

A photograph showing two people laughing and smiling. One person is in the foreground, wearing a yellow hoodie, and another person is visible behind them. They appear to be working on a project together, with colorful blocks or Legos on a table in front of them. In the background, there's a whiteboard with various notes and a window with green plants outside.

GRAPH NEURAL NETWORKS FÜR VORHERSAGEN IM SPORT

viadee 
IT-Unternehmensberatung

UNIVERSITY
OF TWENTE.



BRAD PITT MONEYBALL

JONAH HILL PHILIP SEYMOUR HOFFMAN
BASED ON A TRUE STORY



HOW TO WIN THE PREMIER LEAGUE

The inside story of
football's data revolution
Ian Graham



THE SUNDAY TIMES BESTSELLER

'Fascinating and educational. An
enjoyable and informative read'
SIR KENNY DALGLISH

'The best book on football
I have ever read'
DANIEL FINKELSTEIN



Bild: punktum.net

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

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and Jochen Baumeister¹

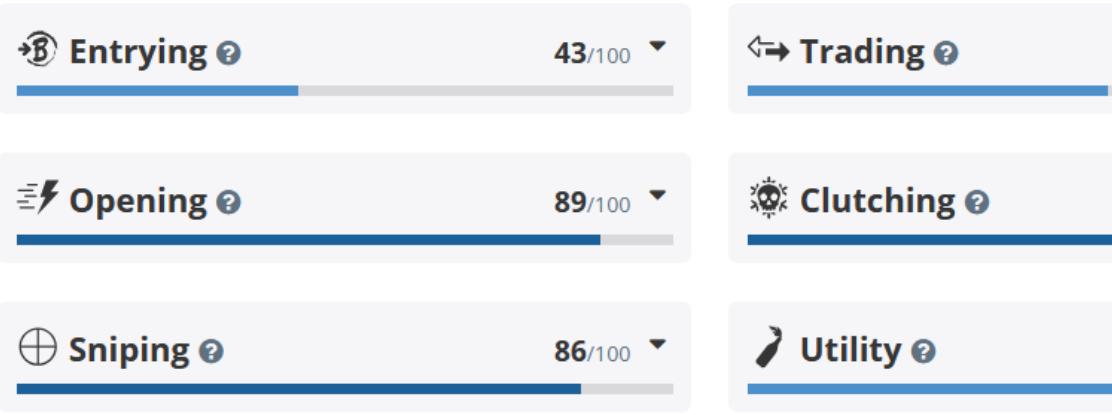
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Abstract. Over the last years, several approaches for the data-driven estimation of expected possession value (EPV) in basketball and association football (soccer) have been proposed. In this paper, we develop and evaluate PIVOT: the first such framework 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



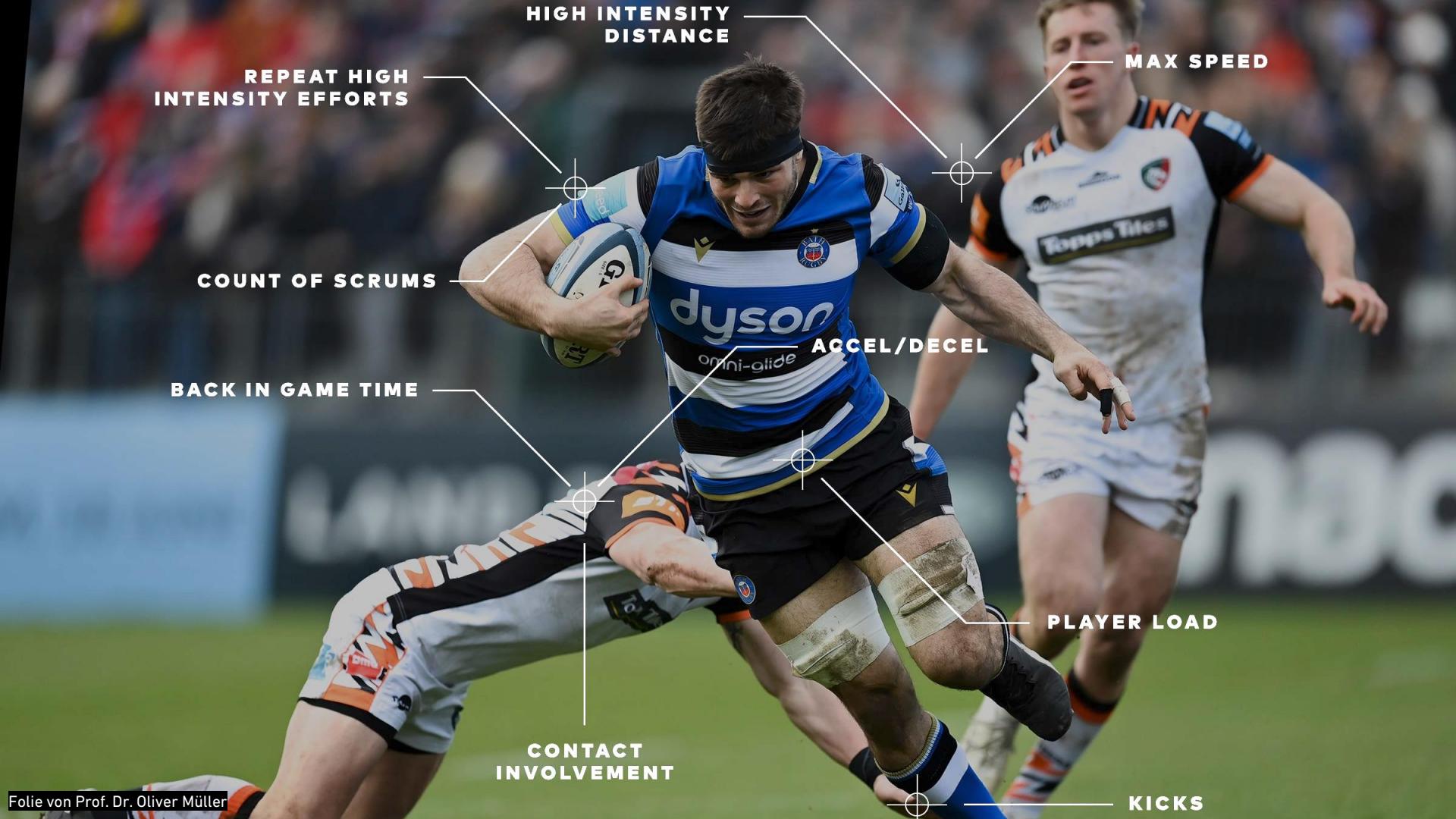
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1 Statistik im Sport ✓

2 Daten

3 Graph Neural Networks

4 Counter-Strike



PERFORMANCE PSYCHOLOGY

&

HEALTH

TEAM ANALYSIS

EYE TRACKING

IN GAME
PERFORMANCE
ANALYSIS

PLAYER
ANALYSIS

INPUT ANALYSIS





Astralis 8 1:47 8 Cloud9

Vollständige
Information

Round 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25

>	
100	Magisk
\$2250	
100	DEV1CE
\$2050	
100	Xyp9x
\$2050	
100	dupreeh
\$2350	
100	gla1ve
\$2000	
100	flusha
\$2850	
100	kiosaken
\$0	
100	RUSH
\$0	
100	automatic
\$150	
100	Zellsis
\$0	

... und noch
mehr Spalten,
aktuell ca. 42

Frame Nummer (sampled at 2 Hz)	Name	Ressourcen: Geld & Ausrüstung	Position & Bewegung
0	39648	huNter	2300
0	39648	NiKo	2250
0	39648	m0NESY	2700
0	39648	jks	3050
0	39648	HooXi	1500
0	39648	YEKINDAR	450
0	39648	EliGE	50
0	39648	nitr0	100
0	39648	NAF-FLY	350
0	39648	oSee	0
1	39776	huNter	2300
1	39776	m0NESY	2700
1	39776	HooXi	1500
1	39776	NiKo	2250
1	39776	jks	2450
1	39776	EliGE	50
1	39776	YEKINDAR	450
1	39776	oSee	0
1	39776	NAF-FLY	350
1	39776	nitr0	100
2	39904	NiKo	2250
2	39904	iks	2250

