GRAPH NEURAL NETWORKS FÜR VORHERSAGEN IM SPORT

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IT-Unternehmensberatung

UNIVERSITY OF TWENTE.

Bild: Sky Sports

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

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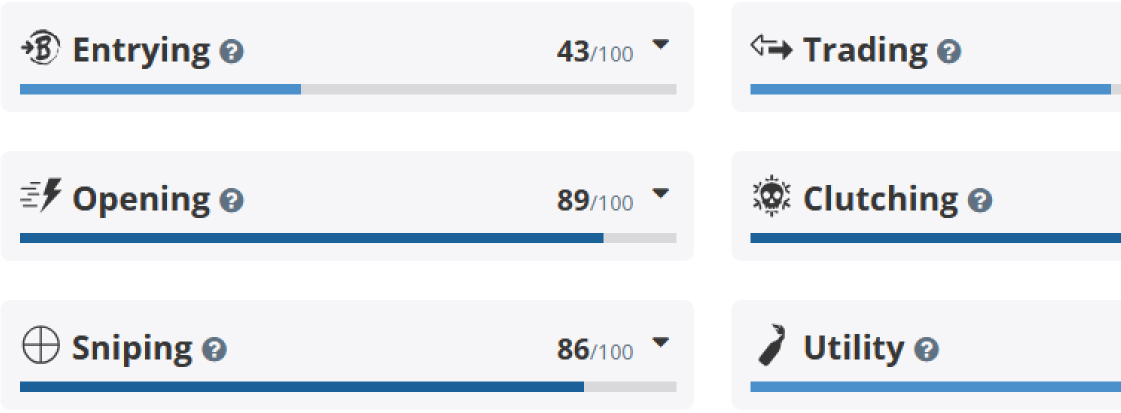
Abstract. Over the last years, several approaches for the data-driven estimation of expected possession value (EPV) in basketball and association football (soccer) have been proposed. In this paper, we develop and evaluate PIVOT: the first such framework for team handball. Accounting for the fast-paced,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



Bilder: hltv.org

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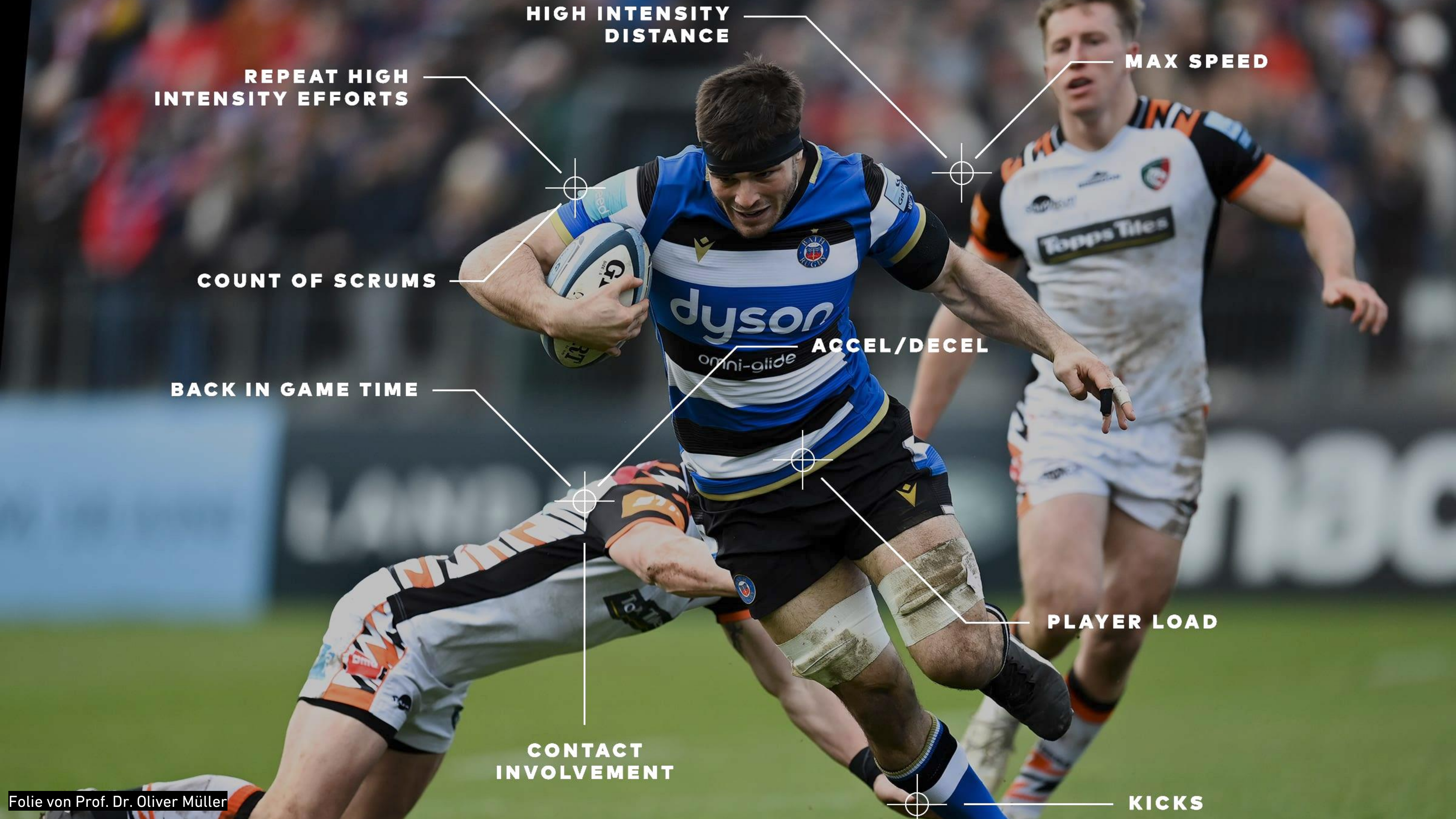


Folie von Prof. Dr. Oliver Müller

PERFORMANCE PSYCHOLOGY & HEALTH

TEAM ANALYSIS

PLAYER ANALYSIS

EYE TRACKING

IN GAME PERFORMANCE ANALYSIS

INPUT ANALYSIS

Folie von Dr. Guido Bruinsma

Bild: noesis.gg

Frame Nummer
(sampled at 2 Hz)

Name

Ressourcen:
Geld &
Ausrüstung

Position &
Bewegung

... und noch
mehr Spalten,
aktuell 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	212.31317138671875	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	163.1445007324218	-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	207.3036804199218	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	235.7156677246093	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	126.88840		
2	39904	jks	2250	Flashbang	-1496.50927734375	-2177.349609375	-247.2598876953125	185.301208		

