

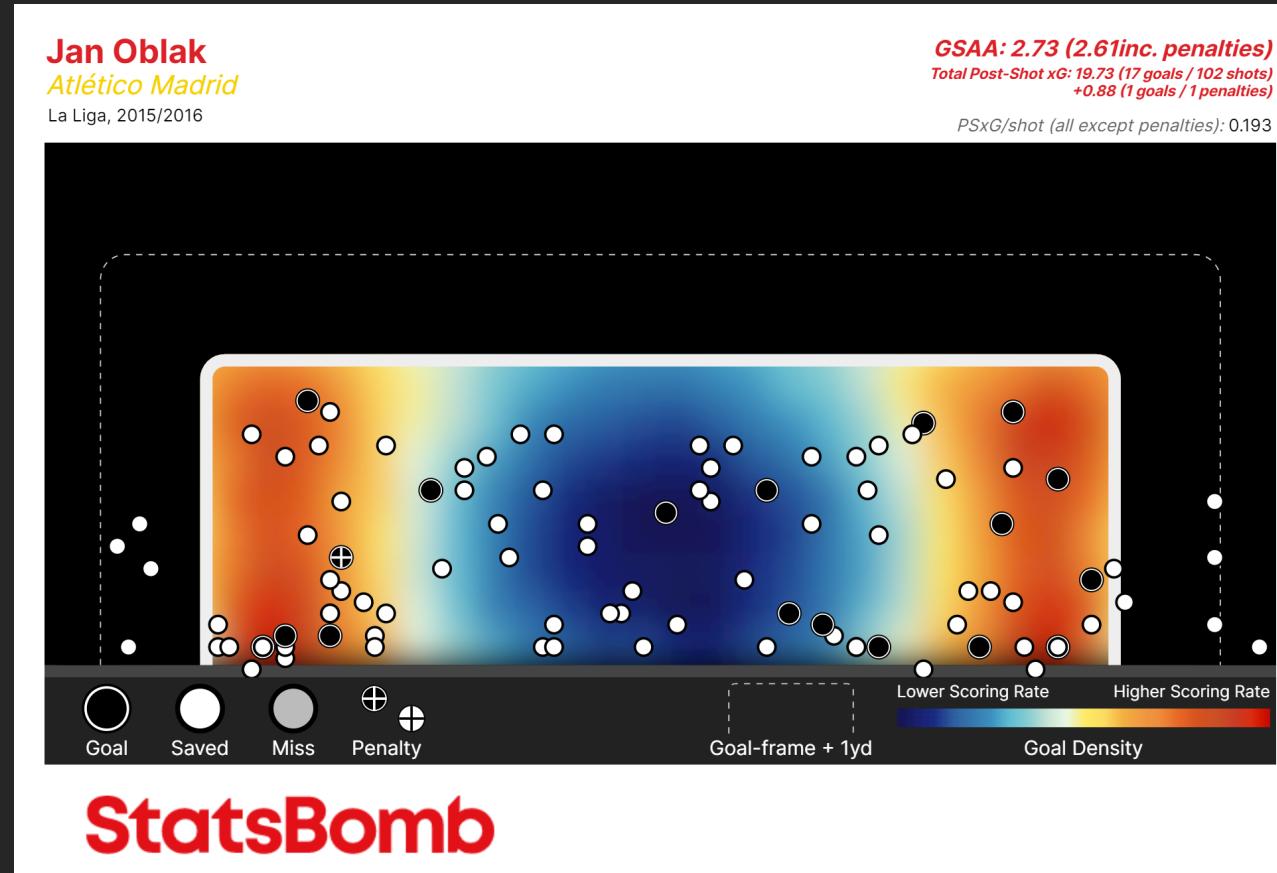
LEVELING UP COLLEGE SOCCER WITH MACHINE LEARNING

SENIOR PROJECT

Alex Fok

BACKGROUND

DATA IS THE GAME



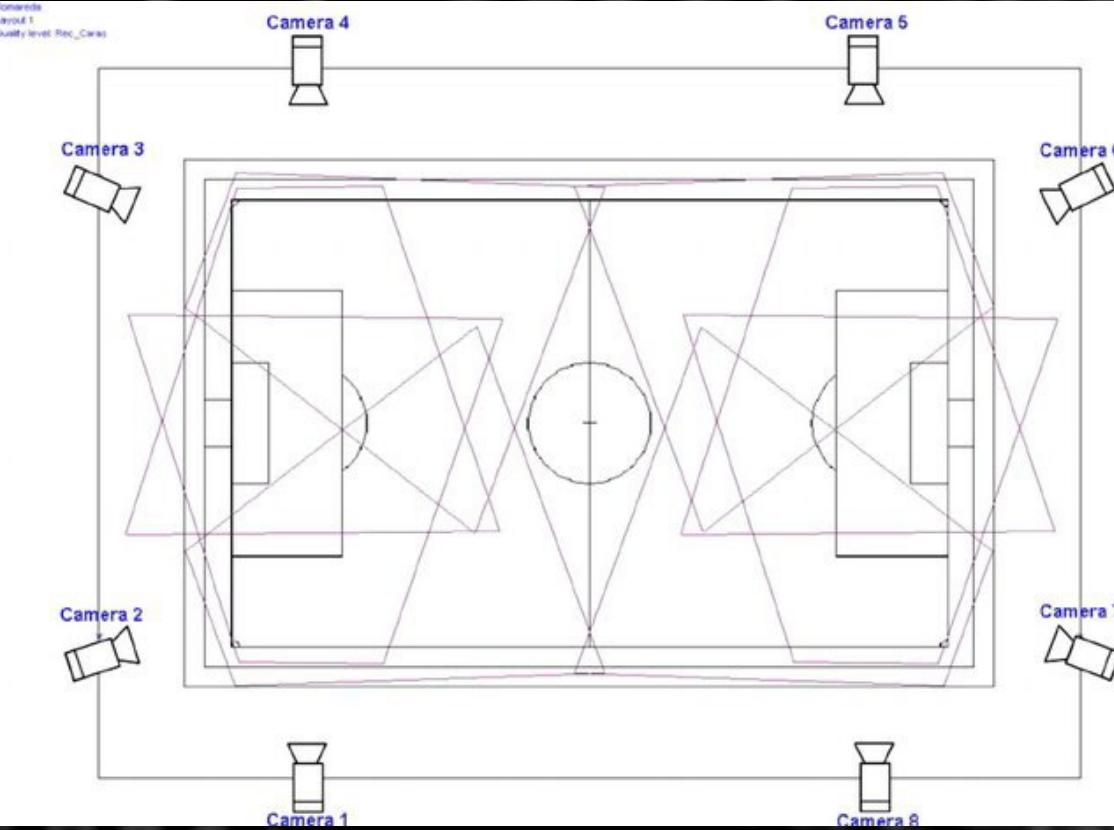
Source: STATSBOMB

Where does data come from?

GPS TRACKER



CAMERA FOOTAGE



Source: STATSports, Martinez-del-Rincon, Jesus & Herrero Jaraba, Elías & Gómez, J. & Orrite, Carlos & Medrano, Carlos & Montañés-Laborda, Miguel. (2009). Multicamera sport player tracking with Bayesian estimation of measurements. Optical Engineering - OPT ENG. 48. 10.1117/1.3114605.

WHAT ABOUT NON-PROFESSIONALS?



Source: Veo

STATISTICS AVAILABLE

Sofascore

Search DROPPING ODDS FAVOURITES

Football American Football Basketball Baseball Ice Hockey Motorsport Tennis Table Tennis Esports Handball Volleyball MMA Cricket Rugby More

Abha 0 - 8 Al-Nassr

A. Al-Aliwa 86' 63' A. Ghareeb 51' A. Al-Sulaheem 44' +4 goals

Full time 1 - 0 +850 X -450 -345

Gamble responsibly 18+ Show more

Attack Momentum

Add Attack Momentum to your website!