128 Events
pro Spieler pro Sekunde
(> 50.000 Events pro Runde)

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Counter-Strike als Graph

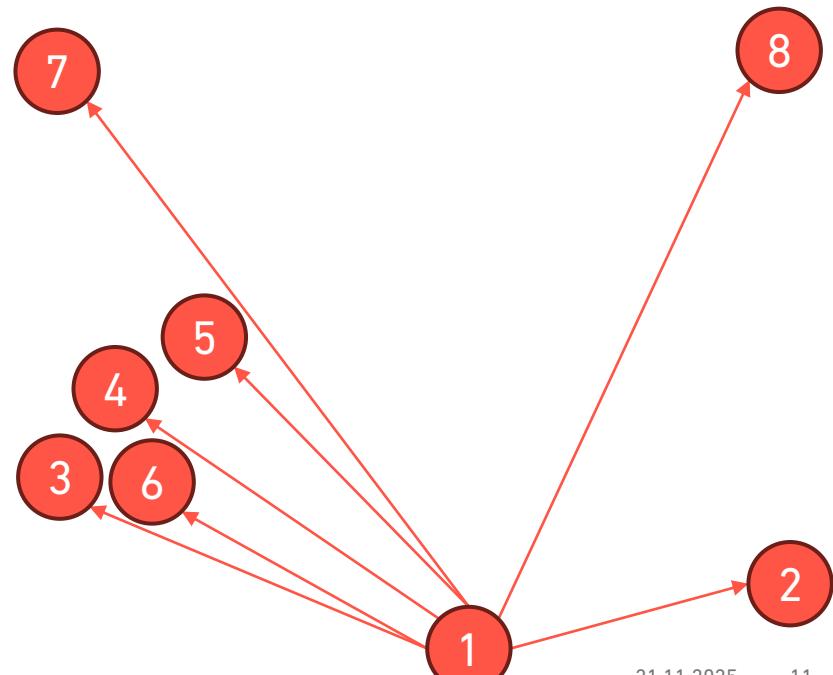
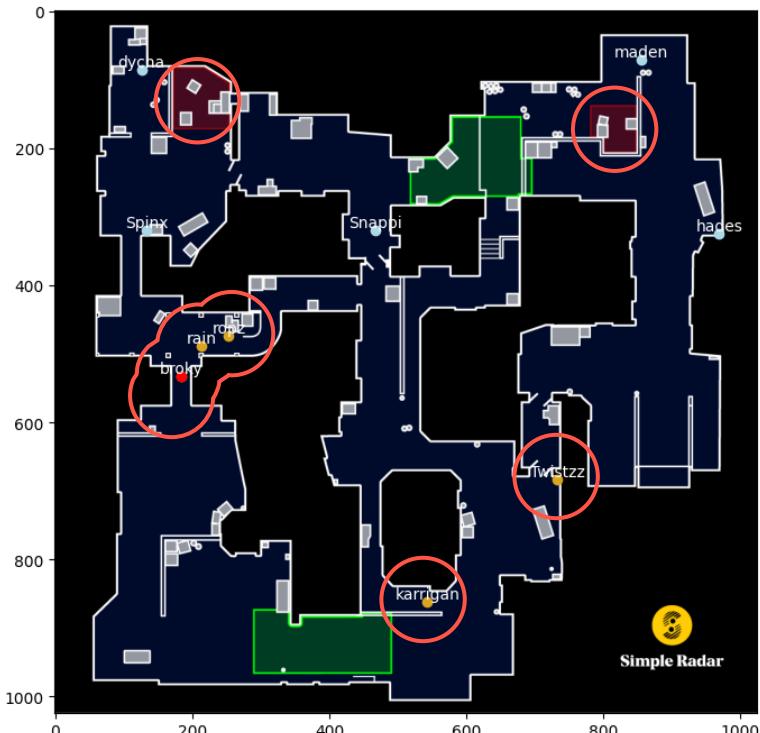
vollständiger Digraph

1-5: Spieler

6: Bomb

7-8: Bombsite A & B

Vom Spiel zum Graphen $G = (V, E, U)$



Counter-Strike als Graph

vollständiger Digraph

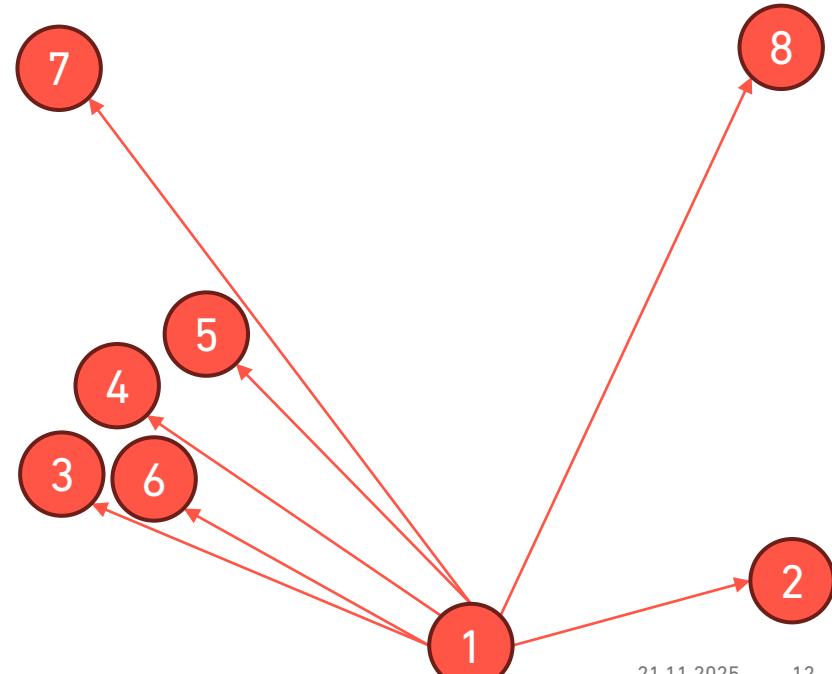
1-5: Spieler

6: Bomb

7-8: Bombsite A & B

Vom Spiel zum Graphen $G = (V, E, U)$

$$E = \left(\begin{array}{cccccccc} 0, 1, 2, 2, 2, 2, 2, 4, 4 \\ 0, 0, 0, 0, 0, 0, 0, 0 \\ 0, 0, 0, 0, 0, 0, 0, 0 \\ 0, 0, 0, 0, 0, 0, 0, 0 \\ 0, 0, 0, 0, 0, 0, 0, 0 \\ 0, 0, 0, 0, 0, 0, 0, 0 \\ 0, 0, 0, 0, 0, 0, 0, 0 \\ 0, 0, 0, 0, 0, 0, 0, 0 \end{array} \right)$$