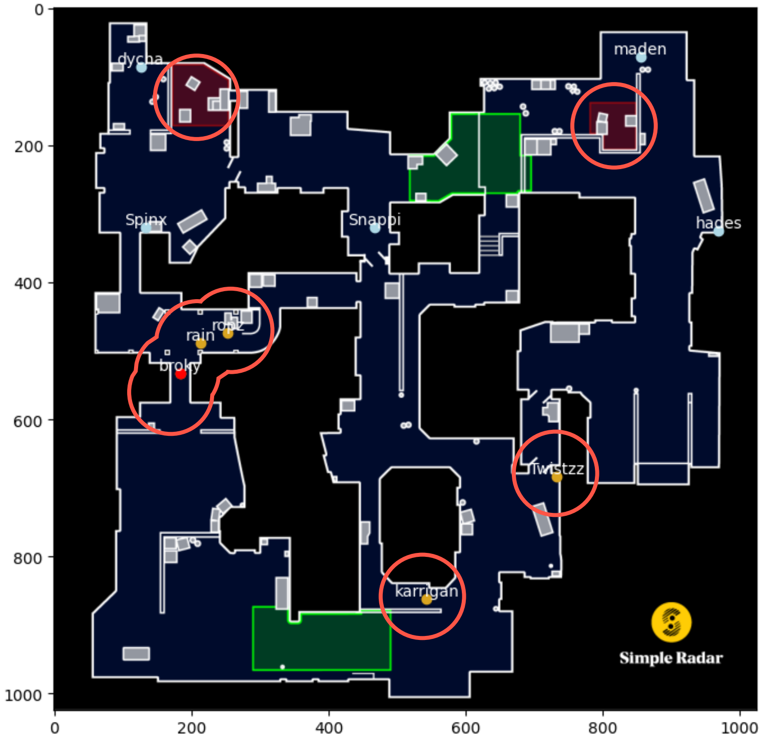
128 Events
pro Spieler pro Sekunde
(> 50.000 Events pro Runde)

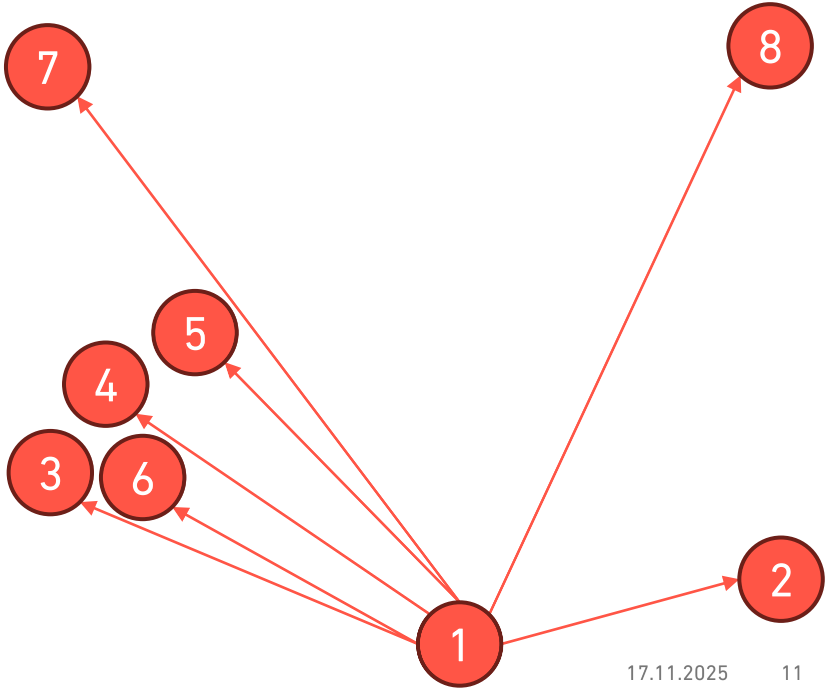
Inhalt

Counter-Strike als Graph

vollständiger Digraph
1-5: Spieler
6: Bomb
7-8: Bombsite A & B
(die meisten GNN-Layer können nur Zahlen)

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





Counter-Strike als Graph

vollständiger Digraph

1-5: Spieler

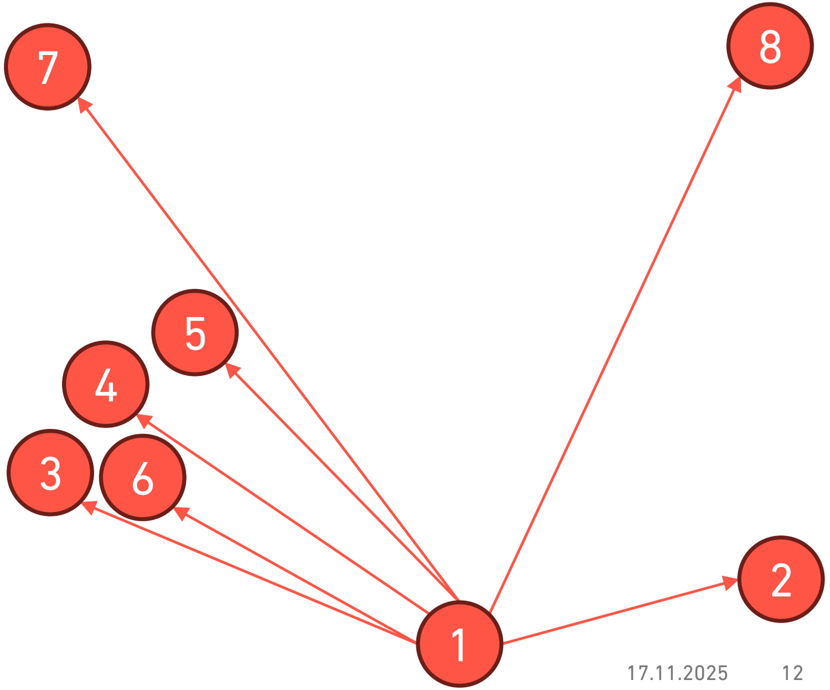
6: Bomb

7-8: Bombsite A & B

(die meisten GNN-Layer können nur Zahlen)