Sofascore Ratings Francois Kamano 8.8 Cristiano Ronaldo 10

FT 0 - 8 Additional time 4'

A. Al-Aliwa 0 - 8 66' Out: A. Ghareeb In: A. Arman 69'

In: S. Bguir Out: G. Krychowiak 67'

In: S. Al Qumayzi Out: F. B. Jumayah 67'

LINEUPS PLAYER STATISTICS

Summary Attack Defence Passing Duels Goalkeeper

	Cristiano Ronaldo	Abdulaziz Al-Aliwa	Otávio	Nawaf Boushal	Abdulmajed Al-Sulaheem	Abdulrahman Ghareeb	David Ospina	Aymeric Laporte	Alex Telles	Mohammed Al-Fatil	Sadio Mané
Goals	3	2	0	0	1	1	0	0	0	0	1
Assists	1	0	3	3	0	1	0	1	1	0	0
Tackles	0	0	3	75/83 (90%)	12 (7)	10 (7)	2 (0)	0 (0)	0 (0)	2 (1)	0 (0)
Accurate passes	8/14 (57%)	16/24 (67%)	75/83 (90%)	46/52 (86%)	45/47 (96%)	29/38 (81%)	27/29 (93%)	89/92 (97%)	48/53 (91%)	60/67 (90%)	11/12 (92%)
Duels (won)	3 (2)	4 (2)	10 (7)	7 (5)	6 (2)	5 (2)	0 (0)	1 (1)	4 (2)	2 (1)	4 (0)
Ground duels (won)	2 (1)	3 (0)	2 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
Aerial duels (won)	1 (1)	1 (0)	2 (0)	0 (0)	0 (0)	0 (0)	0 (0)	3 (3)	1 (1)	2 (1)	2 (0)
Possession lost	0	0	0	0	0	0	0	0	0	0	0
Fouls	1	1	1	0	0	0	0	0	0	0	0
Was fouled	0	0	0	0	0	0	0	0	0	0	0
Offsides	0	0	0	0	0	0	0	0	0	0	0
Position	F	M	M	D	M	M	G	D	D	D	M
Minutes played	45'	45'	90'	90'	58'	69'	90'	90'	90'	90'	45'
Match Shotmap											
Minutes played	45'										
Goals	3										
Assists	1										
Shots on target	4										
Shots off target	1										
Shots blocked	1										
Dribble attempts (succ.)	0 (0)										

JESSUP UNIVERSITY ATHLETICS

SPORTS INSIDE ATHLETICS FAN ZONE MEDIA GIVE JESSUP.EDU

Men's Soccer Schedule Roster Coaching Staff Statistics More

2023 Men's Soccer Cumulative Statistics

View PDF Select a Season...

TEAM INDIVIDUAL GAME-BY-GAME MISCELLANEOUS

OVERALL CONFERENCE

OFFENSIVE GOALKEEPING

Offensive

#	GP	GS	MIN	G	A	PTS	SH	SH%	SOC	SOC%	YC-RC	GW	PG-PW	
13	Morfin, Isaac	19	18	1308	6	2	14	40	0.150	19	0.475	3-0	2	1-1
09	Nunez, Diego	16	13	1082	9	1	19	37	0.243	19	0.514	8-1	2	1-1
26	Guillen, Eduardo	18	8	950	2	1	5	35	0.057	10	0.286	3-1	0	0-0
07	Ionescu, Paolo	18	13	980	5	2	12	33	0.152	17	0.515	0-0	2	0-0
14	Burridge, Eliza	19	8	948	1	1	3	17	0.059	4	0.235	1-0	0	0-0
11	Bailias, Albert	13	5	548	2	2	6	10	0.200	6	0.600	2-0	1	0-0
20	Castillo, Luis	19	16	1045	0	0	0	10	0.000	4	0.400	1-0	0	0-0
12	Cruz, Luis	17	17	1530	2	1	5	8	0.250	5	0.625	3-0	0	0-0
10	Camilo, Donovan	19	19	1636	0	2	2	7	0.000	1	0.143	1-0	0	0-0
17	Hes, Dylan	16	9	829	0	1	1	6	0.000	2	0.333	4-0	0	0-0
02	Yang, Andrew	12	7	788	0	0	0	6	0.000	1	0.167	2-0	0	0-0
29	Ganesh, Maximus	19	18	1639	1	0	2	5	0.200	2	0.400	2-0	0	0-0
22	Garcia, Jeffrey	11	6	644	1	0	2	5	0.200	1	0.200	2-0	0	0-0