Counter-Strike als Graph

Daten auf Graphen

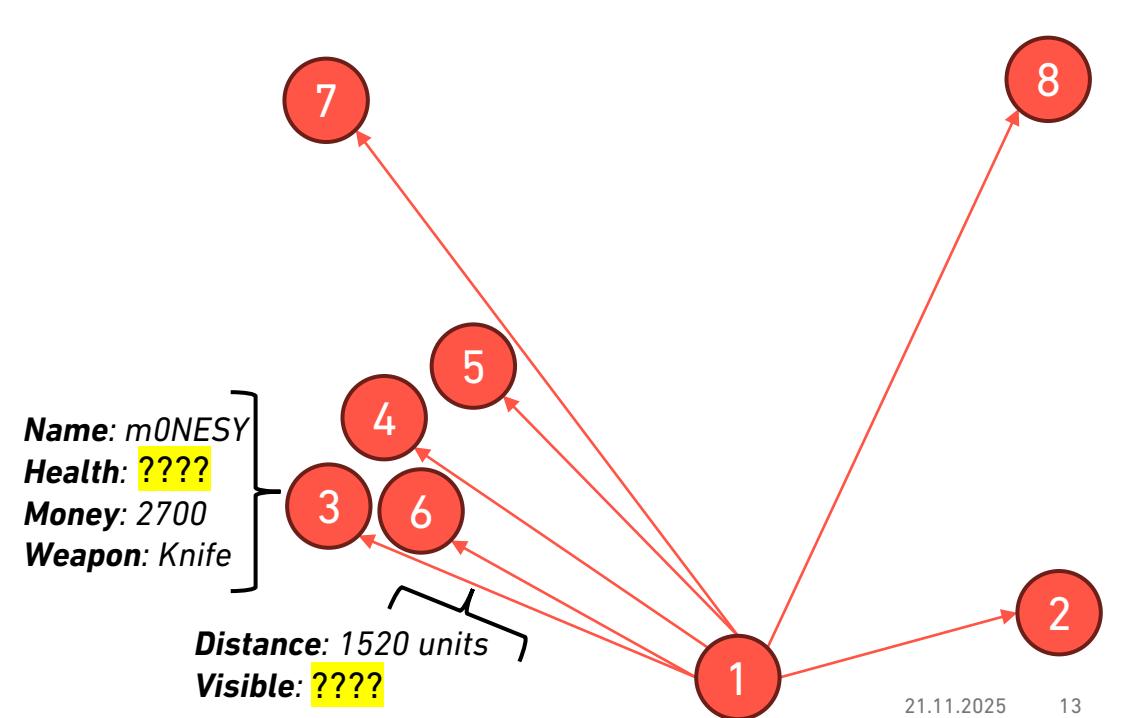
$G = (V, E, U)$ mappen.

playerName	money	equippedWeapon	positionX
huNter	2300	Knife	-1890.5278320312
NiKo	2250	USP-S	-1647.7130126953
m0NESY	2700	Knife	-1917.4442138671

Score: 12:5

RoundWin: ????

Time: 1:03

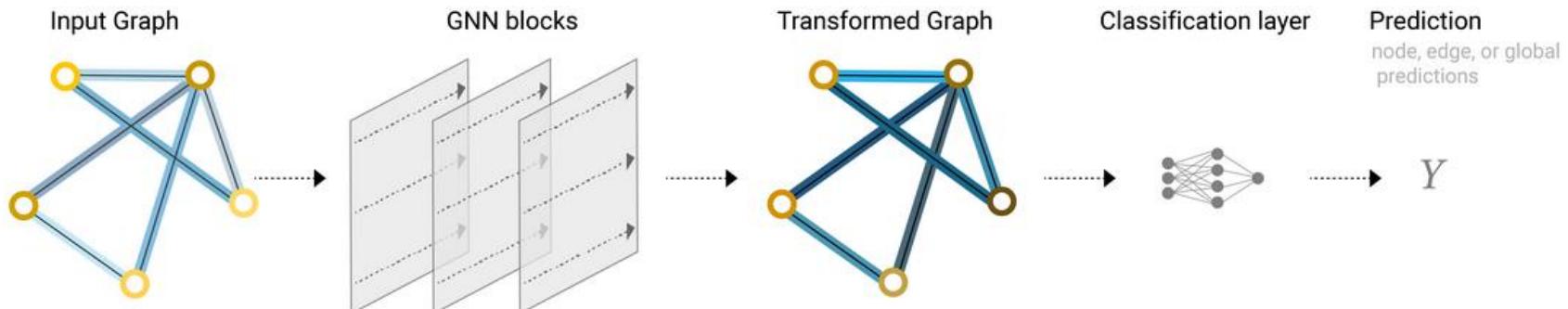


Graph Neural Networks

Zusammenfassung:

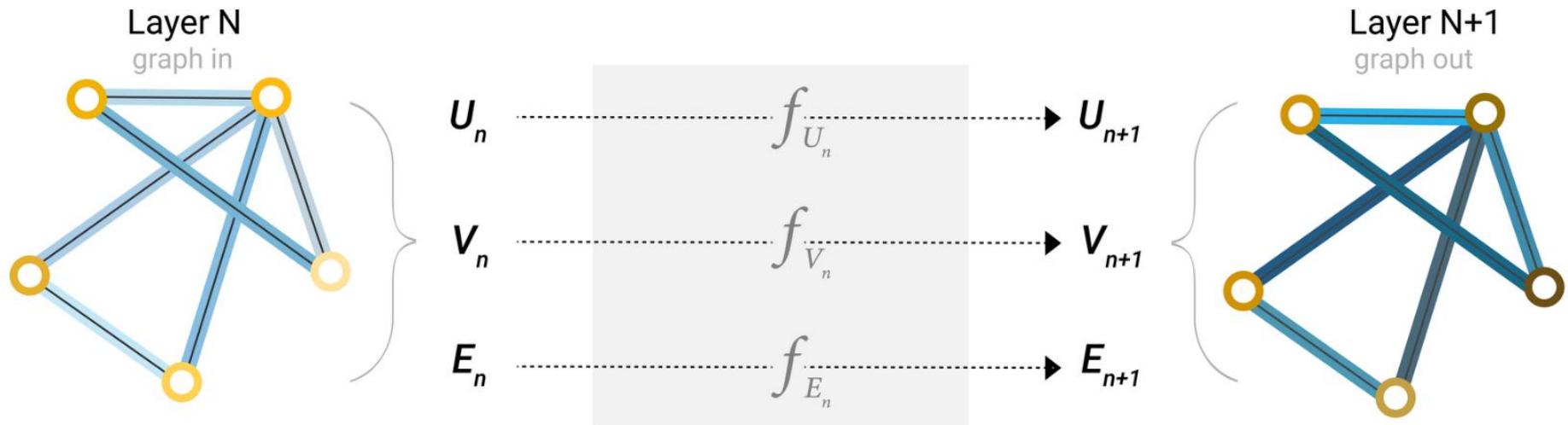
Wie CNNs mit

- Pooling
 - Message Passing
1. collect neighbor embeddings
 2. aggregate with focal element
 3. transform



An end-to-end prediction task with a GNN model.

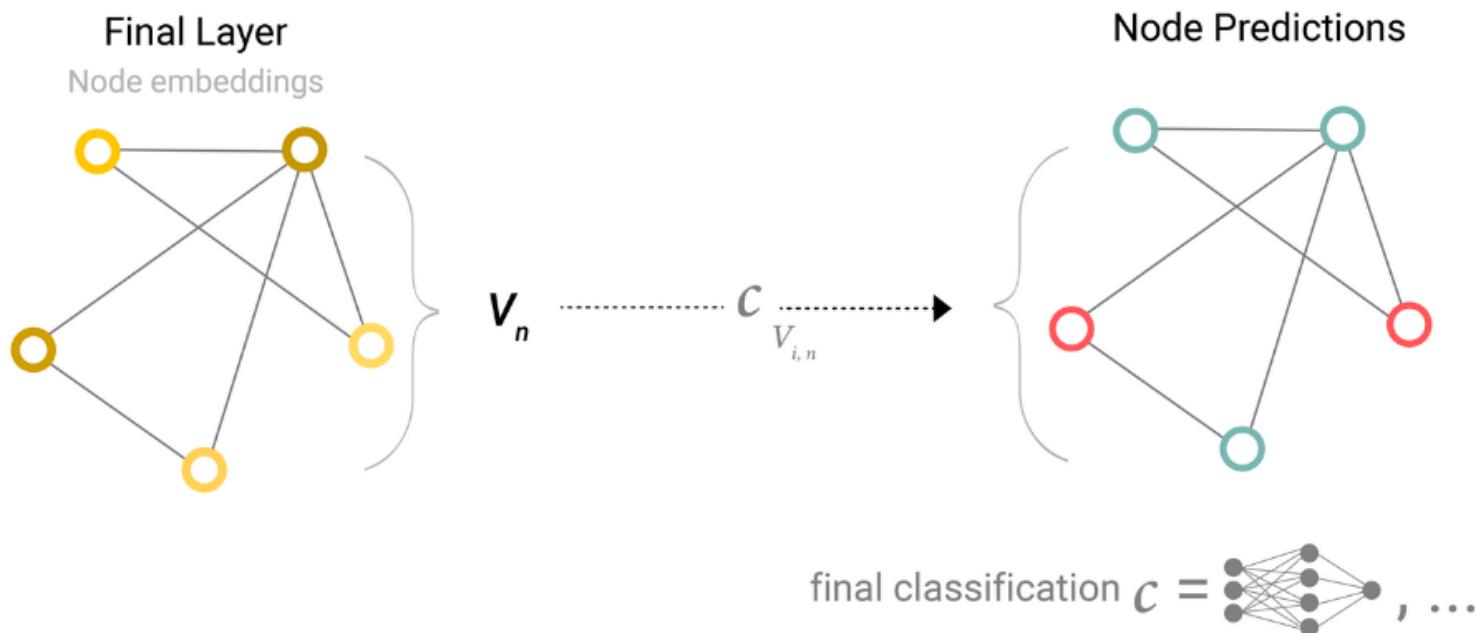
Graph Neural Networks



update function $f = \begin{array}{c} \bullet \\ \bullet \\ \bullet \\ \bullet \\ \bullet \end{array} \xrightarrow{\text{MLP}} \begin{array}{c} \bullet \\ \bullet \end{array}, \dots$