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

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

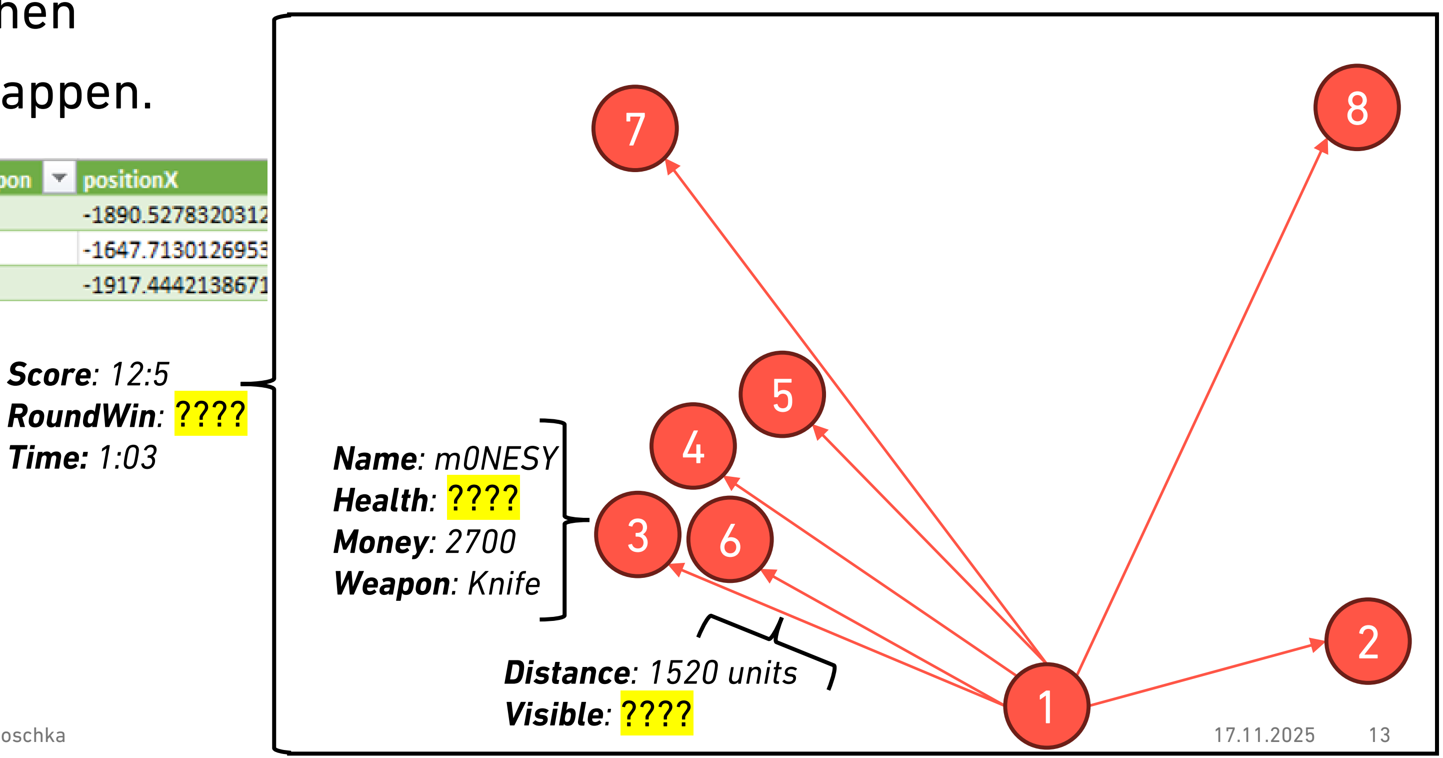


Counter-Strike als Graph

Daten auf Graphen

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

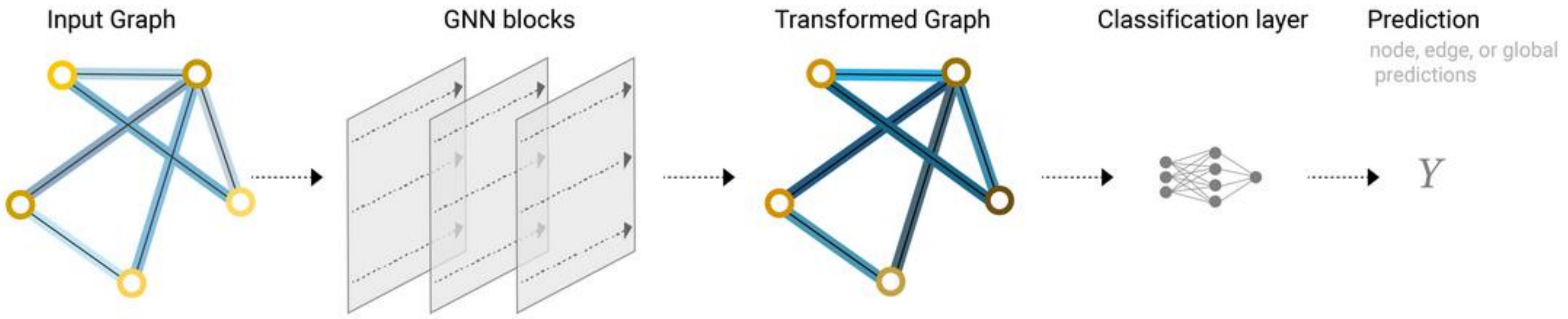
playerNan	money	equippedWeapon	positionX
huNter	2300	Knife	-1890.5278320312
NiKo	2250	USP-S	-1647.7130126953
m0NESY	2700	Knife	-1917.4442138671



Graph Neural Networks

Zusammenfassung:
Wie CNNs mit
- Pooling
- Message Passing

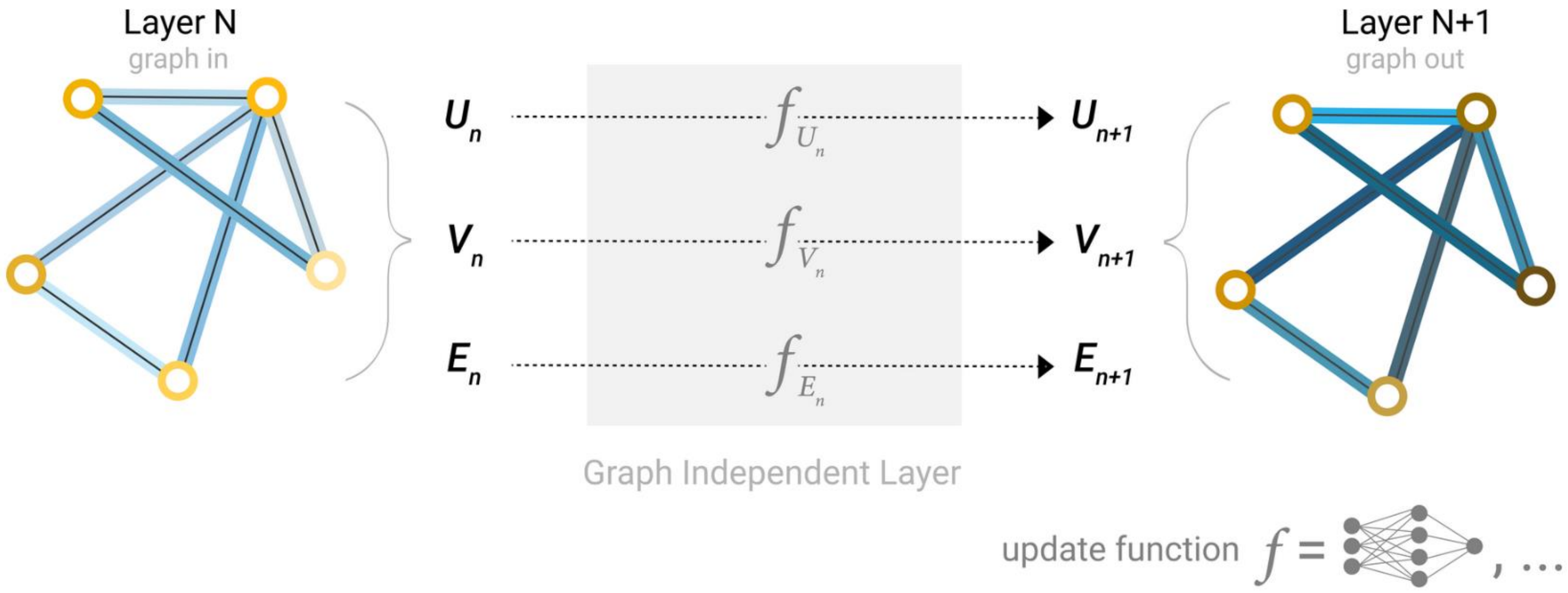
1. collect neighbor embeddings
2. aggregate with focal element
3. transform



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

Sanchez-Lengeling et al. (2021)

