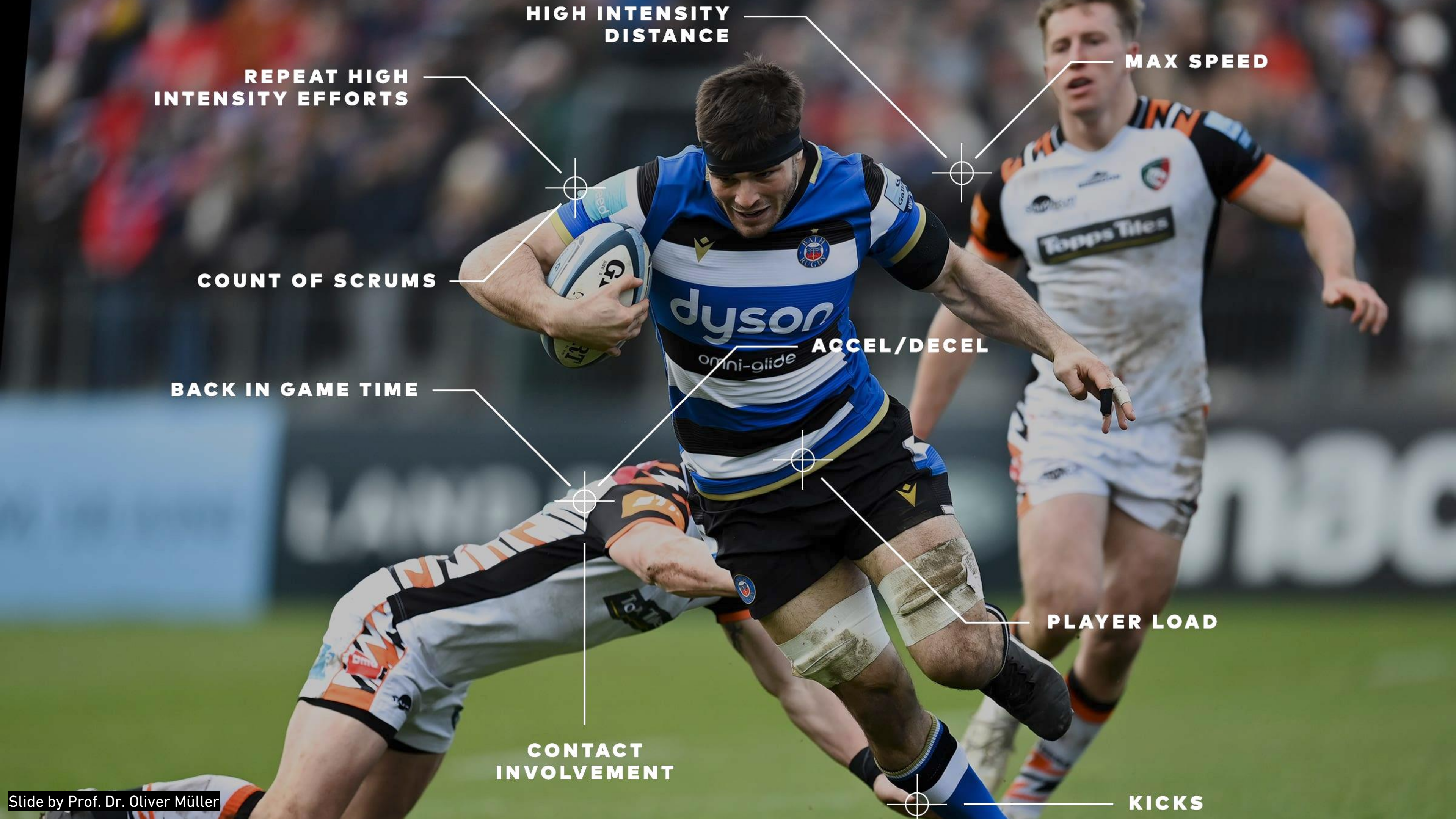
Abstract. Over the last years, several approaches for the data-driven estimation of expected possession value (EPV) in basketball and association football (soccer) have been proposed. In this paper, we develop and evaluate PIVOT: the first such framework for team handball. Accounting for the fast-paced, dynamic nature and relative data scarcity of handball, we propose a parsimonious end-to-end deep learning architecture that relies solely on tracking data. This efficient approach is capable of predicting the probability that a team will score within the near future given the fine-grained spatio-temporal distribution of all players and the ball over the last seconds of the game. Our experiments indicate that PIVOT is able to produce accurate and calibrated probability estimates, even when trained on a relatively small dataset. We also showcase two interactive applications of PIVOT for valuing actual and counterfactual player decisions and actions in real-time.

Keywords: expected possession value · handball · tracking data · time series classification · deep learning

Images: hltv.org



Contents



Slide by Prof. Dr. Oliver Müller

PERFORMANCE PSYCHOLOGY
&
HEALTH

TEAM ANALYSIS

PLAYER
ANALYSIS

EYE TRACKING

IN GAME
PERFORMANCE
ANALYSIS

INPUT ANALYSIS

Slide by Dr. Guido Bruinsma

Complete Information

Image: noesis.gg

Frame Number (sampled at 2 Hz)

Name

Resources: Money & Equipment

Position & Movement

... and many more Columns, currently ca. 42

frameNumb	tick	playerNan	money	equippedWeapon	positionX	positionY	positionZ	velocityX	velocityY	velocityZ
0	39648	huNter	2300	Knife	-1890.52783203125	-1926.513916015625	-272.6513977050781	24.067602157592773	207.66348266601562	0
0	39648	NiKo	2250	USP-S	-1647.7130126953125	-1751.55078125	-267.00885009765625	2.8965365886688232	212.3131713867875	0
0	39648	m0NESY	2700	Knife	-1917.4442138671875	-1988.952392578125	-275.78729248046875	217.28811645507812	16.706663131713867	0
0	39648	jks	3050	Smoke Grenade	-1862.55419921875	-1852.1279296875	-269.392333984375	163.14450073242188	-149.42337036132812	0
0	39648	HooXi	1500	Knife	-1588.443603515625	-2100.6005859375	-261.7655334472656	195.41571044921875	-40.07478332519531	0
0	39648	YEKINDAR	450	Knife	1194.6082763671875	34.34914779663086	-163.96875	-89.71636199951172	207.30368041992198	0
0	39648	EliGE	50	Knife	1257.71435546875	-129.3793487548828	-167.96875	-174.17926025390625	116.17582702636719	0
0	39648	nitr0	100	Knife	1352.462158203125	32.7823486328125	-167.96875	-60.999237060546875	207.0345458984375	0
0	39648	NAF-FLY	350	Smoke Grenade	1349.2615966796875	-347.0602722167969	-167.96875	220.2783660888672	20.513959884643555	0
0	39648	oSee	0	Smoke Grenade	1291.2513427734375	-64.99573516845703	-129.70213317871094	-29.361520767211914	-6.156399726867676	167.61837768554688
1	39776	huNter	2300	Knife	-1738.5645751953125	-1751.976318359375	-265.7339782714844	174.7530975341797	167.43191528320312	0
1	39776	m0NESY	2700	Knife	-1733.7813720703125	-1887.3614501953125	-269.3951110839844	187.29823303222656	129.50033569335938	0
1	39776	HooXi	1500	Knife	-1401.8992919921875	-2242.906982421875	-231.3541259765625	225.61524963378906	-107.69291687011719	0
1	39776	NiKo	2250	USP-S	-1701.48291015625	-1522.598388671875	-260.2001037597656	-45.145591735839844	235.71566772460938	0
1	39776	jks	2450	Smoke Grenade	-1682.6693115234375	-2015.855224609375	-267.4348449707031	184.0242156982422	-161.74081420898438	0
1	39776	EliGE	50	Knife	1167.0523681640625	91.2852554321289	-167.70266723632812	1.4166944026947021	249.13259887695312	0
1	39776	YEKINDAR	450	Knife	1111.1298828125	269.0081481933594	-110.6728744506836	-91.596817		
1	39776	oSee	0	Knife	1244.753173828125	7.93682336807251	-167.96875	-49.343482		
1	39776	NAF-FLY	350	Smoke Grenade	1422.9967041015625	-367.96270751953125	-167.96875	0		
1	39776	nitr0	100	Knife	1272.0584716796875	265.54974365234375	-199.96875	-118.98352		
2	39904	NiKo	2250	Incendiary Grenade	-1671.8433837890625	-1290.548583984375	-260.2633361816406	126.888404		
2	39904	jks	2250	Flashbang	-1496.50927734375	-2177.349609375	-247.2598876953125	185.301208		