A single layer of a simple GNN. A graph is the input, and each component (V, E, U) gets updated by a MLP to produce a new graph. Each function subscript indicates a separate function for a different graph attribute at the n -th layer of a GNN model.

Graph Neural Networks

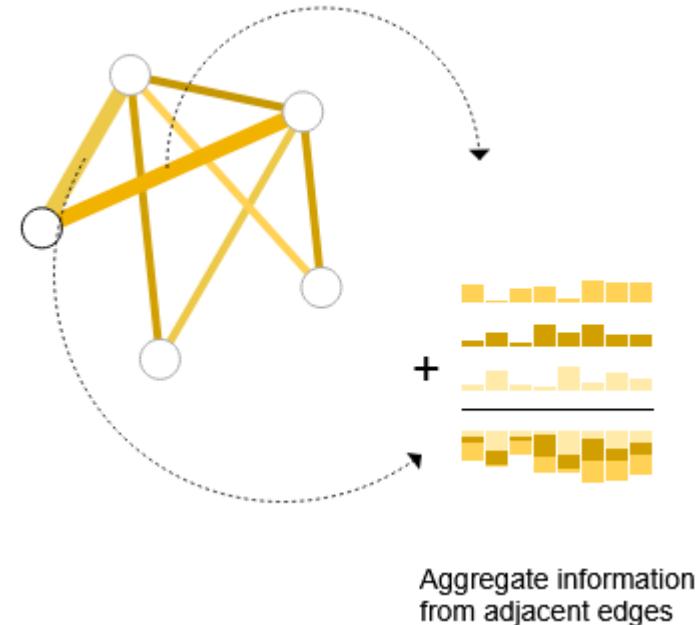


Graph Neural Networks

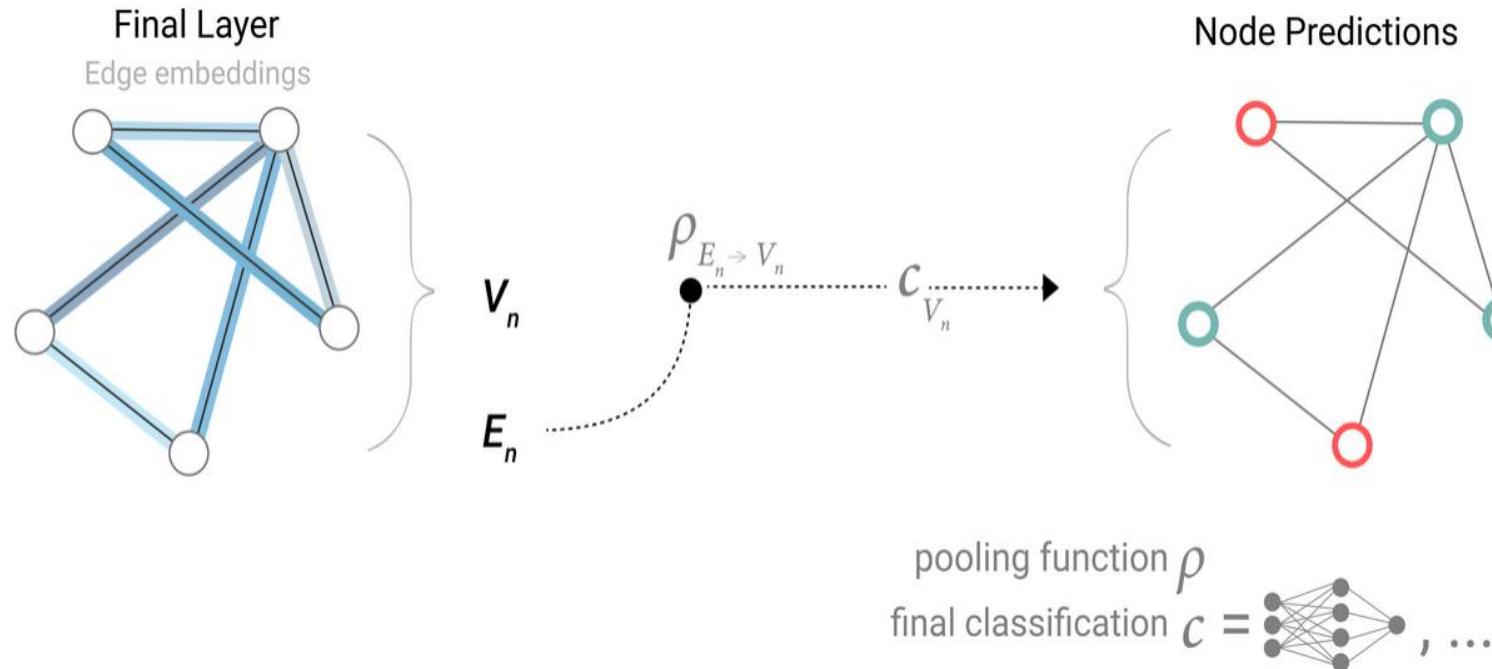
<https://distill.pub/2021/gnn-intro/#node-step-small>

Pooling

- Für jeden zu poolenden Element werden alle Embeddings **gesammelt** und zu einer Matrix verknüpft.
- Die gesammelten Embeddings werden **aggregiert**. In der Regel durch eine Summenoperation.