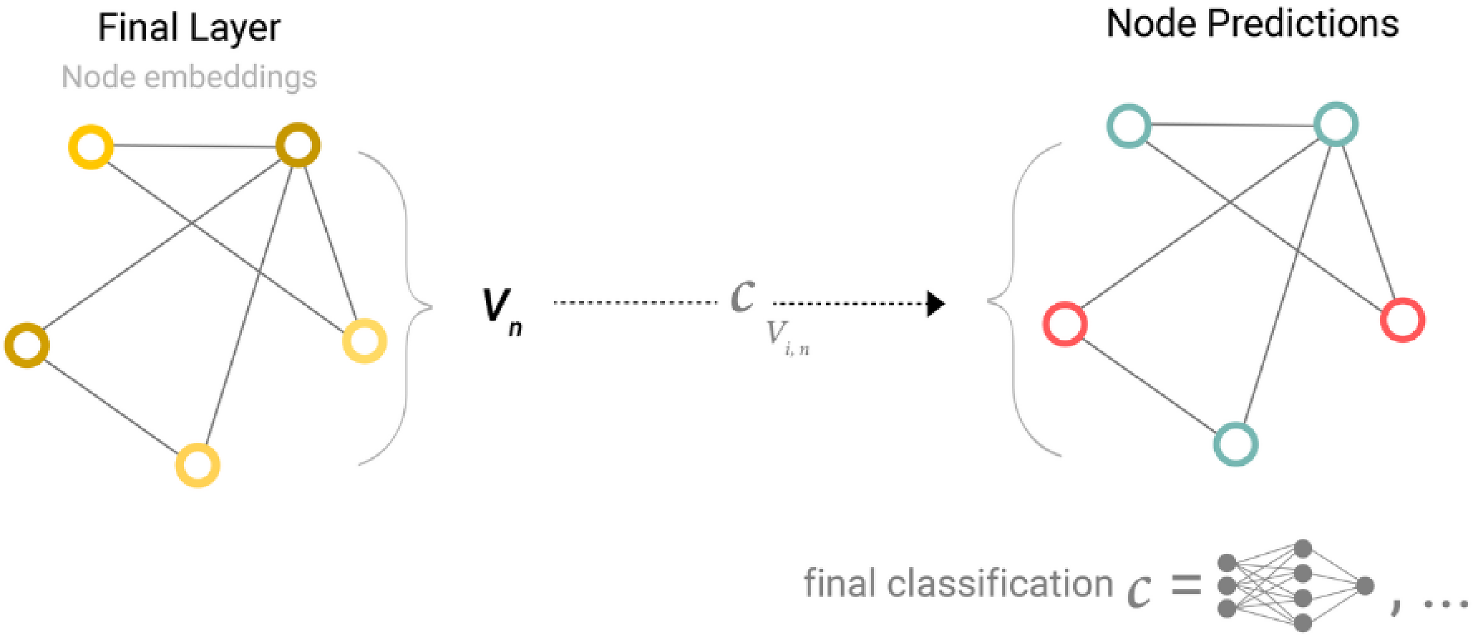
Graph Neural Networks



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.

Sanchez-Lengeling et al. (2021)

Graph Neural Networks



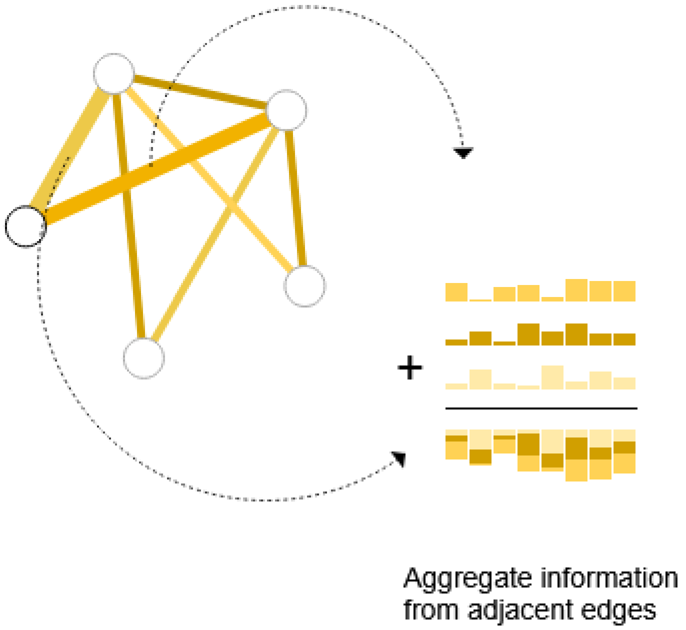
Sanchez-Lengeling et al. (2021)

Graph Neural Networks

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

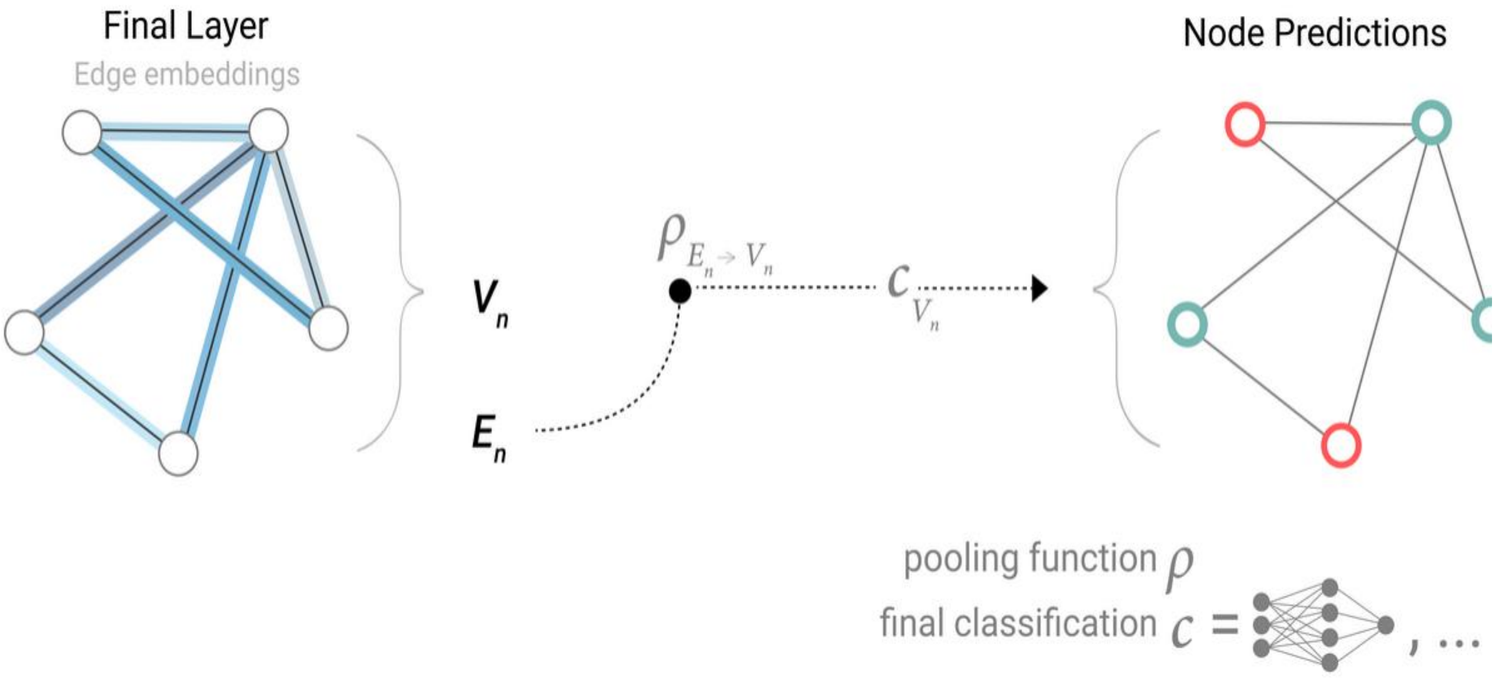
Pooling

- 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.