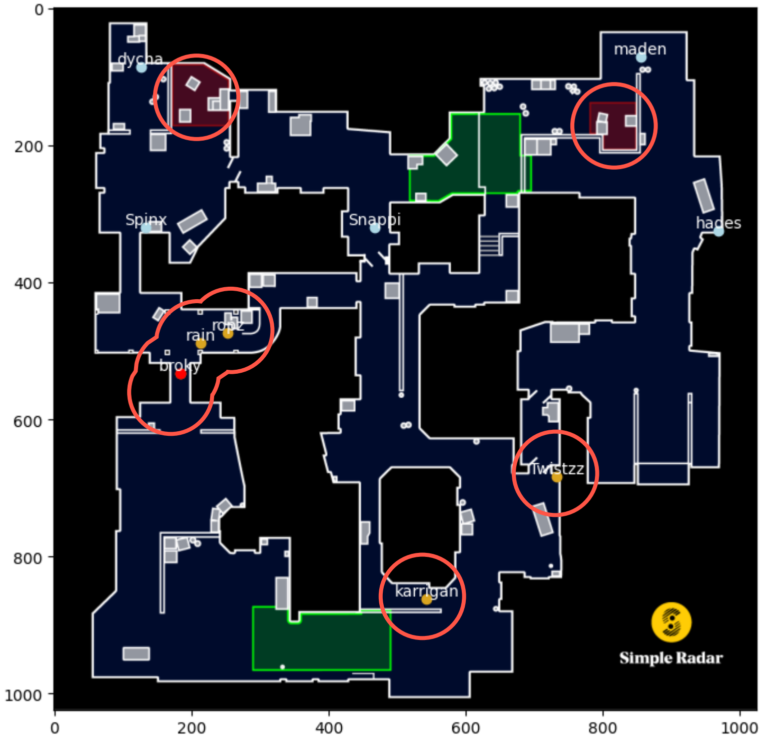
128 Events per Player per Second (> 50.000 Events per Round)

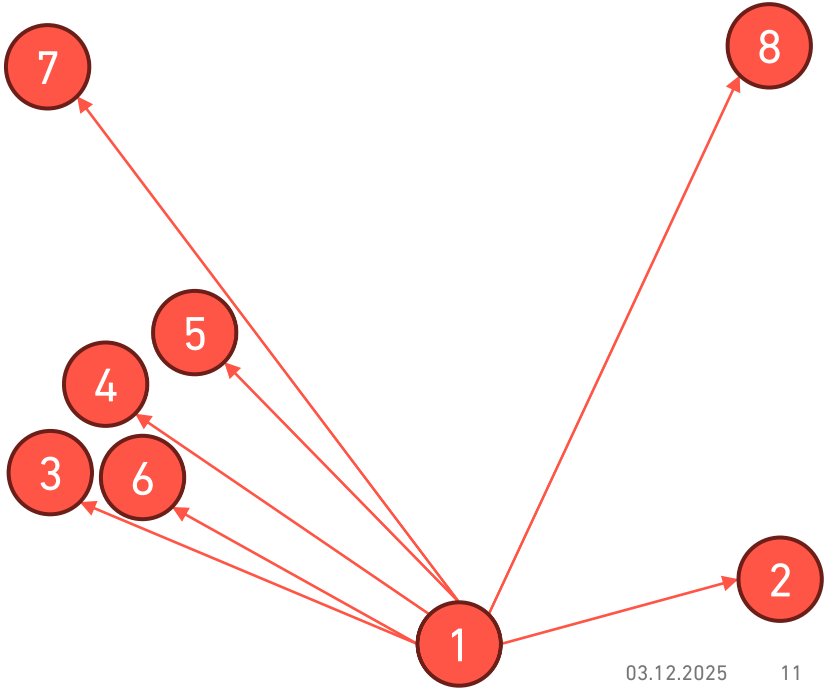
Contents

Counter-Strike as Graph

Complete Digraph
1-5: Players
6: Bomb
7-8: Bombsites A & B

From Game to Graph $G = (V, E, U)$





Counter-Strike as Graph

Complete Digraph

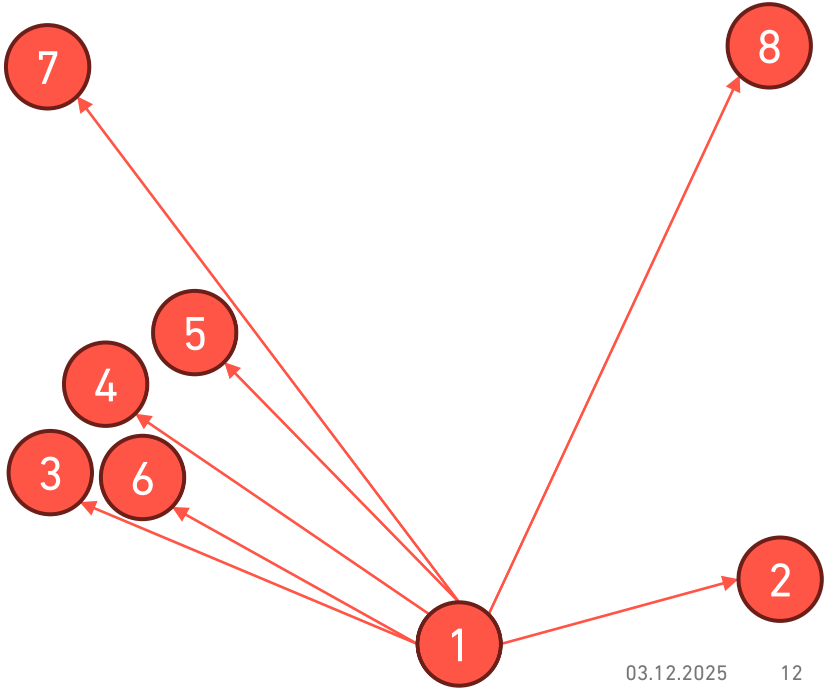
1-5: Players

6: Bomb

7-8: Bombsites A & B

From Game to Graph $G = (V, E, U)$

$$E = \begin{pmatrix} 0, 1, 2, 2, 2, 2, 4, 4 \\ 0, 0, 0, 0, 0, 0, 0, 0 \\ 0, 0, 0, 0, 0, 0, 0, 0 \\ 0, 0, 0, 0, 0, 0, 0, 0 \\ 0, 0, 0, 0, 0, 0, 0, 0 \\ 0, 0, 0, 0, 0, 0, 0, 0 \\ 0, 0, 0, 0, 0, 0, 0, 0 \\ 0, 0, 0, 0, 0, 0, 0, 0 \end{pmatrix}$$