Graph Neural Networks

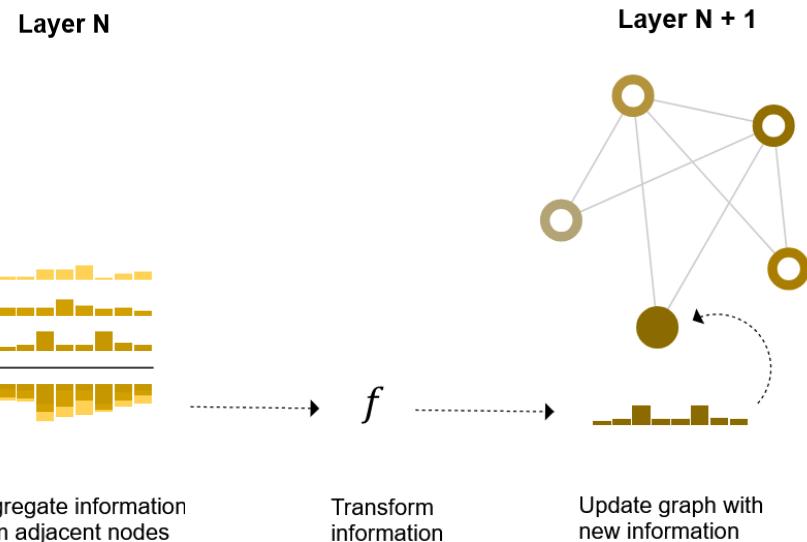


Graph Neural Networks

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

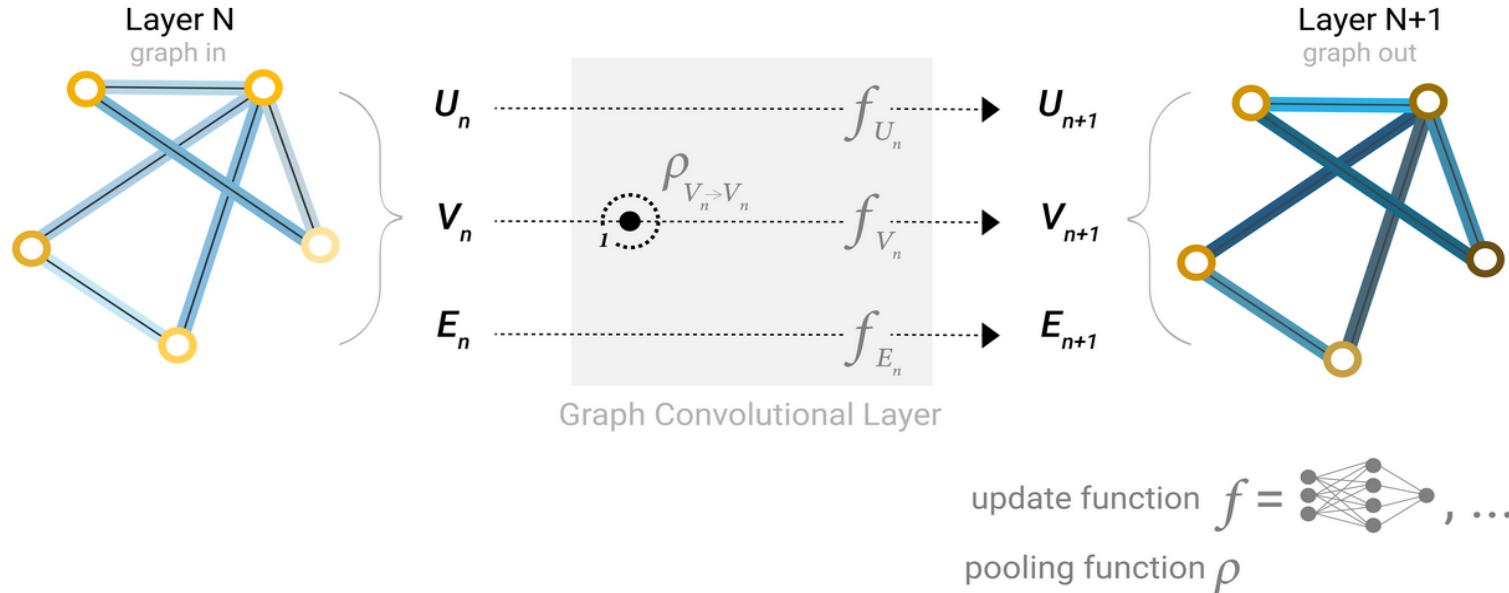
Message Passing

- Für jeden zu poolenden Vektor werden alle Embeddings **gesammelt** und zu einer Matrix verknüpft.
- Die gesammelten Embeddings werden **aggregiert**. In der Regel durch eine Summenoperation.
- Die gepoolten Embeddings werden durch die **Update Function** geleitet.



Graph Neural Networks

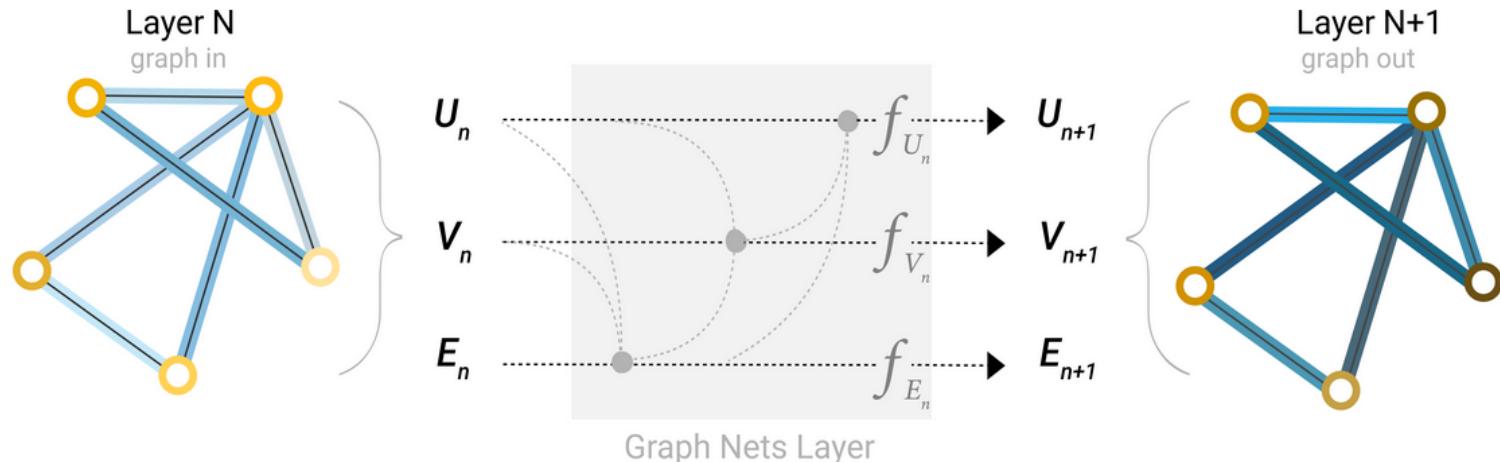
<https://distill.pub/2021/gnn-intro/#node-step>



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

Graph Neural Networks

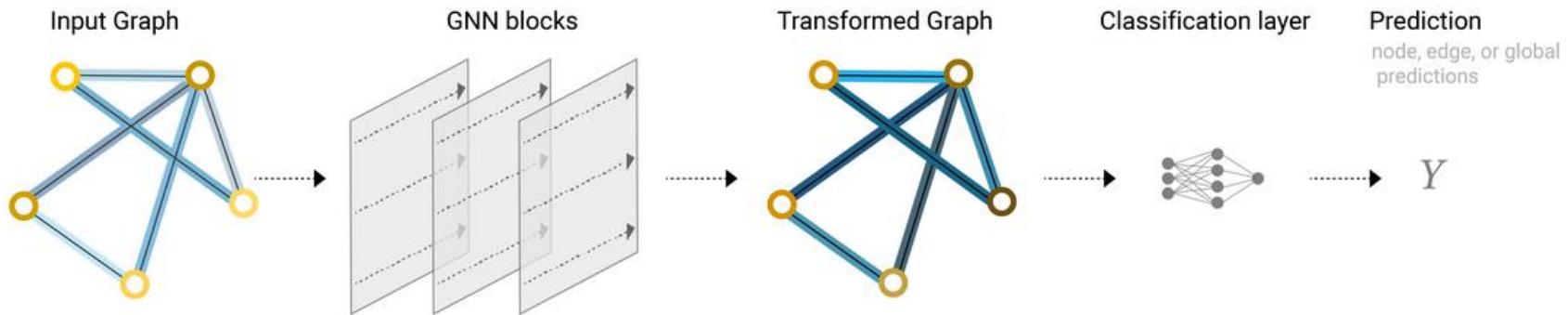
<https://distill.pub/2021/gnn-intro/#node-step>



update function $f = \begin{array}{c} \text{---} \\ \vdots \\ \text{---} \end{array}, \dots$
pooling function ρ

Schematic of a Graph Nets architecture leveraging global representations.

Graph Neural Networks



An end-to-end prediction task with a GNN model.