Sanchez-Lengeling et al. (2021)

Graph Neural Networks



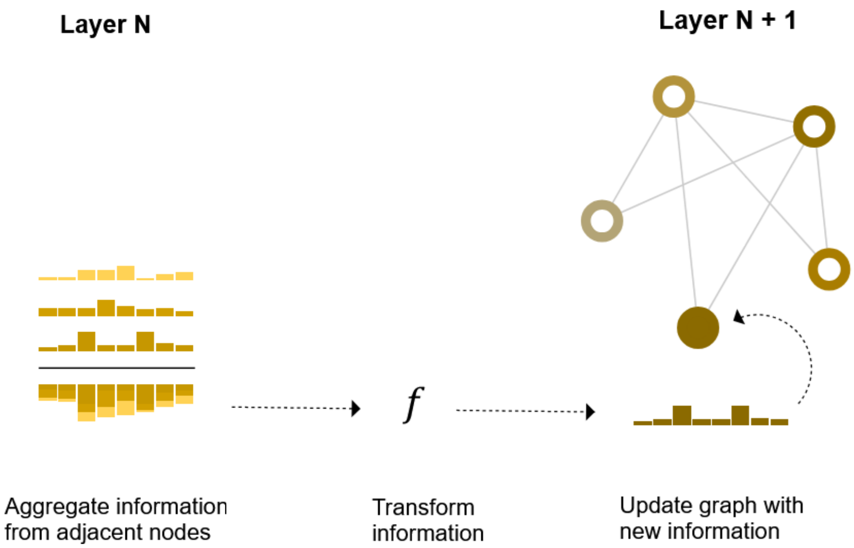
Sanchez-Lengeling et al. (2021)

Graph Neural Networks

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

Message Passing

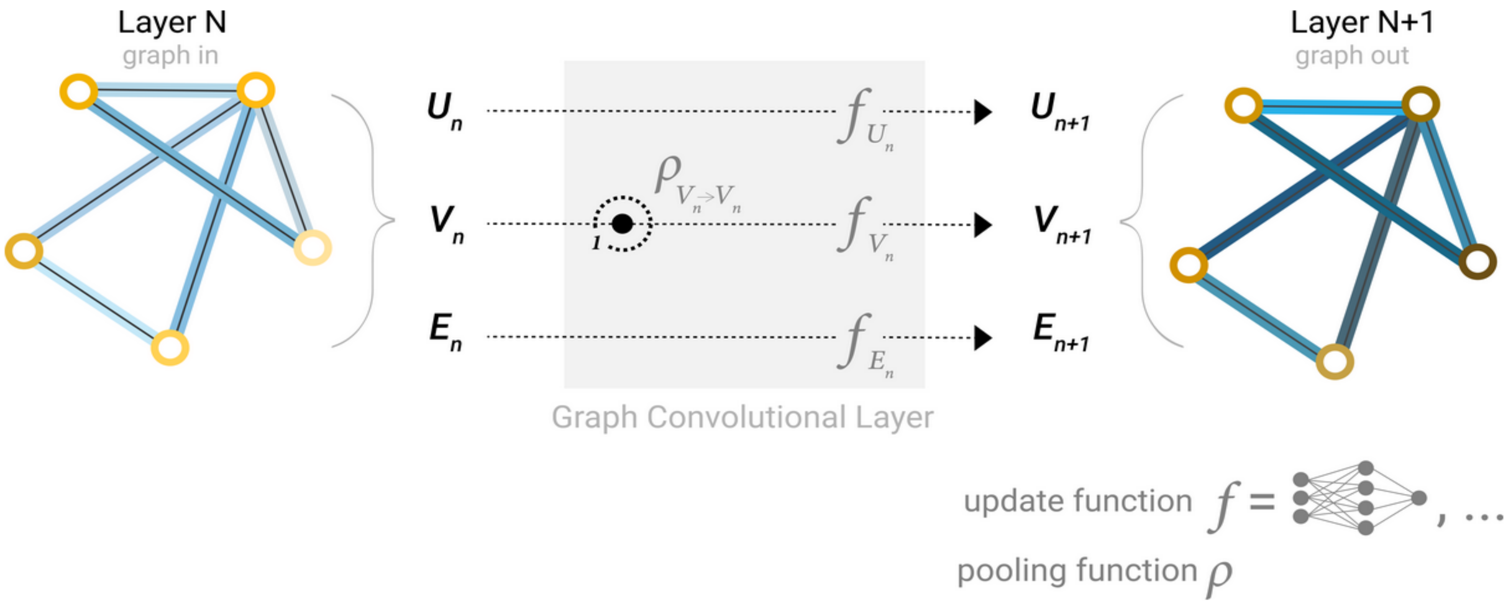
- Für jeden zu poolenden Vektor werden alle Embeddings **gesammelt** und zu einer Matrix verknüpft.
- Die gesammelten Embeddings werden **aggregiert**. In der Regel durch eine Summenoperation.
- Die gepoolten Embeddings werden durch die **Update Function** geleitet.



Sanchez-Lengeling et al. (2021)

Graph Neural Networks

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

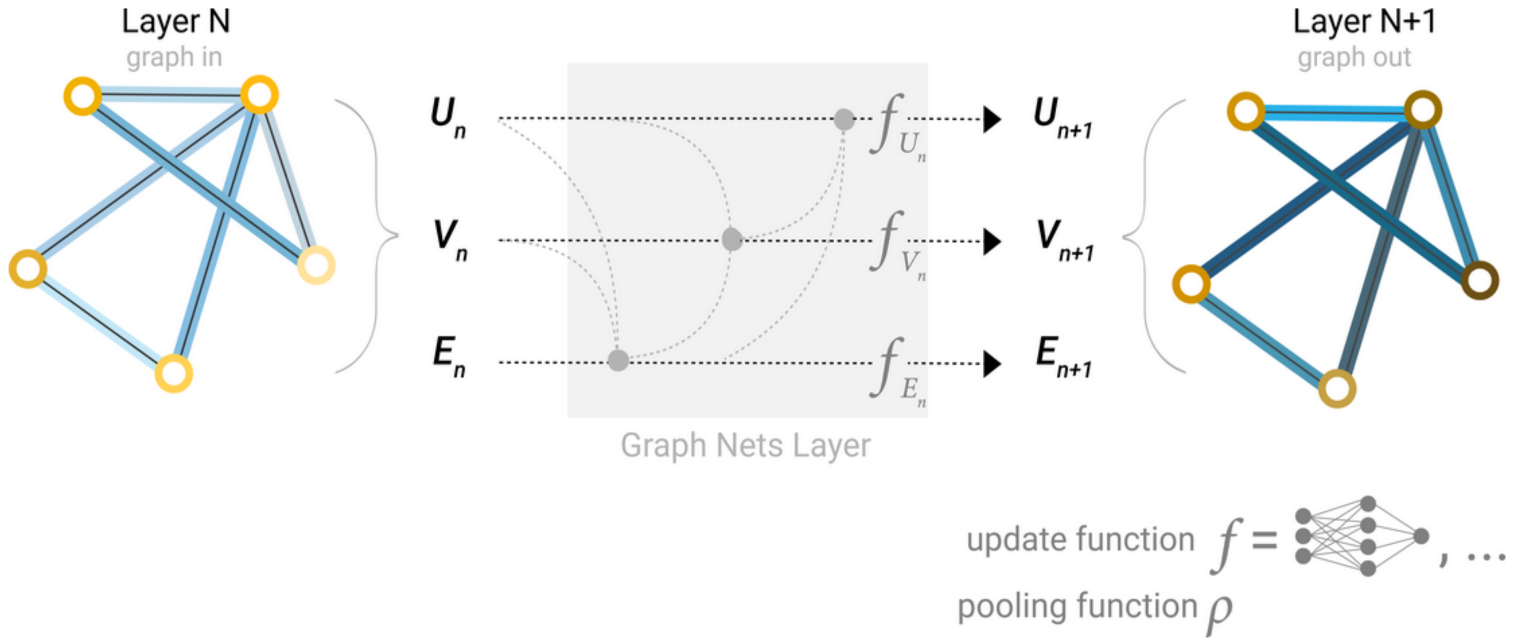


Schematic for a GCN architecture, which updates node representations of a graph by pooling neighboring nodes at a distance of one degree.