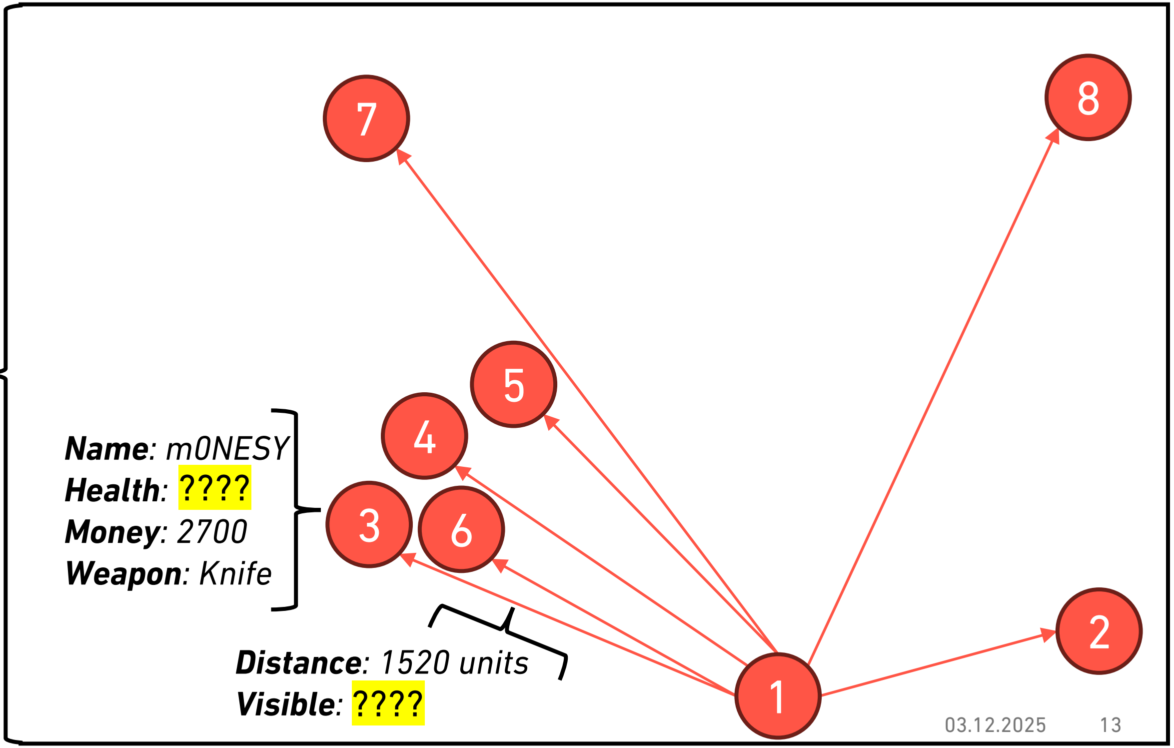
Counter-Strike as Graph

Data in the Graph

$\mathrm{G} = (V, E, U)$ mapping.

playerNan	money	equippedWeapon	positionX
huNter	2300	Knife	-1890.5278320312
NiKo	2250	USP-S	-1647.713012695
m0NESY	2700	Knife	-1917.4442138671

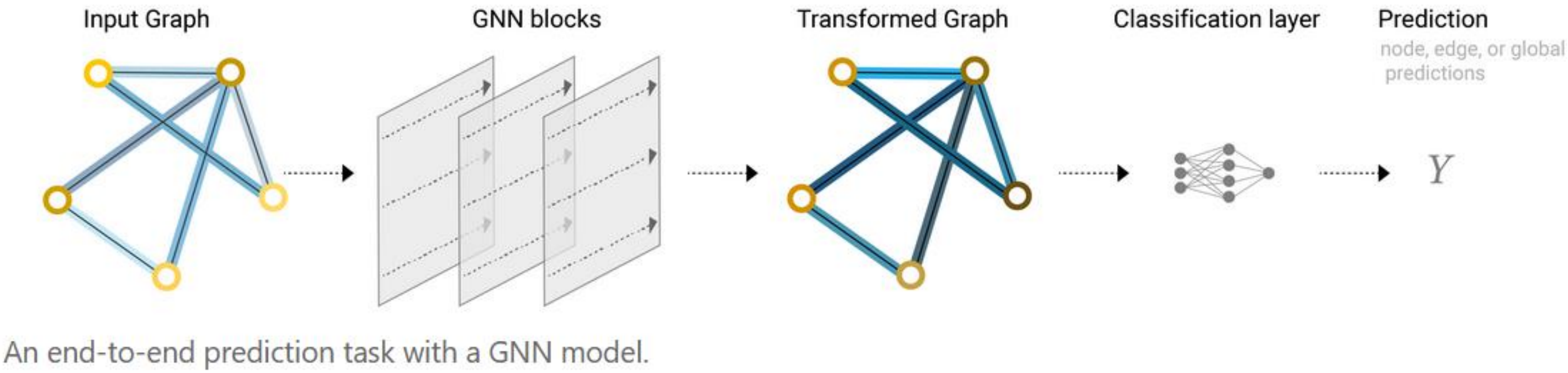
***Score**: 12:5*
***RoundWin**:* ????
***Time:** 1:03*