	Touches	Accurate passes	Key passes	Crosses (acc.)	Long balls (acc.)	Notes	Position	Sofascore rating
Cristiano Ronaldo	22	8/14 (57%)	1	0 (0)	0 (0)	Big chances created: 1	F	
Abdulaziz Al-Aliwa	31	16/24 (67%)	1	3 (0)	1 (0)	Big chances created: 1	M	
Cristiano Ronaldo	3 (2)	2 (1)	1 (1)	7	0	1	1	
Abdulaziz Al-Aliwa	4 (2)	3 (2)	1 (0)	11	1	1	0	
Otávio	12 (7)	10 (7)	2 (0)	11	0	4	0	

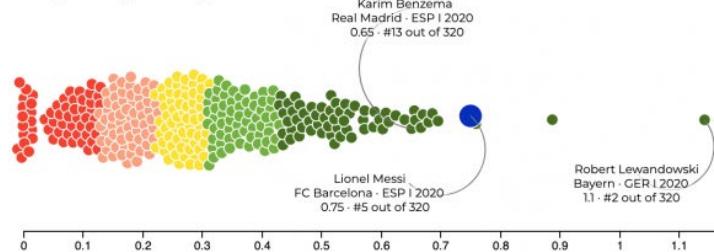


Lionel Messi

Messi vs Benzema vs Lewandowski

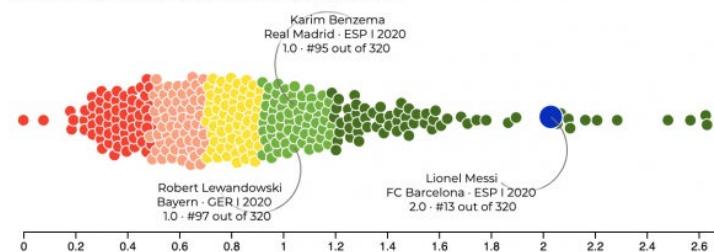
Non-Penalty Goals

Goals (excluding penalties) per 90 minutes



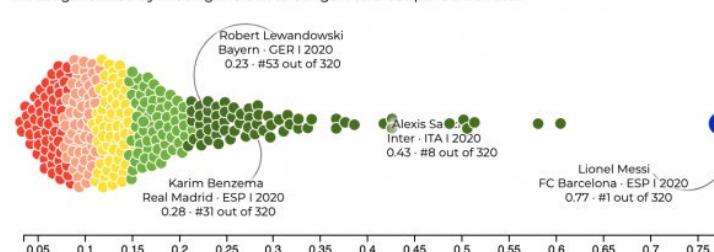
Chances Created

Number of Passes that precede a Shot per 90 minutes



Expected Threat

Threat generated by moving the ball to dangerous areas per 90 minutes



Stats of top 3 Ballon d'Or 2021 contenders until end of voting			
Players	Messi	Lewandowski	Benzema
Games	49	45	50
Goals	40	54	35
Assists	16	8	14
Shots on target	103	98	87
Big chances missed	12	35	24
Accurate passes	2525	715	1589
Dribbles completed	224	48	60
Chances created	118	55	75
Big chances created	26	16	14
Tackles	31	12	23
Recoveries	107	98	101
Points won by goals	22	20	19
Points won by G/A	39	25	30
Match winning goals	9	8	6
Match winning G/A	15	10	10
Man of the match	27	13	11
Team trophies	Copa del Rey Copa America	Bundesliga Club World Cup	UEFA Nations League
Individual awards	LaLiga top scorer Copa America top scorer Copa America top assister Copa America POTT	Bundesliga top scorer European Golden Shoe CWC Golden Ball	
Records broken	Most NT goals in CONMEBOL Most goals in a single club	Most goals in a single BuLi season	

Stats from January 1, 2021 until October 24, 2021 (Ballon d'Or 2021 voting deadline day)

BEST PLAYER DEBATE



Position	Club	Played	Won	Drawn	Lost	GF	GA	GD	Points
1 ▲	Arsenal	33	23	5	5	77	26	51	74
2 ▲	Liverpool	33	22	8	3	75	32	43	74
3 ▼	Manchester City	32	22	7	3	76	32	44	73
4 ▪	Aston Villa	34	20	6	8	71	50	21	66
5 ▪	Tottenham Hotspur	32	18	6	8	65	49	16	60
6 ▪	Newcastle United	32	15	5	12	69	52	17	50
7 ▪	Manchester United	32	15	5	12	47	48	-1	50
8 ▪	West Ham United	34	13	9	12	54	63	-9	48
9 ▪	Chelsea	31	13	8	10	61	52	9	47
10 ▪	Brighton And Hove Albion	32	11	11	10	52	50	2	44