Sanchez-Lengeling et al. (2021)

Graph Neural Networks

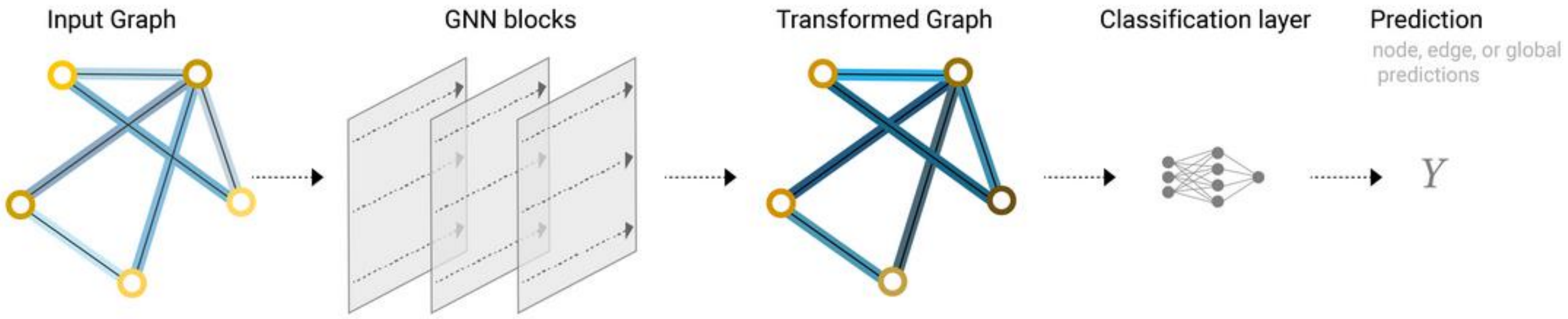
https://distill.pub/2021/gnn-intro/#node-step



Schematic of a Graph Nets architecture leveraging global representations.

Sanchez-Lengeling et al. (2021)

Graph Neural Networks



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

Sanchez-Lengeling et al. (2021)

Inhalt

Technology Stack

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

1 Team-Theorie

2 **Daten Vorbereitung**

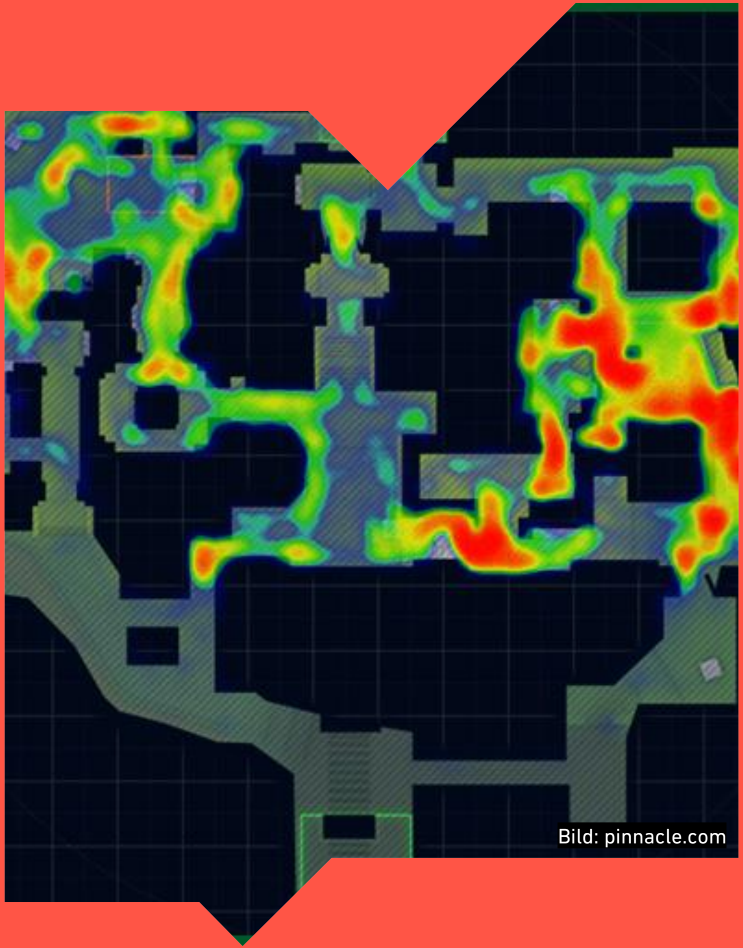
3 Modellierung

4 Evaluation

5 Bereitstellung

Possession Value und Expected Threat (xT)

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



Pollard & Reep (1997), Graham (2024)