Graph Neural Networks

Summary:
Just like CNNs with
- Pooling
- Message Passing

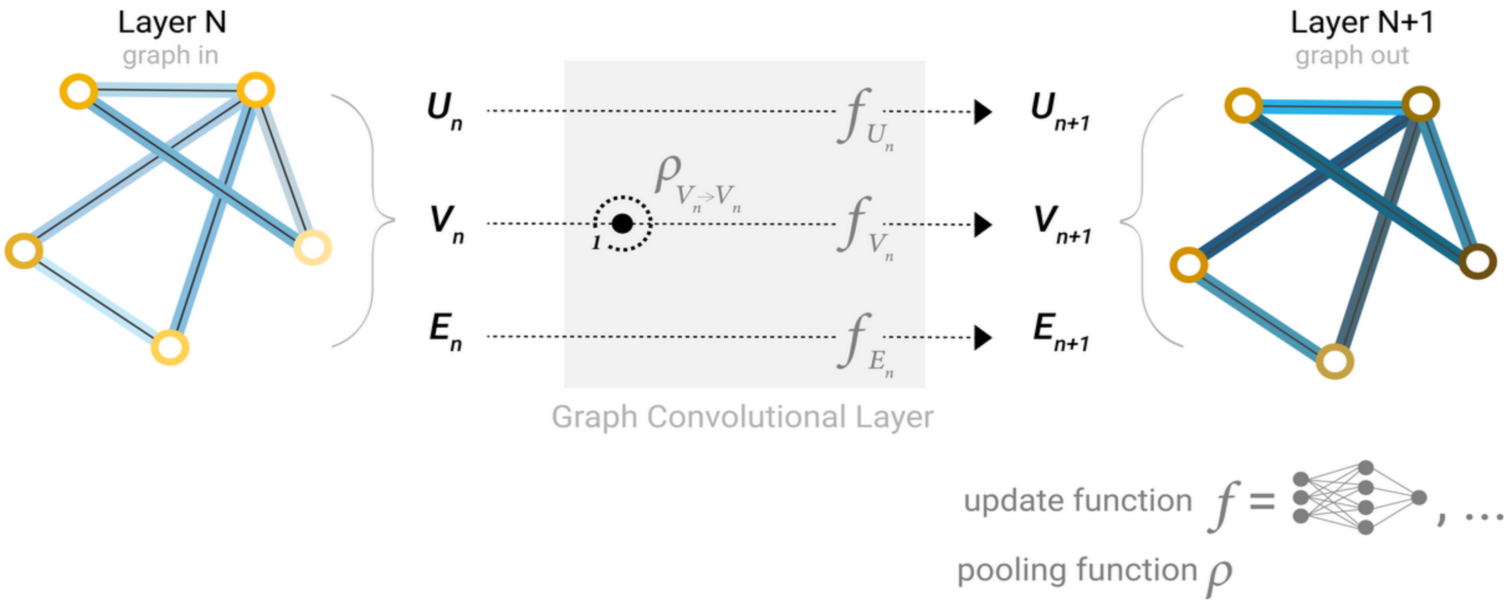
1. collect neighbor embeddings
2. aggregate with focal element
3. transform



Sanchez-Lengeling et al. (2021)

Graph Neural Networks

https://distill.pub/2021/gnn-intro/#node-step



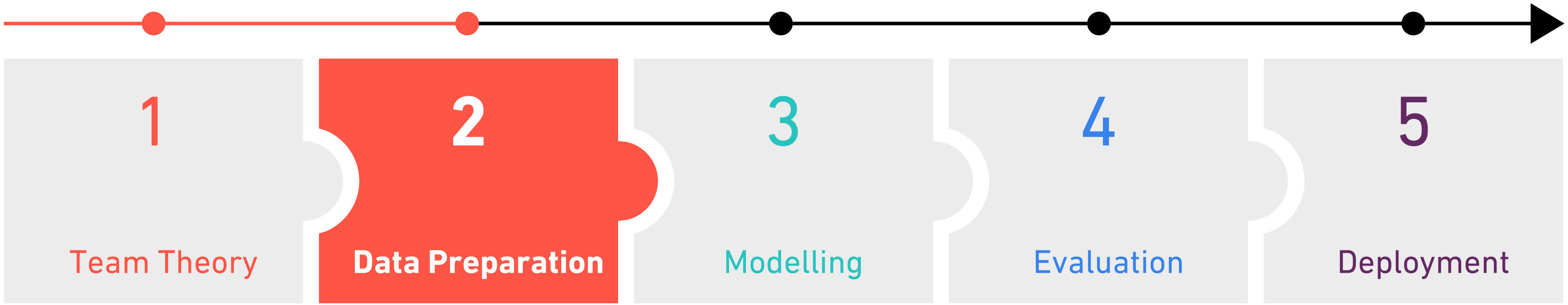
Schematic for a GCN architecture, which updates node representations of a graph by pooling neighboring nodes at a distance of one degree.

Sanchez-Lengeling et al. (2021)

Contents

Technology Stack

- PyTorch Geometric
- Awpy 1.3.1
- ESTA dataset
- Python 3.12



Possession Value and Expected Threat (xT)

- Focus on teams and individuals.
- Positions and space control are important.
- Estimate tactics and when they are successful.
- Theory instead of data.

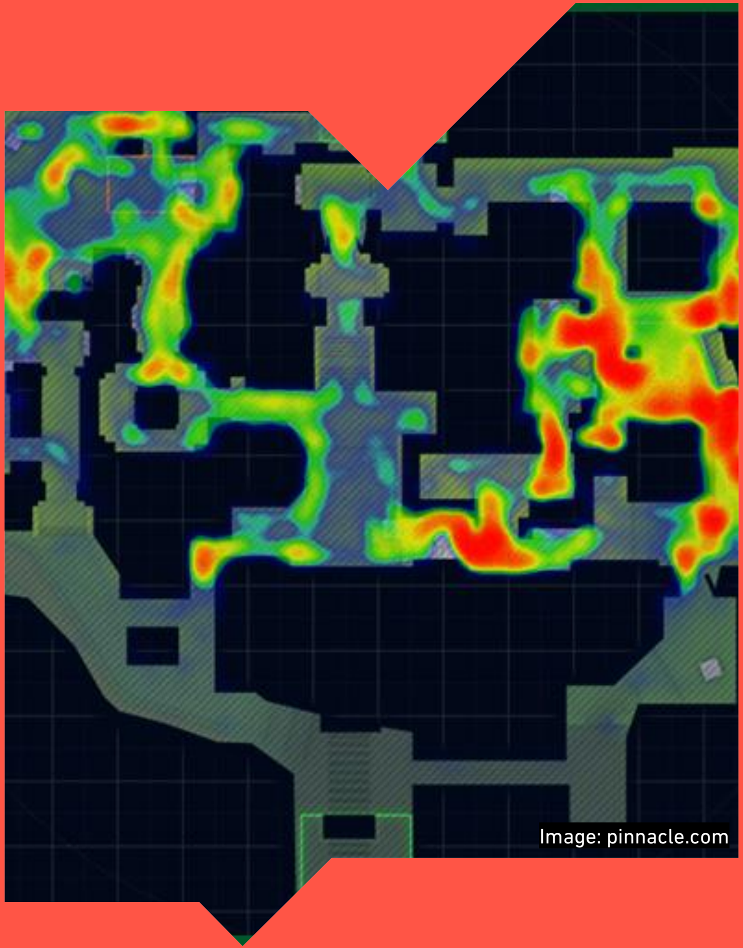


Image: pinnacle.com

Pollard & Reep (1997), Graham (2024)