DATA ACCURATE AS OF 4/21/2024

"Data is important in football, but at the end of the day I prefer my own eyes." – Ten Hag

"I use data a lot to understand certain concepts of the game, and I try to amplify performance." – Arteta



SOURCE: LIVERPOOL FC



Google DeepMind

TACTIC AI

4 YEARS OF DEVELOPMENT

Only about 10 corner kicks are played in each match in the Premier League every season.

Sealed a spot to the Final and won the club's 6th European Cup in 2019

GETTING DATA

BE ONE STEP AHEAD



PROJECT GOALS



Track player locations
from single camera
footage



Perform Data Analysis

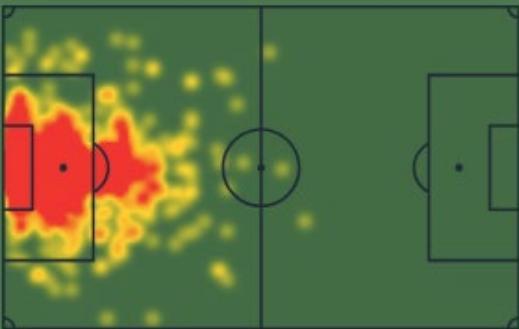


Generate Heat Maps

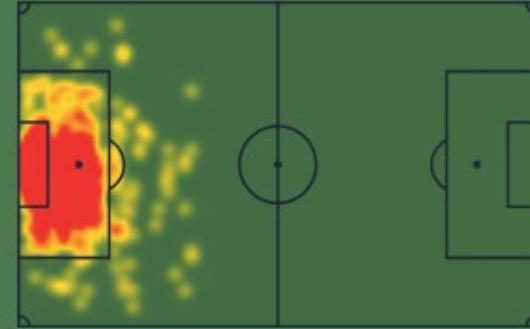


Plot Average Position

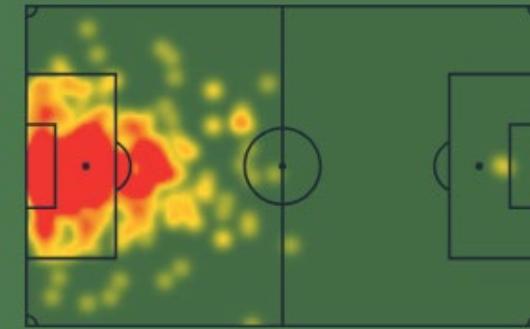
HEAT MAPS



Andre Onana



Jan Oblak



Manuel Neuer



IMPORTANCE OF SPACE



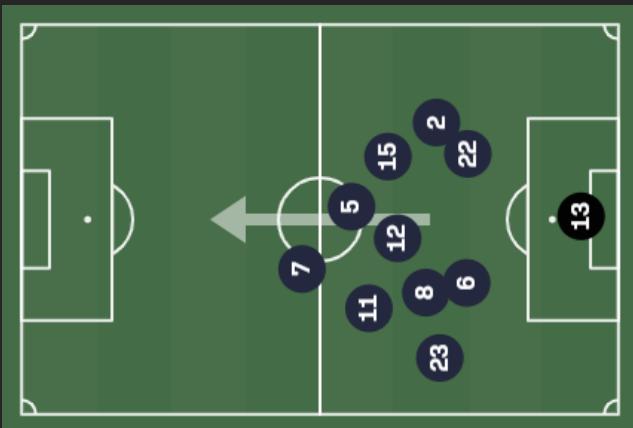
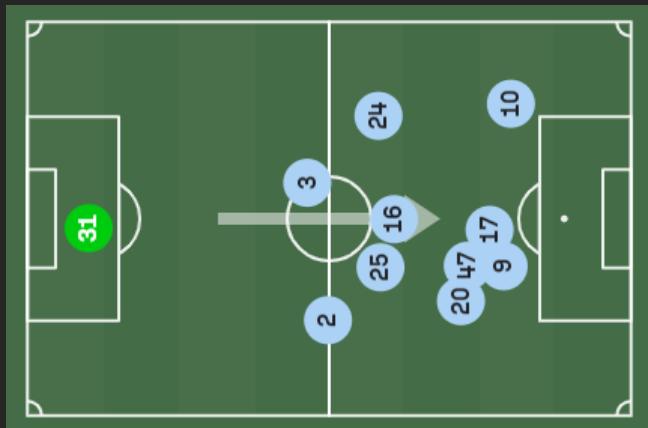
TACTICS - POSITION SHIFTING