Inhalt

1 Statistik im Sport ✓

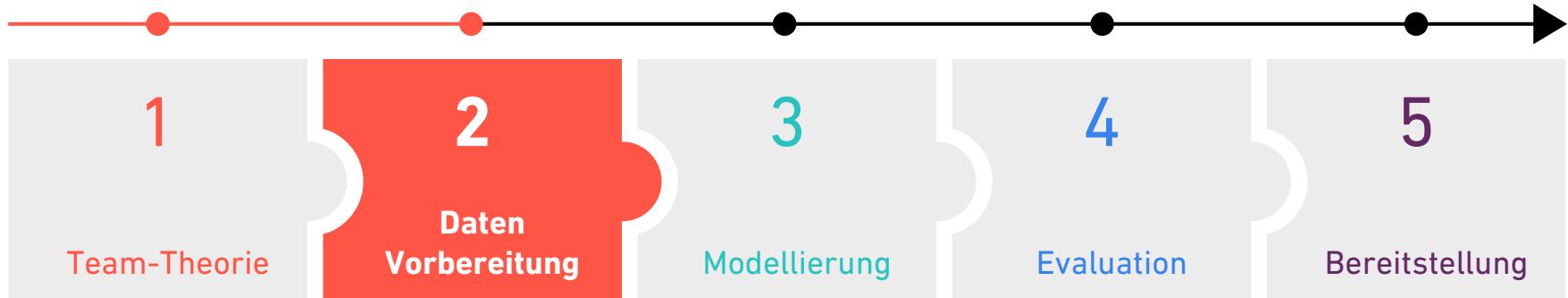
2 Daten ✓

3 Graph Neural Networks ✓

4 Counter-Strike

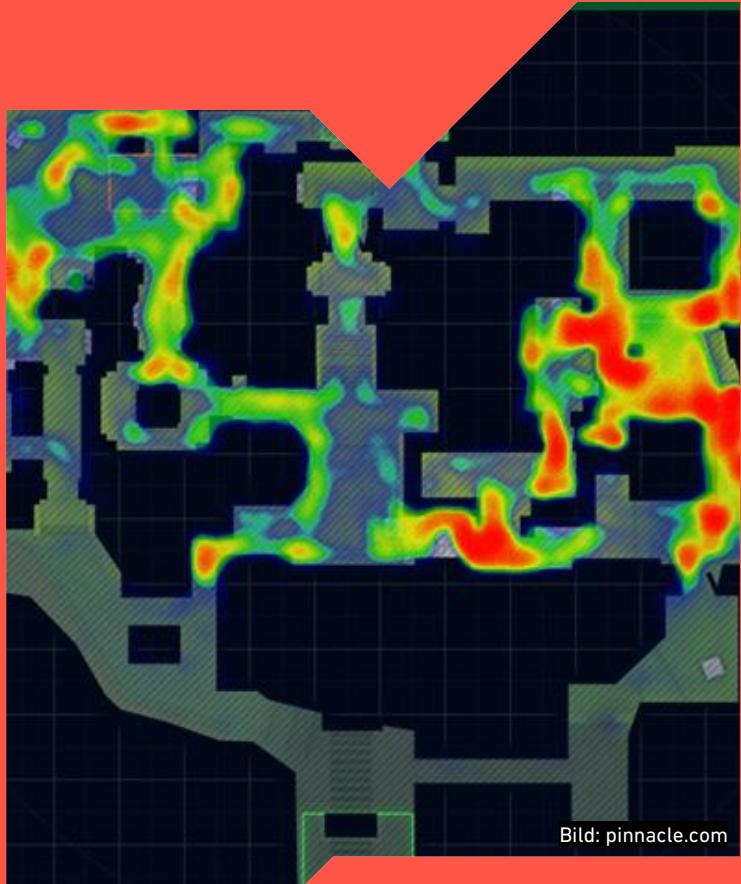
Technology Stack

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



Possession Value und Expected Threat (xT)

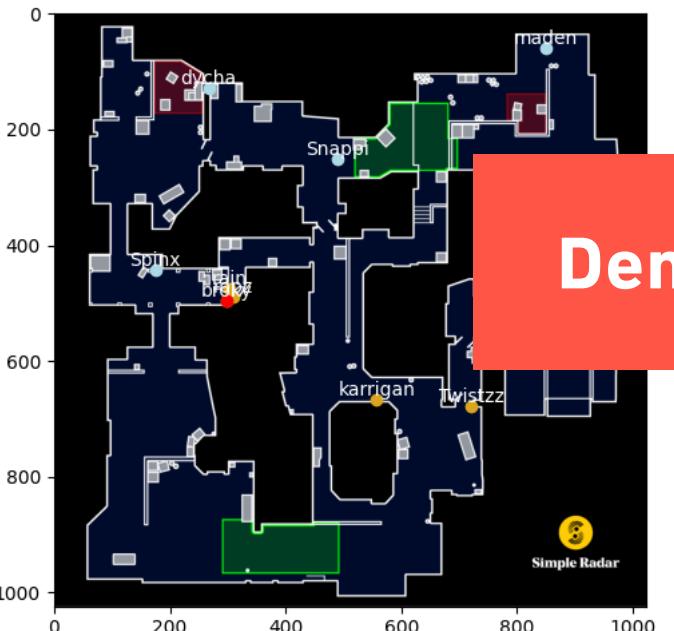
- Fokus auf das Team statt Individuum.
- Positionen und Raumkontrolle sind wichtig.
- Taktiken schätzen und wann sie wann erfolgreich sind.
- Theorie statt nur Daten.



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

Snapshot | HP: 100 | Armor : 100
 Weapons: P90
 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

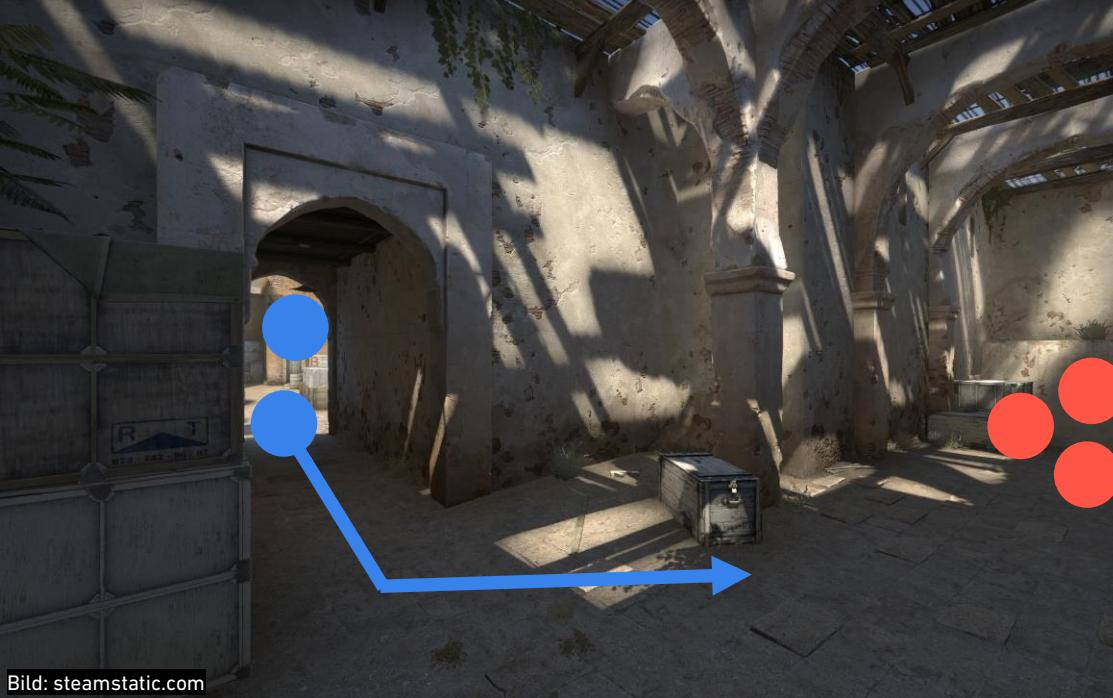
1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28
---	---	---	---	---	---	---	---	---	----	----	----	----	----	----	----	----	----	----	----	----	----	----	----	----	----	----	----