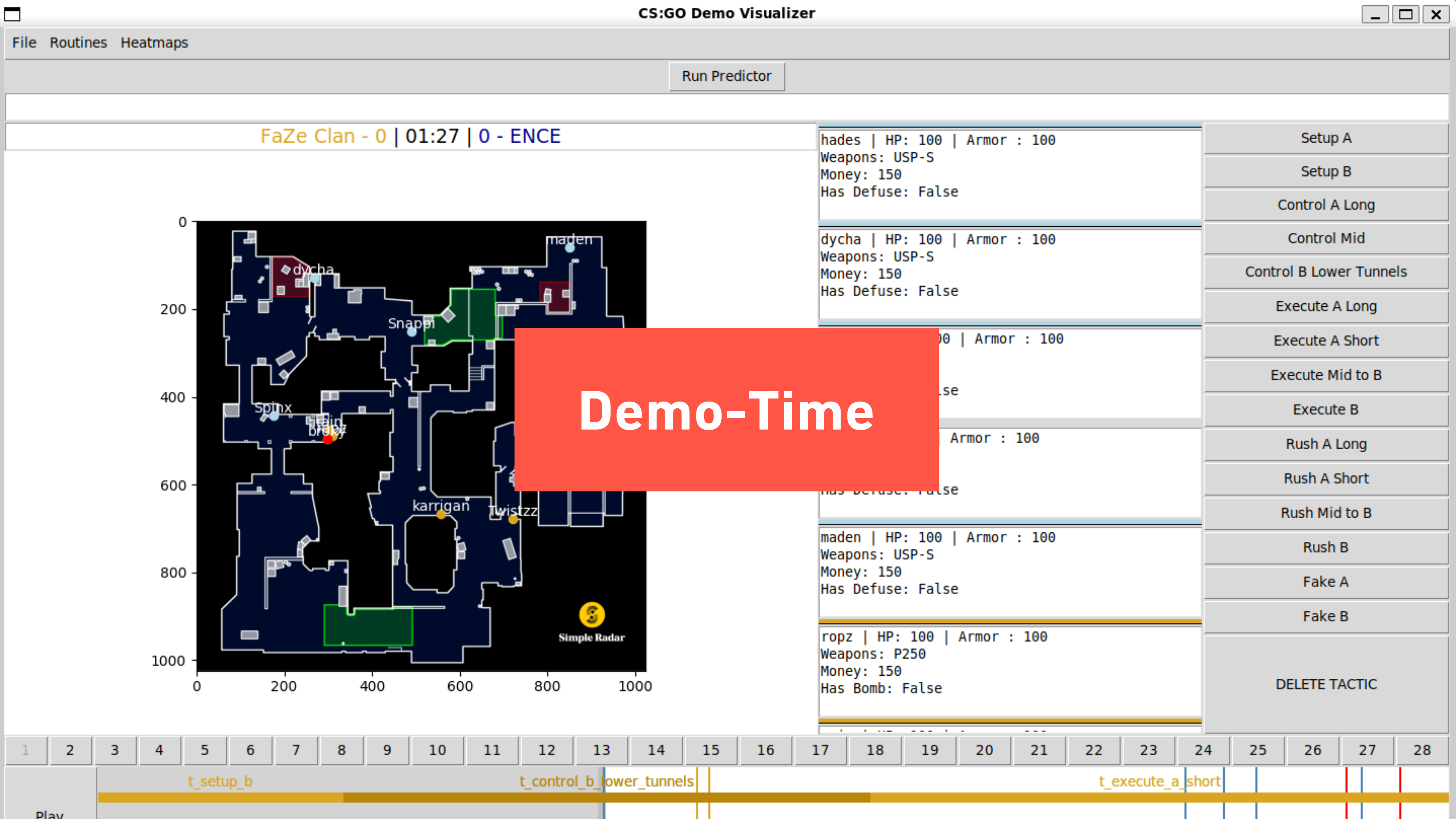

CS:GO Demo Visualizer
File
Routines
Heatmaps
Run Predictor
FaZe Clan - 0 | 01:27 | 0 - ENCE
hades | HP: 100 | Armor : 100
Weapons: USP-S
Money: 150
Has Defuse: False
dycha | HP: 100 | Armor : 100
Weapons: USP-S
Money: 150
Has Defuse: False
maden | HP: 100 | Armor : 100
Weapons: USP-S
Money: 150
Has Defuse: False
ropz | HP: 100 | Armor : 100
Weapons: P250
Money: 150
Has Bomb: False
Setup A
Setup B
Control A Long
Control Mid
Control B Lower Tunnels
Execute A Long
Execute A Short
Execute Mid to B
Execute B
Rush A Long
Rush A Short
Rush Mid to B
Rush B
Fake A
Fake B
DELETE TACTIC
maden
dycha
Snappi
Spinx
karrigan
Twistzz
Simple Radar
t_setup_b
t_control_b_lower_tunnels
t_execute_a_short
Play
Demo-Time

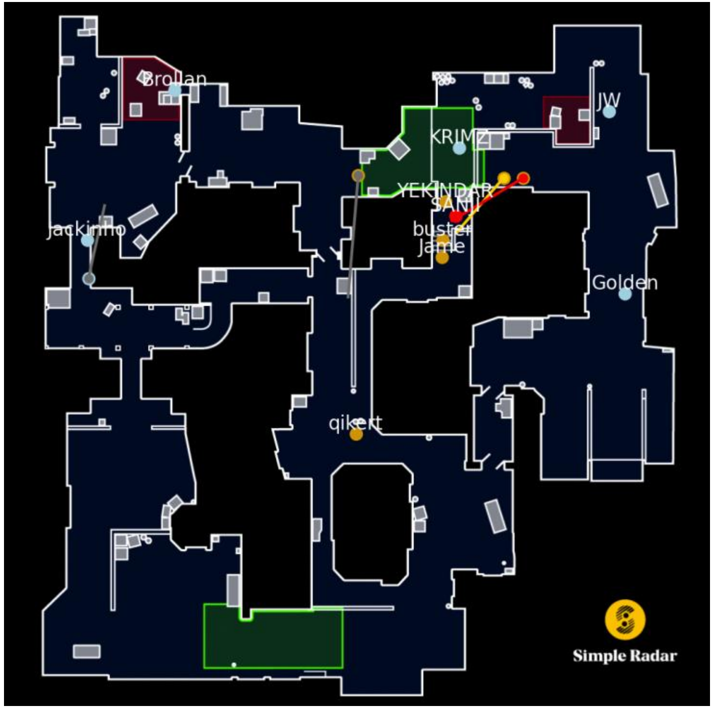

Image: steamstatic.com


SKINLORDS
Image: skinlords.com

Tactics

Tactic Label	Description
t_setup_a	Slow map control with lean toward A site
t_setup_b	Passive default with eventual B site lean
t_control_a_long	Gaining map control through A Long area
t_control_mid	Controlling the mid-area for flexibility or split
t_control_b_lower_tunnels	Slow approach through lower tunnels for B control
t_execute_a_long	Structured push through A Long with utility
t_execute_a_short	Execution via short (catwalk) with nades
t_execute_mid_to_b	Mid-to-B split with CT smoke and tunnel join
t_execute_b	Full B site execute through tunnels
t_rush_a_long	Fast rush through A Long
t_rush_a_short	Aggressive rush through short (catwalk)
t_rush_mid_to_b	Fast-paced mid-to-B attack
t_rush_b	Direct rush into B site via upper tunnels
t_fake_a	Fake towards A to draw rotations
t_fake_b	Fake towards B to manipulate defenders