UEFA Champions League,
Knockout stage,
Quarterfinal Second Leg

4-17-2024

Manchester City vs Real Madrid



Source: Sofascore

PROJECT SETUP

Programming Language: Python

Object Detection and Classification Model: Custom YOLOv8 model

Machine Learning Framework: TensorFlow

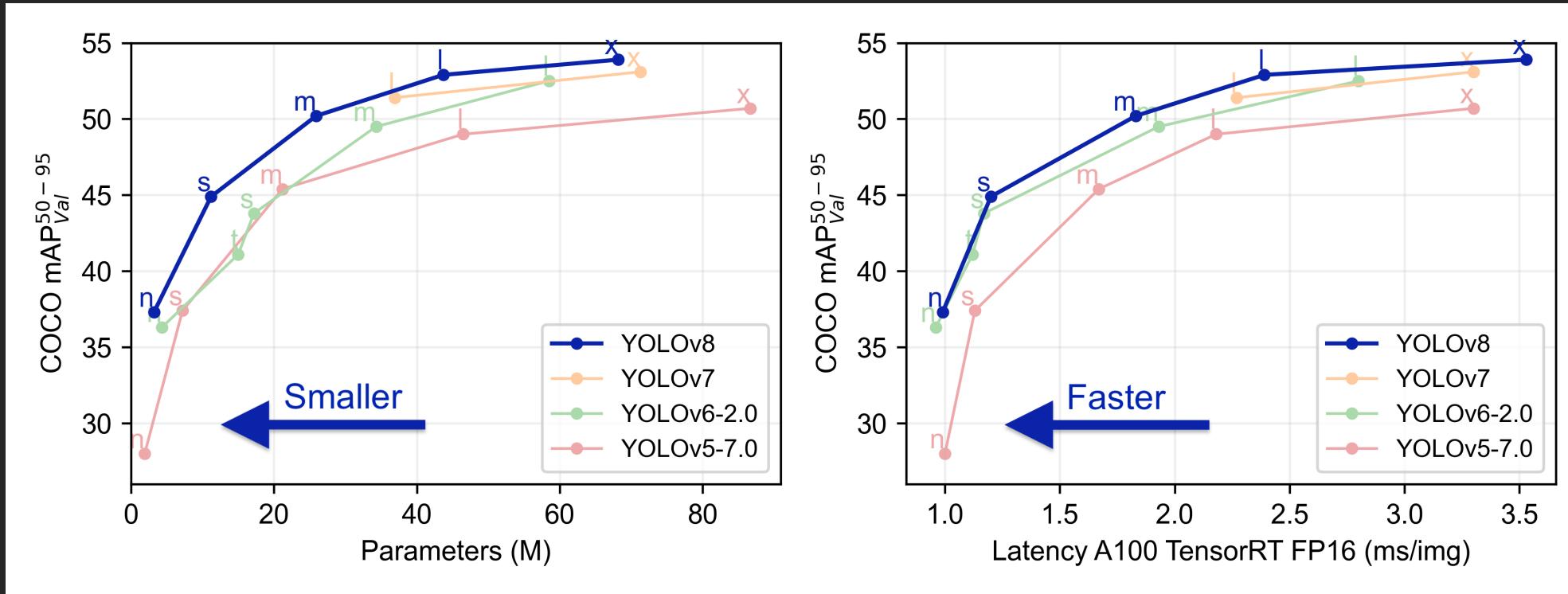
Computer Vision Library: OpenCV

Graphing Library: Matplotlib, PyGWalker

Front-end: Streamlit



DETECTING PLAYERS



Open-Source Computer Vision Model

Convolutional Neural Network (CNN)