t_setup_b

t_control_b_lower_tunnels

t_execute_a_short

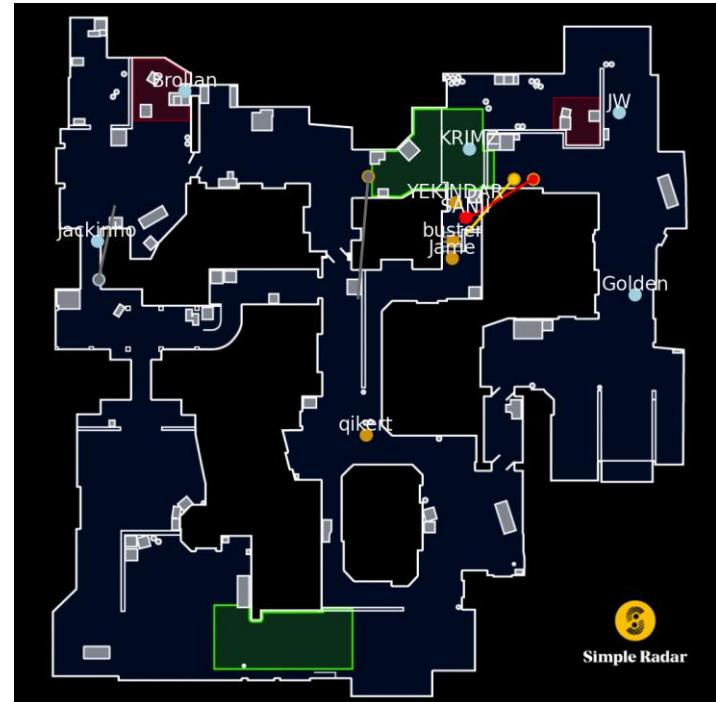
Play



Taktiken

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

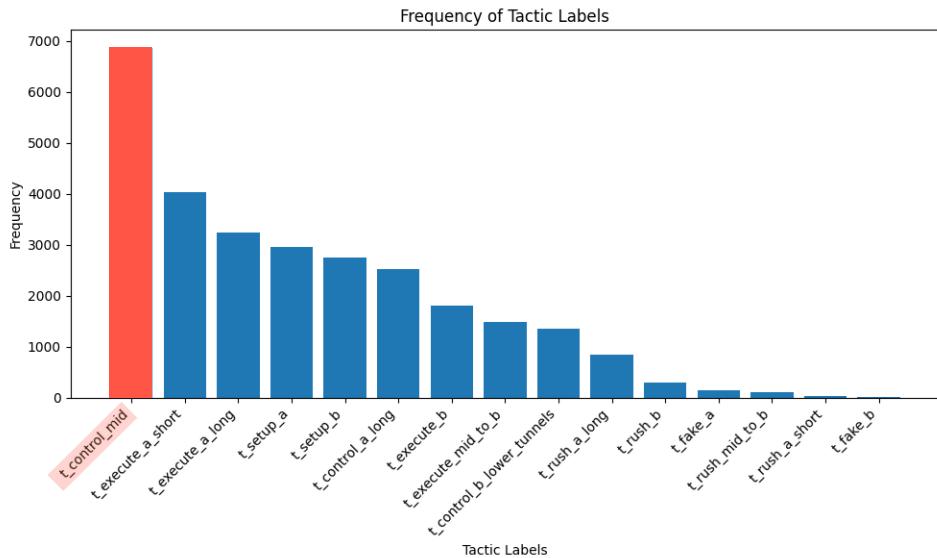
Example of player positioning during a "A short execute" tactic: 4 players are advancing on short; 1 is catching up from the middle.