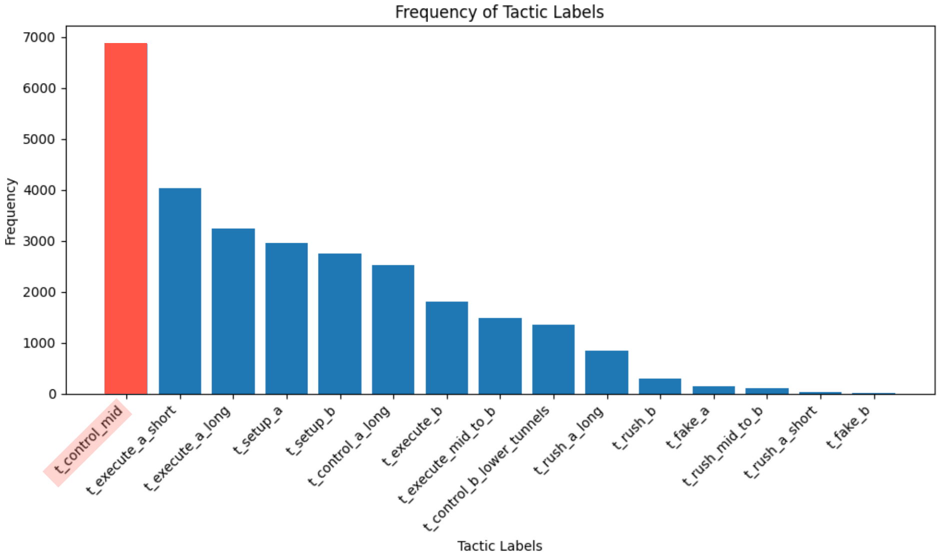
Example of player positioning during a “A short execute” tactic: 4 players are advancing on short; 1 is catching up from the middle.



Annotated Tactics

Out of >1000 games

Only de_dust2



Number of games labeled	20
Number of frames labeled	28,468
Number of *uncertain tactic* frames	18,705
Number of unique tactics annotated	15
Most common tactic	*t_control_mid*

Table 3. Labeling statistics

Slide by Kirna, Vlad, & Szabolcs

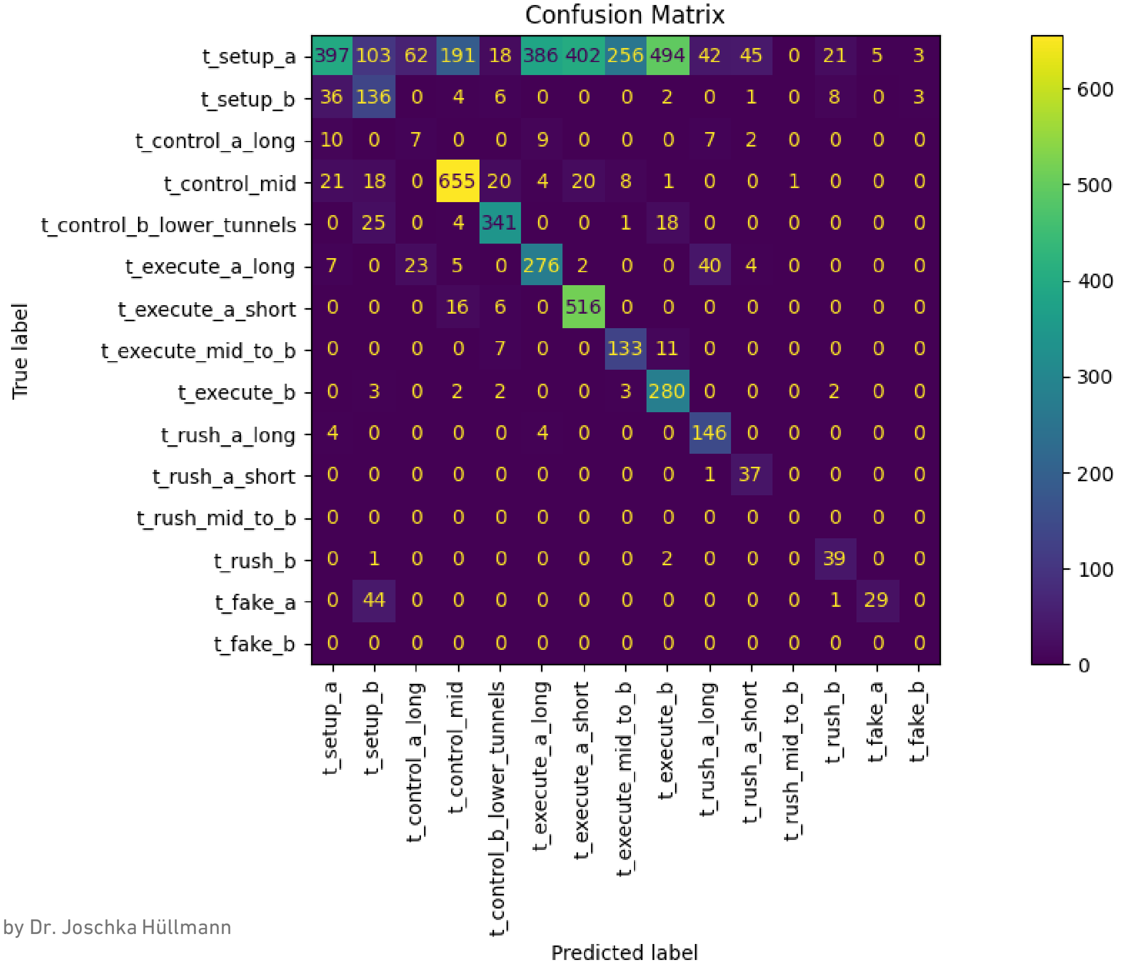
Data Preprocessing

- Convert demo data to graph data
- Estimate spatio-temporal features per frame errechnen

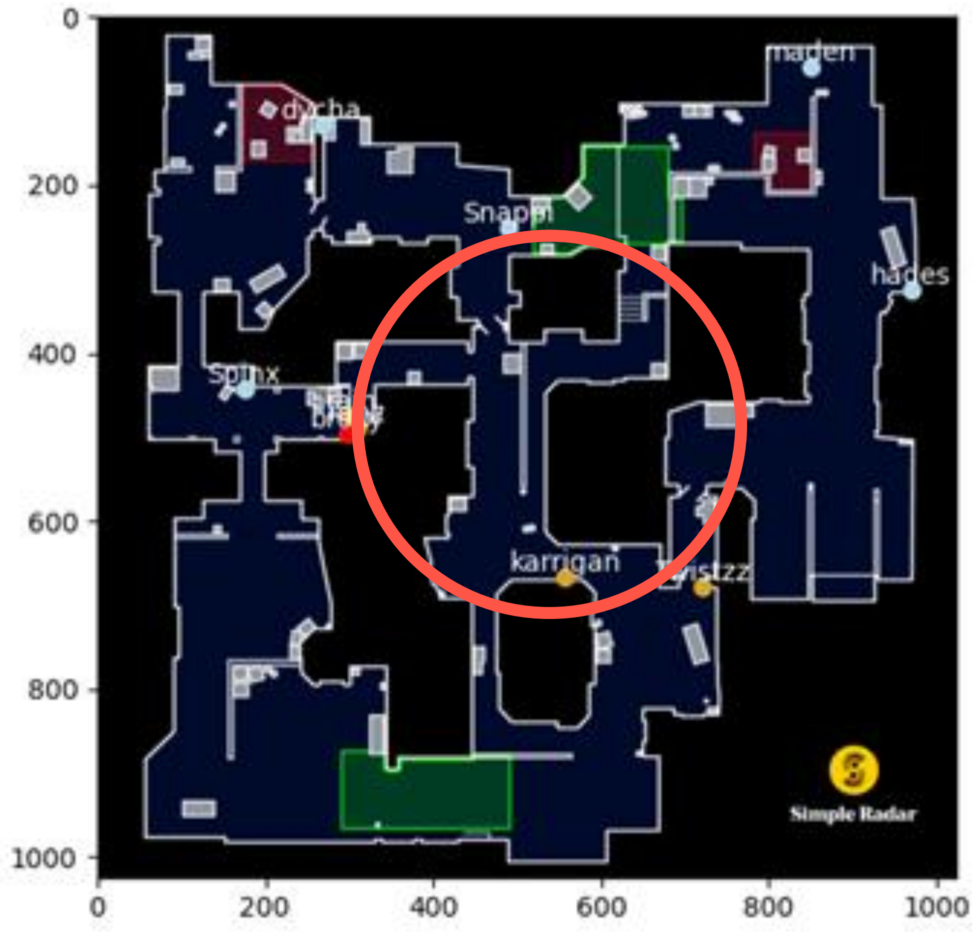
Number of demo files processed	195
Total rounds extracted	5133
Frames skipped due to issues	0 per game
Average number of frames per round	≈ 186
Processing time per frame	≈ 1 to 4 seconds
# games that could be proccessed parallely	64
Number of node features extracted	29 per graph