OBJECT DETECTION

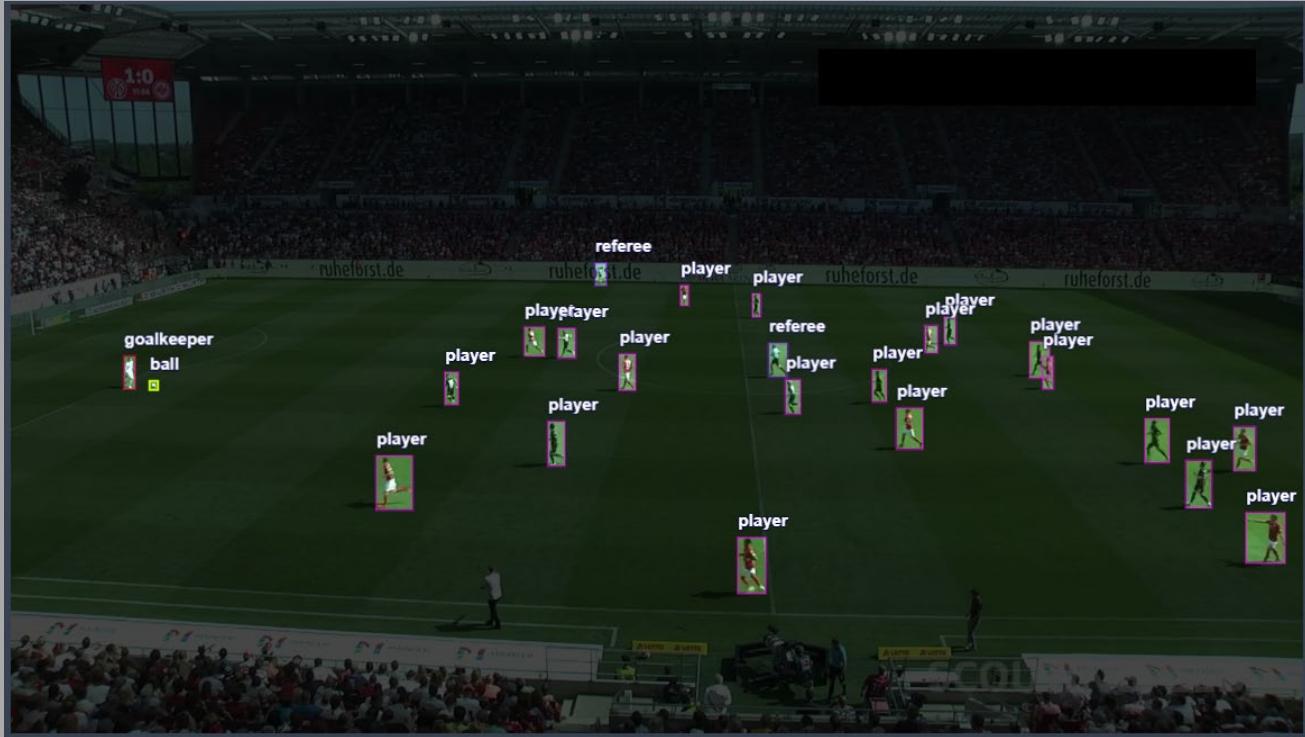


MESSY



Image Source: Manuel Stein at FC Barcelona Sports Tomorrow

TRAINING A MODEL WITH CUSTOM DATA



- Limiting detections to 4 classes
- Free Dataset from Roboflow
- Trained on ~200 images

TRAINING A MODEL WITH CUSTOM DATA

epochs	Total number of training epochs. Each epoch represents a full pass over the entire dataset. Adjusting this value can affect training duration and model performance.
patience	Number of epochs to wait without improvement in validation metrics before early stopping the training. Helps prevent overfitting by stopping training when performance plateaus.