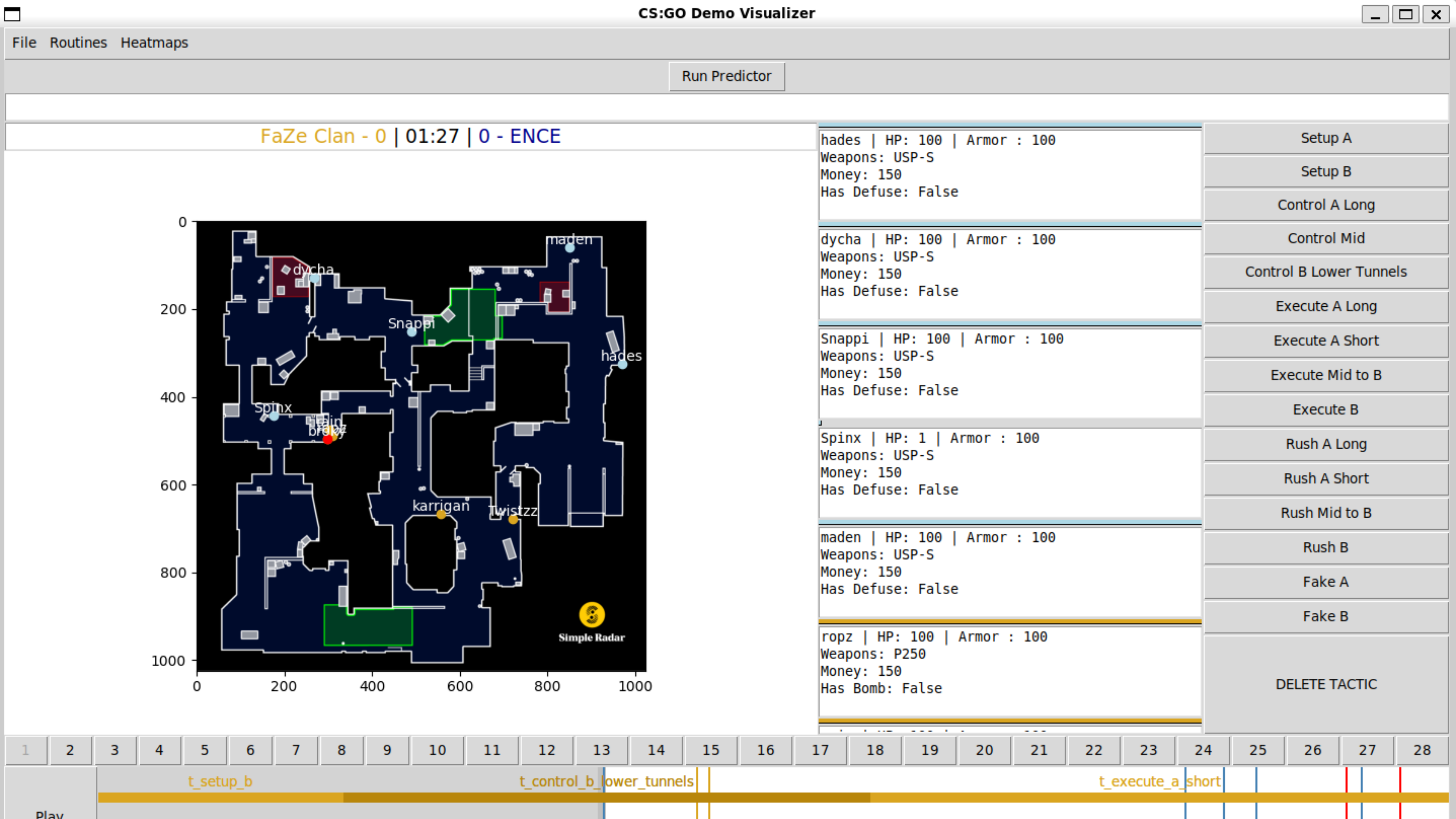

CS:GO Demo Visualizer
File
Routines
Heatmaps
Run Predictor
FaZe Clan - 0 | 01:27 | 0 - ENCE
maden
dycha
Snappi
hades
Spinx
karrigan
Twistzz
Simple Radar
0
200
400
600
800
1000
hades | HP: 100 | Armor : 100
Weapons: USP-S
Money: 150
Has Defuse: False
dycha | HP: 100 | Armor : 100
Weapons: USP-S
Money: 150
Has Defuse: False
Snappi | HP: 100 | Armor : 100
Weapons: USP-S
Money: 150
Has Defuse: False
Spinx | HP: 1 | 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
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
Play
t_setup_b
t_control_b_lower_tunnels
t_execute_a_short

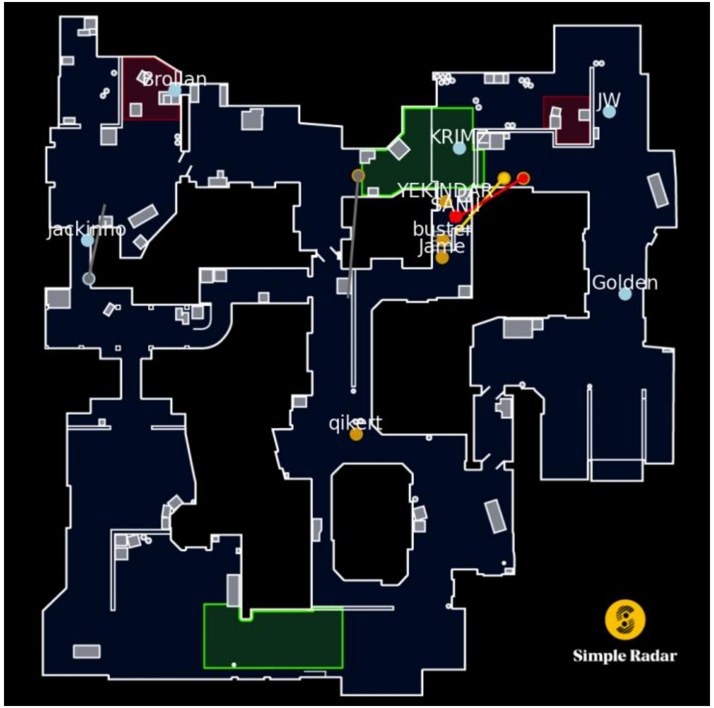

Bild: steamstatic.com

Bild: skinlords.com

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.



Daten Vorbereitung

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

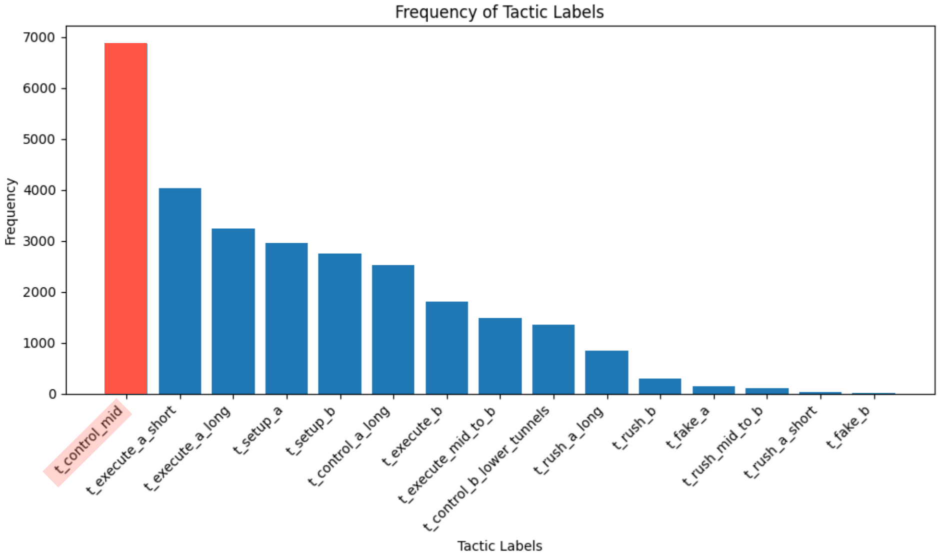
Number of demo files processed	195
Total rounds extracted	5133
Frames skipped due to issues	0 per game
Average number of frames per round	≈ 186
Processing time per frame	≈ 1 to 4 seconds
# games that could be proccessed parallely	64
Number of node features extracted	29 per graph