Slide by Kirna, Vlad, & Szabolcs

Results

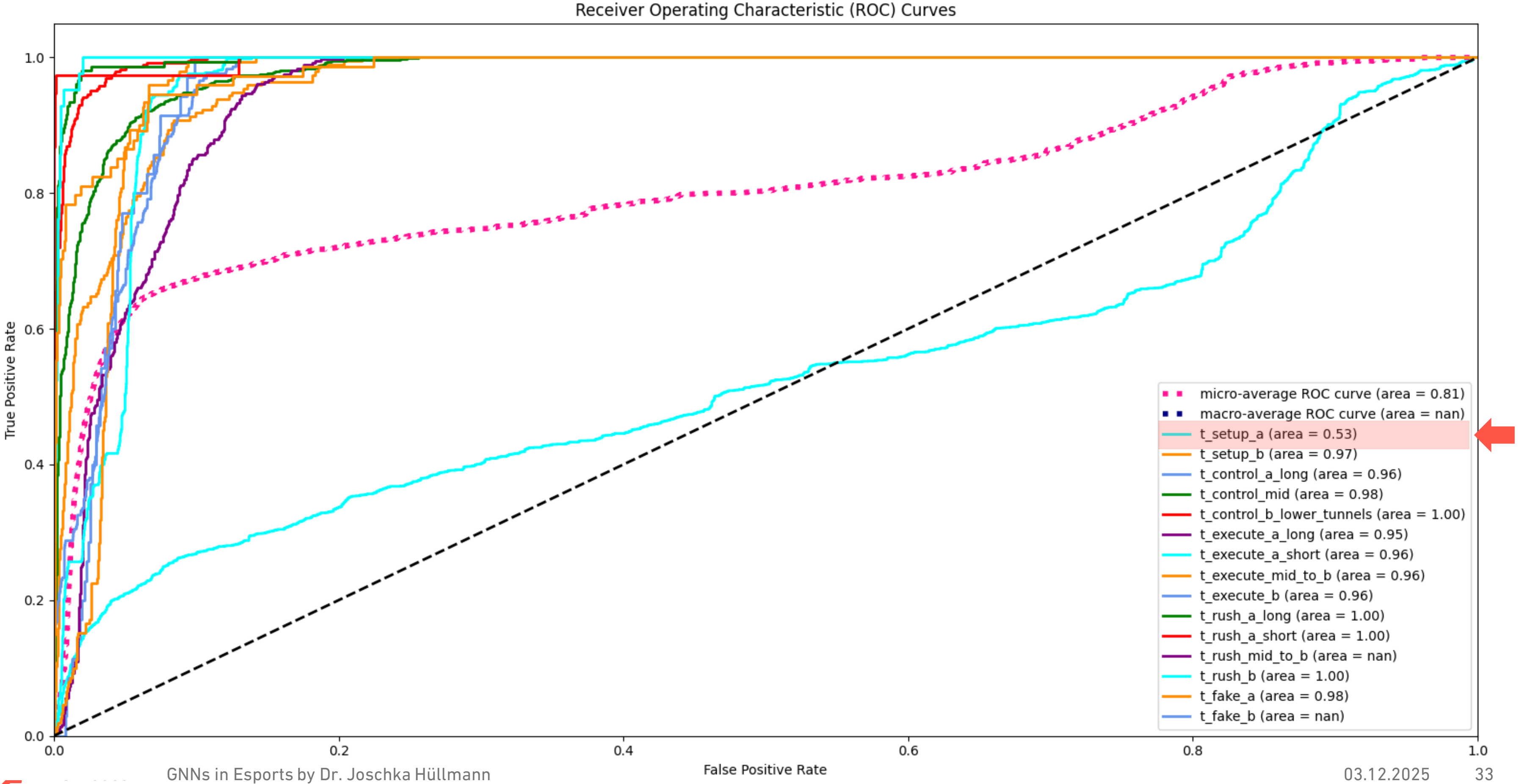

Confusion Matrix
True label
Predicted label
t_setup_a: 397 103 62 191 18 386 402 256 494 42 45 0 21 5 3
t_setup_b: 36 136 0 4 6 0 0 0 2 0 1 0 8 0 3
t_control_a_long: 10 0 7 0 0 9 0 0 0 7 2 0 0 0 0
t_control_mid: 21 18 0 655 20 4 20 8 1 0 0 1 0 0 0
t_control_b_lower_tunnels: 0 25 0 4 341 0 0 1 18 0 0 0 0 0 0
t_execute_a_long: 7 0 23 5 0 276 2 0 0 40 4 0 0 0 0
t_execute_a_short: 0 0 0 16 6 0 516 0 0 0 0 0 0 0 0
t_execute_mid_to_b: 0 0 0 0 7 0 0 133 11 0 0 0 0 0 0
t_execute_b: 0 3 0 2 2 0 0 3 280 0 0 0 2 0 0
t_rush_a_long: 4 0 0 0 0 4 0 0 0 146 0 0 0 0 0
t_rush_a_short: 0 0 0 0 0 0 0 0 0 1 37 0 0 0 0
t_rush_mid_to_b: 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
t_rush_b: 0 1 0 0 0 0 0 0 2 0 0 0 39 0 0
t_fake_a: 0 44 0 0 0 0 0 0 0 0 0 0 1 29 0
t_fake_b: 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
t_setup_a t_setup_b t_control_a_long t_control_mid t_control_b_lower_tunnels t_execute_a_long t_execute_a_short t_execute_mid_to_b t_execute_b t_rush_a_long t_rush_a_short t_rush_mid_to_b t_rush_b t_fake_a t_fake_b
600
500
400
300
200
100
0

Results



maden
Snappi
hades
spinx
karrigan
Simple Radar
0
200
400
600
800
1000
0
200
400
600
800
1000