Annotierte Taktiken

Out of >1000
games

Only de_dust2



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

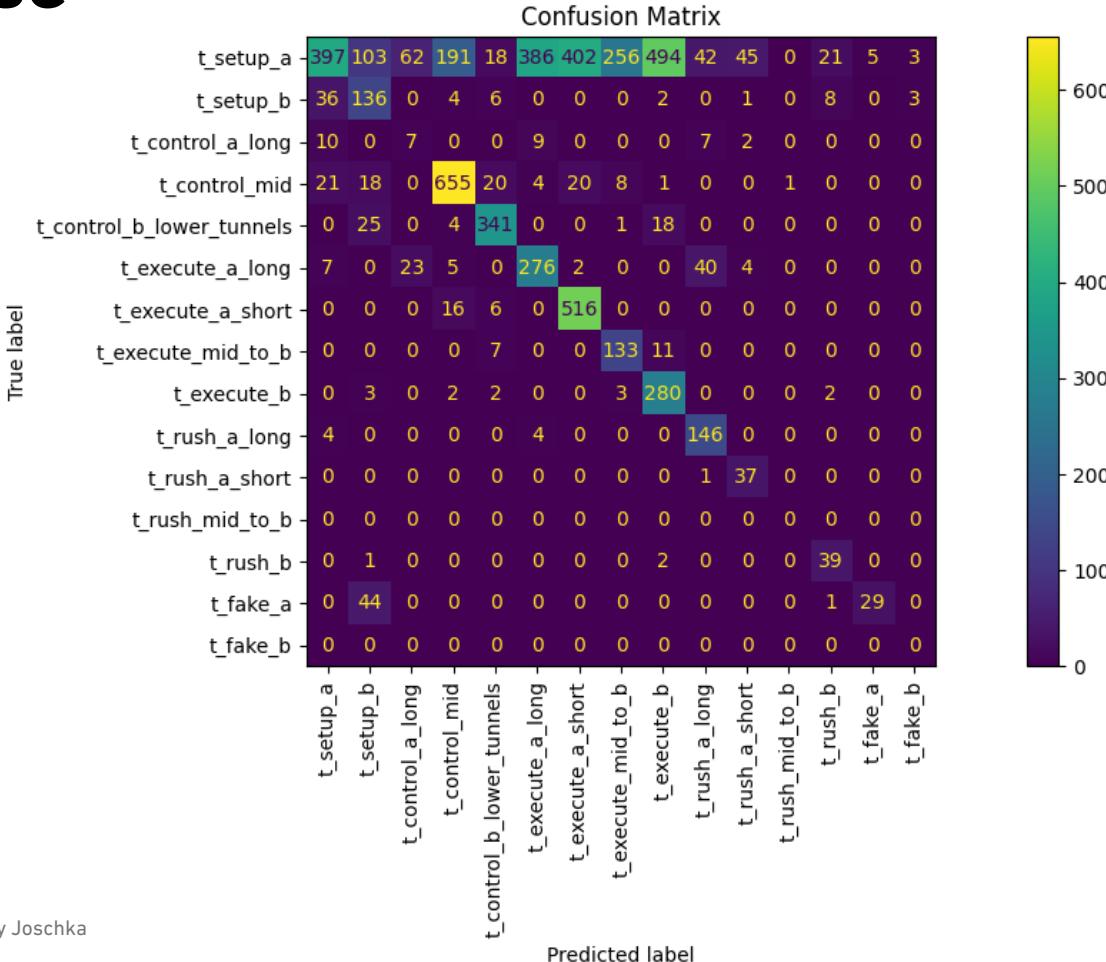
Table 3. Labeling statistics

Daten Vorbereitung

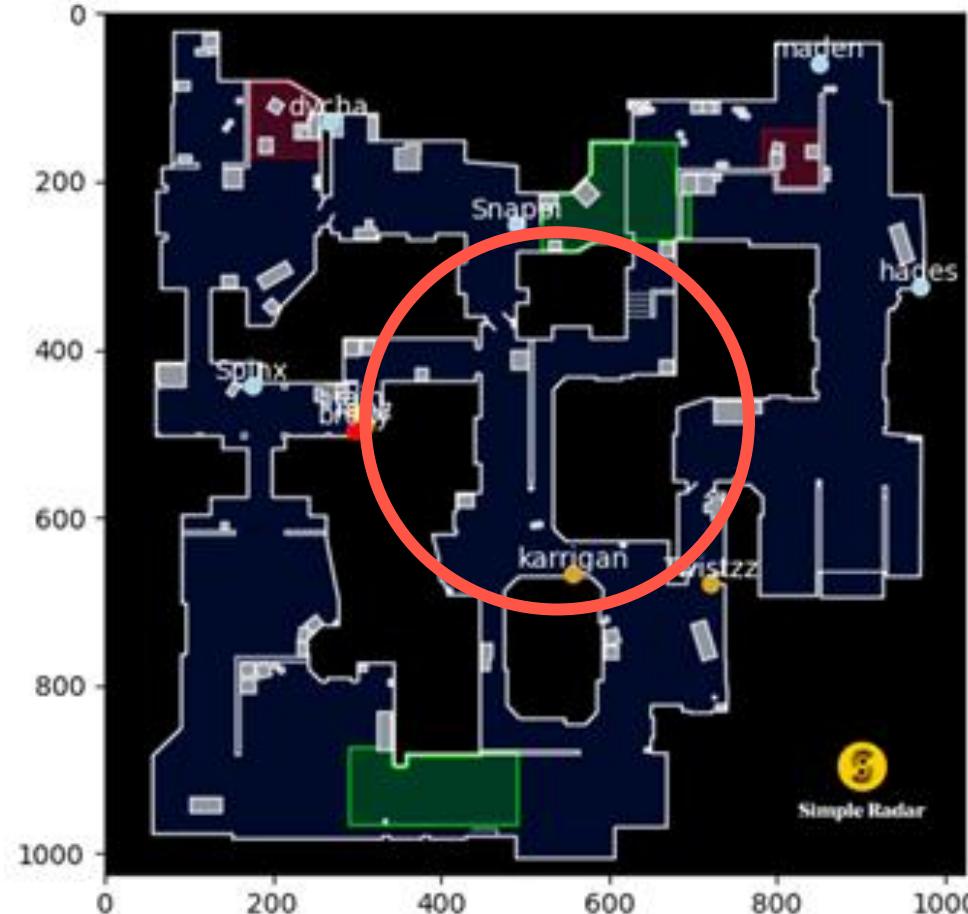
- Demo Daten zu Graphdaten konvertieren
- Spatio-temporal Features pro Frame errechnen

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 proccesed parallely	64
Number of node features extracted	29 per graph

Ergebnisse

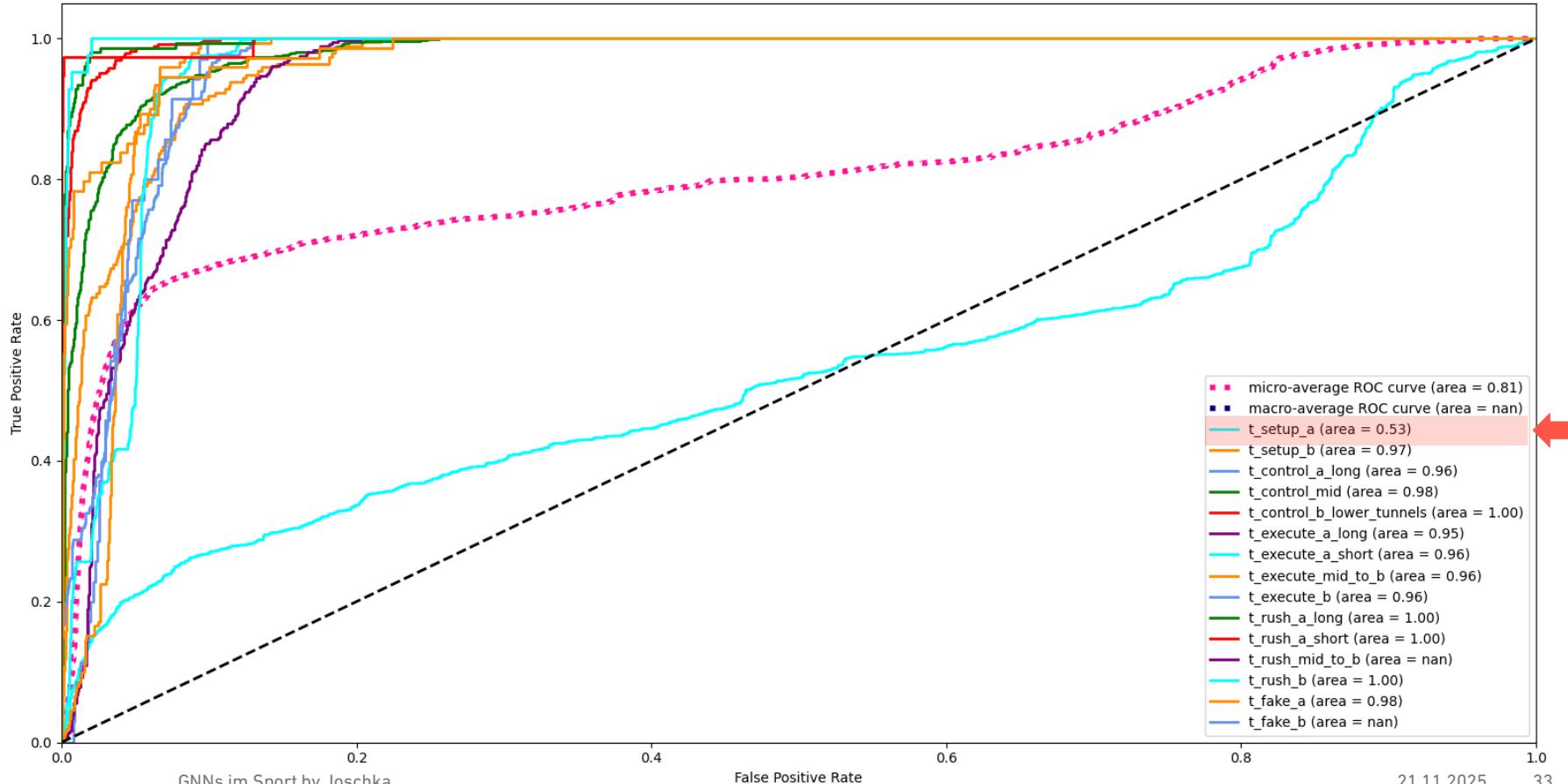


Ergebnisse



Ergebnisse

Receiver Operating Characteristic (ROC) Curves



Ergebnisse

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



Nächste Schritte

1. Regression der Taktiken
2. Annotationen steigern
3. Verbesserung der Prediction

Zum Nachlesen

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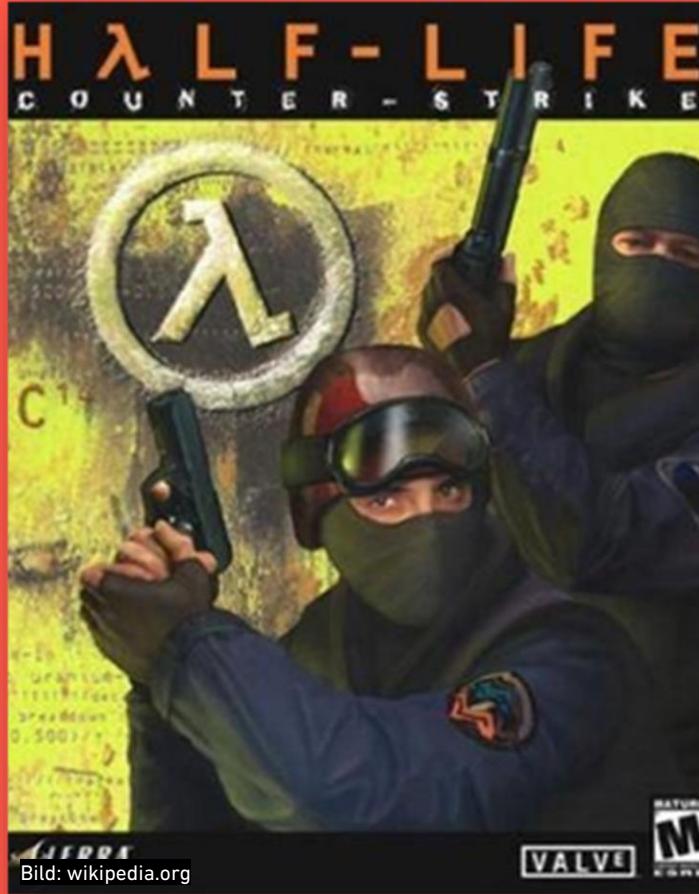


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