Folie von Kirna, Vlad, & Szabolcs

Annotierte Taktiken

Out of >1000 games

Only de_dust2

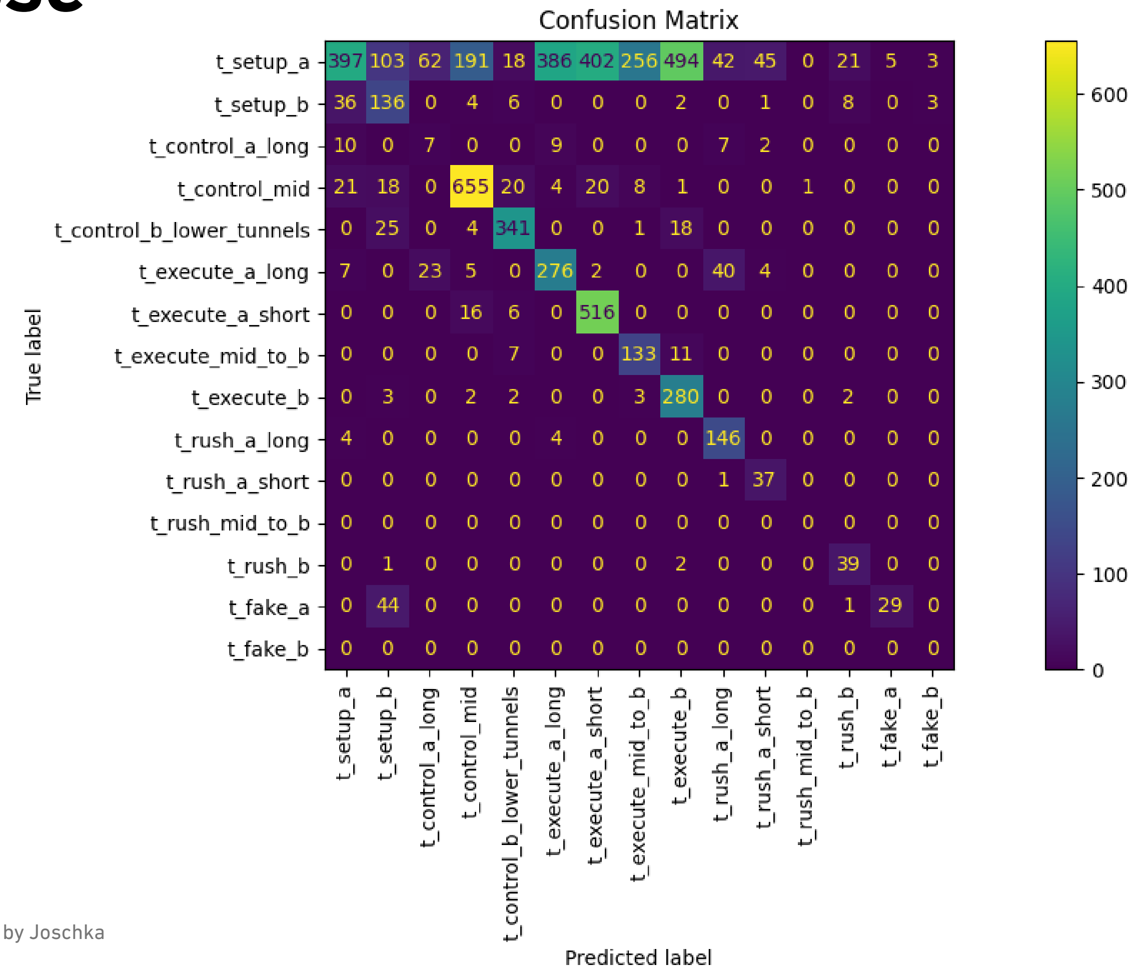


Number of games labeled	20
Number of frames labeled	28,468
Number of *uncertain tactic* frames	18,705
Number of unique tactics annotated	15
Most common tactic	*t_control_mid*

Table 3. Labeling statistics

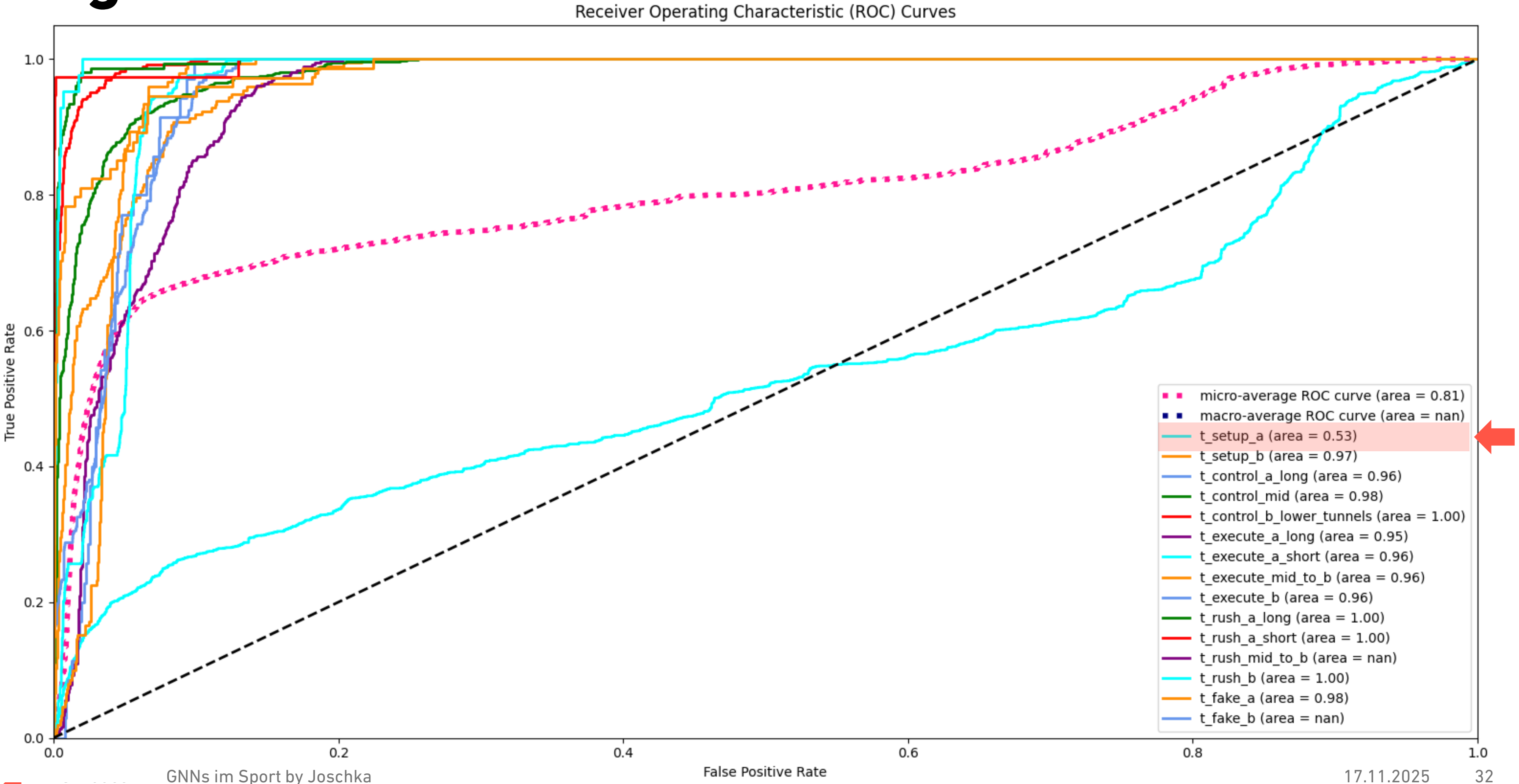
Folie von Kirna, Vlad, & Szabolcs

Ergebnisse



Folie von Kirna, Vlad, & Szabolcs

Ergebnisse



Folie von Kirna, Vlad, & Szabolcs

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

Folie von Kirna, Vlad, & Szabolcs

Nächste Schritte

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

Bild: wikipedia.org

Zum Nachlesen

- 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.

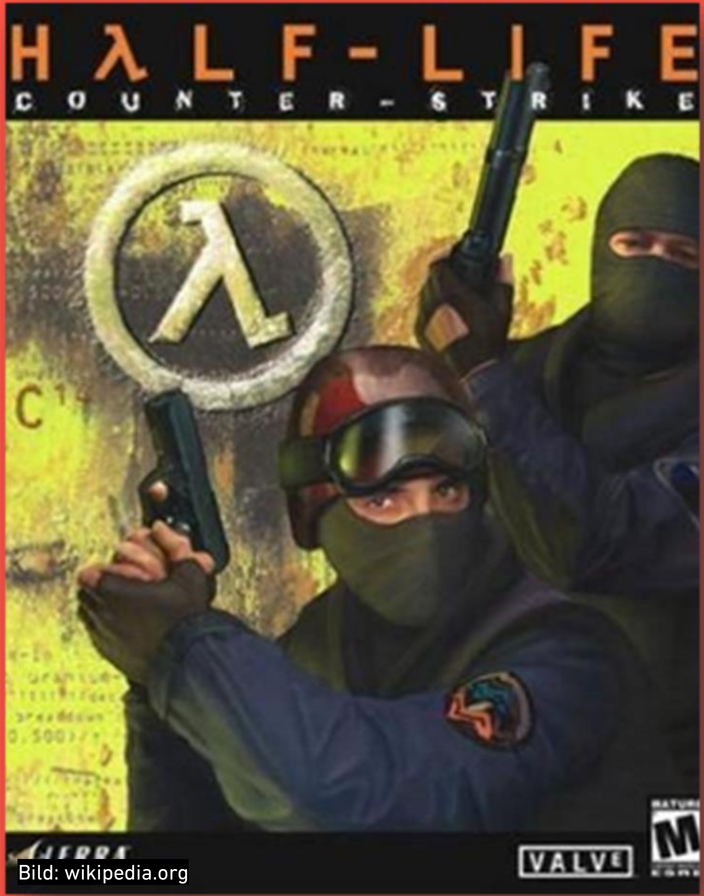


Bild: wikipedia.org