Results



Slide by Kirna, Vlad, & Szabolcs

Results

Table 1. Feature combinations

Features	Accuracy	Recall	Precision	F1-score
Position	79.16%	0.7068	0.6301	0.6568
Position + Health + Armor	79.07%	0.7069	0.6130	0.6417
Position + Utility	80.09%	0.7131	0.6517	0.6707
All Features	81.17%	0.7510	0.6643	0.6945

Table 2. GNN architecture combinations

Model	Training Accuracy	Test Accuracy	F1-score
2-layered GAT	78.04%	78.10%	0.6831
2-layered GCN	82.79%	81.17%	0.6945
3-layered GAT	77.65%	77.16%	0.6692
3-layered GCN	81.94%	78.78%	0.6672

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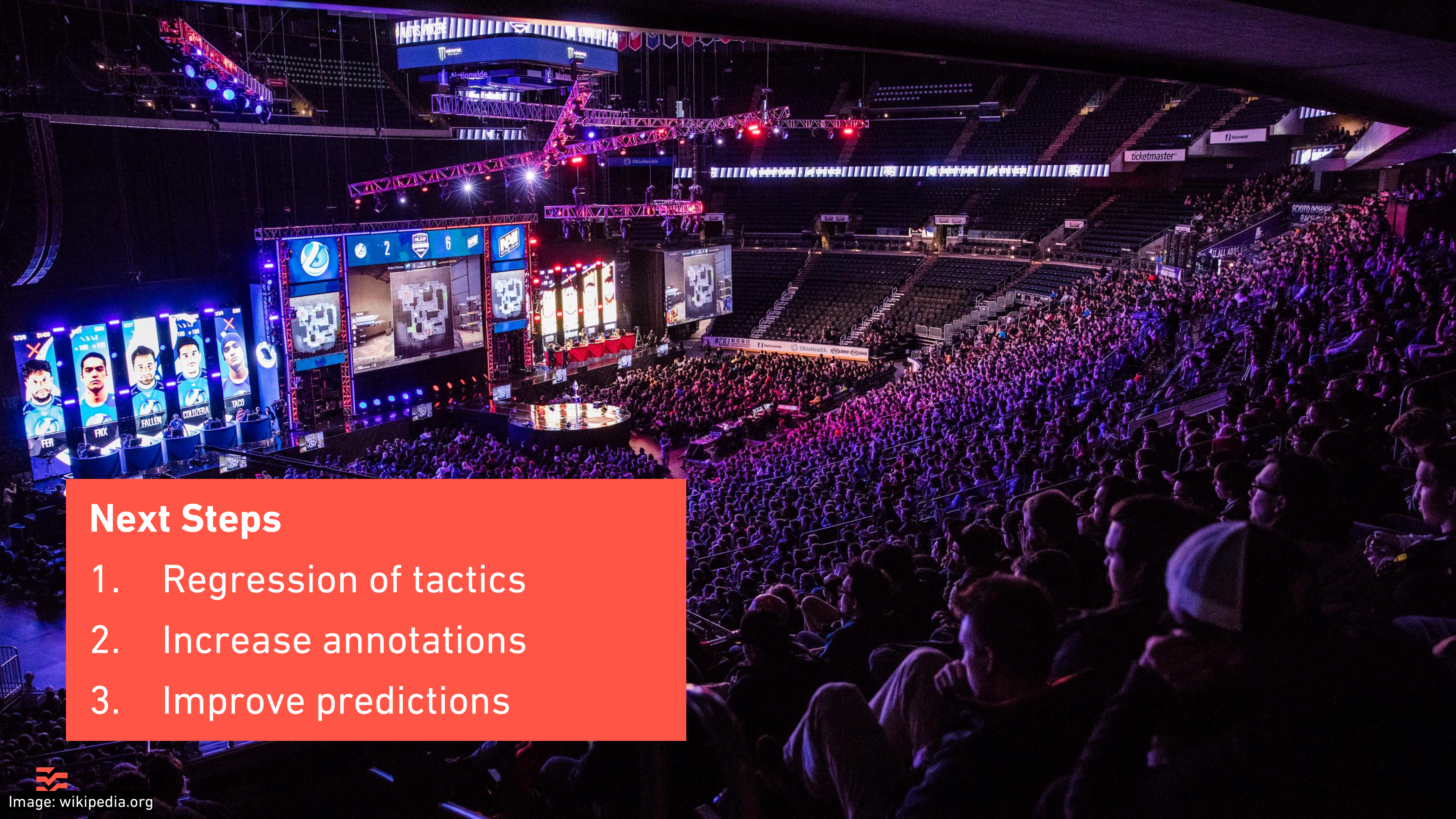

Next Steps

1. Regression of tactics
2. Increase annotations
3. Improve predictions

Image: wikipedia.org

Reading Materials

- Sanchez-Lengeling, B., Reif, E., Pearce, A., & Wiltschko, A. B. (2021). A gentle introduction to graph neural networks. *Distill, 6*(9), e33.
- Pollard, R., & Reep, C. (1997). Measuring the effectiveness of playing strategies at soccer. *Journal of the Royal Statistical Society Series D: The Statistician, 46*(4), 541-550.
- Graham, I. (2024). *How to Win the Premier League: The Sunday Times Bestselling Inside Story of Football's Data Revolution*. Random House.

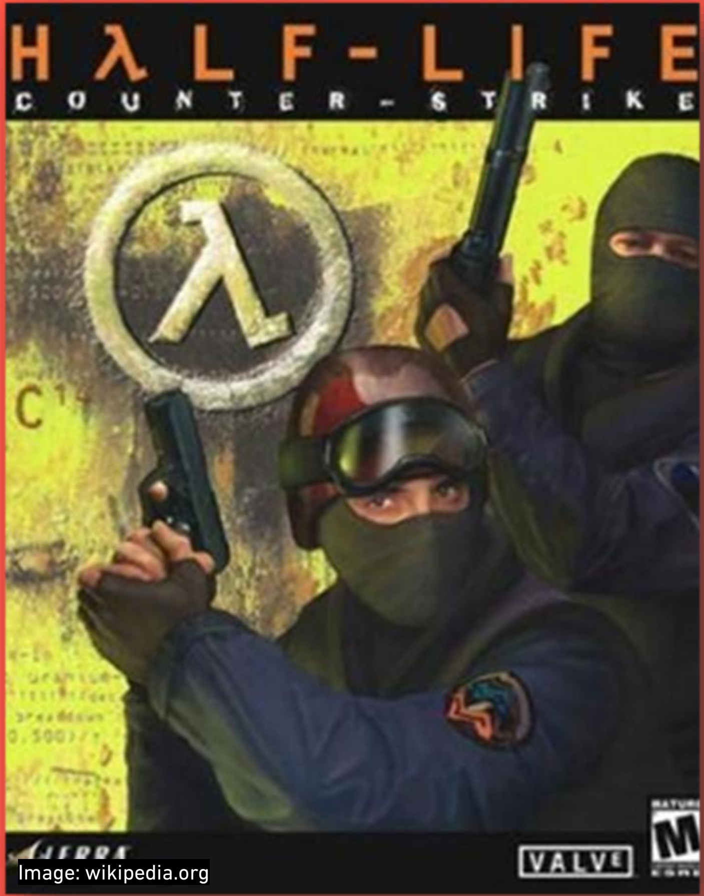

Image: wikipedia.org