Source: [Ultralytics](#)

- Training Parameters:
 - Epochs: 50
 - Patience: 5

TRAINING A MODEL

Cloud Setup

32GB RAM



Tesla V100 GPU w/16GB VRAM

~\$1500

My laptop

16GB RAM

MX250 w/ 2GB VRAM



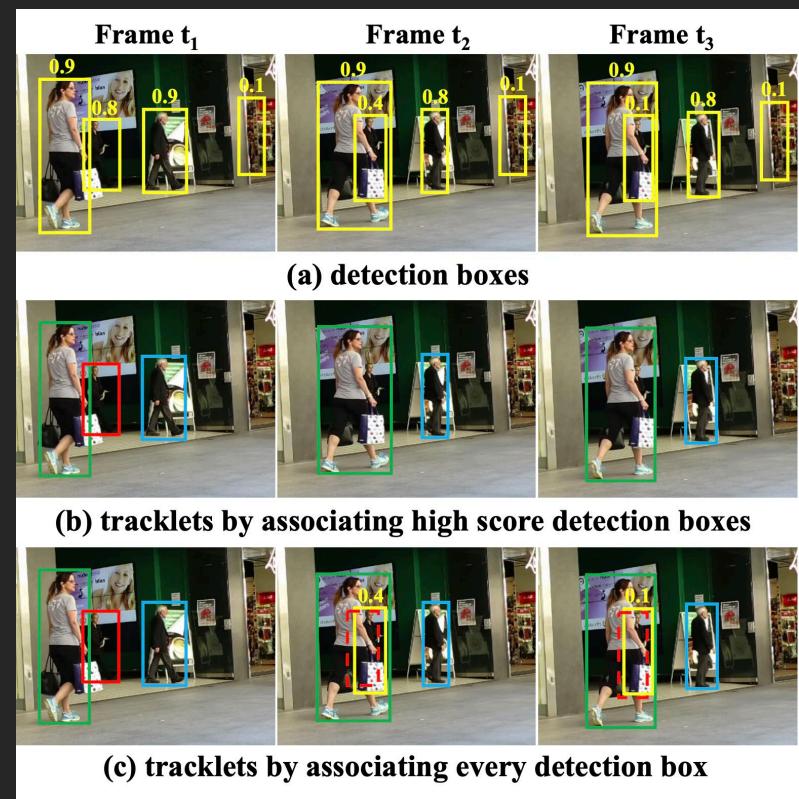
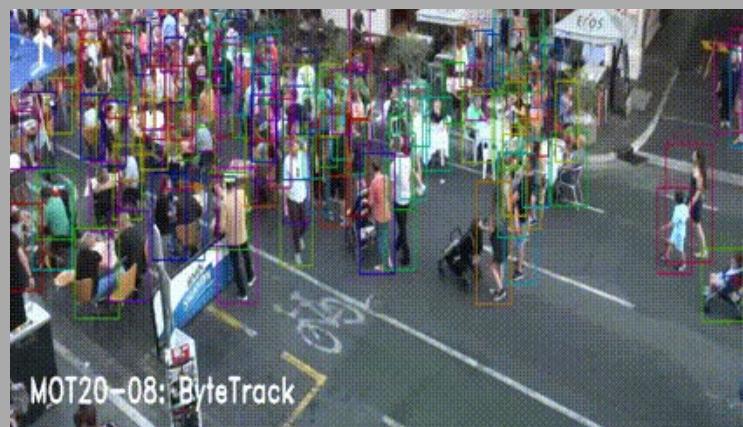
BEFORE AND AFTER

```
Epoch    GPU_mem   box_loss   cls_loss   dfl_loss   Instances   Size
 1/50      3.57G     1.901     4.184     0.9688      499       640: 100%|██████████| 13/13 [00:13<00:00,  1.00s/it]
           Class     Images  Instances     Box(P)        R   mAP50  mAP50-95): 100%|██████████| 2/2 [00:00<00:00,  4.00it/s]
```

```
Epoch    GPU_mem   box_loss   cls_loss   dfl_loss   Instances   Size
 44/50     2.45G     1.119     0.7021     0.8158      284       640: 100%|██████████| 13/13 [00:01<00:00,  9.86it/s]
           Class     Images  Instances     Box(P)        R   mAP50  mAP50-95): 100%|██████████| 2/2 [00:00<00:00,  9.71it/s]
Stopping training early as no improvement observed in last 5 epochs. Best results observed at epoch 39, best model saved as best.pt.
To update EarlyStopping(patience=5) pass a new patience value, i.e. `patience=300` or use `patience=0` to disable EarlyStopping.
```

~2 minutes in training time

PROBLEMS WITH MULTIPLE OBJECT DETECTION

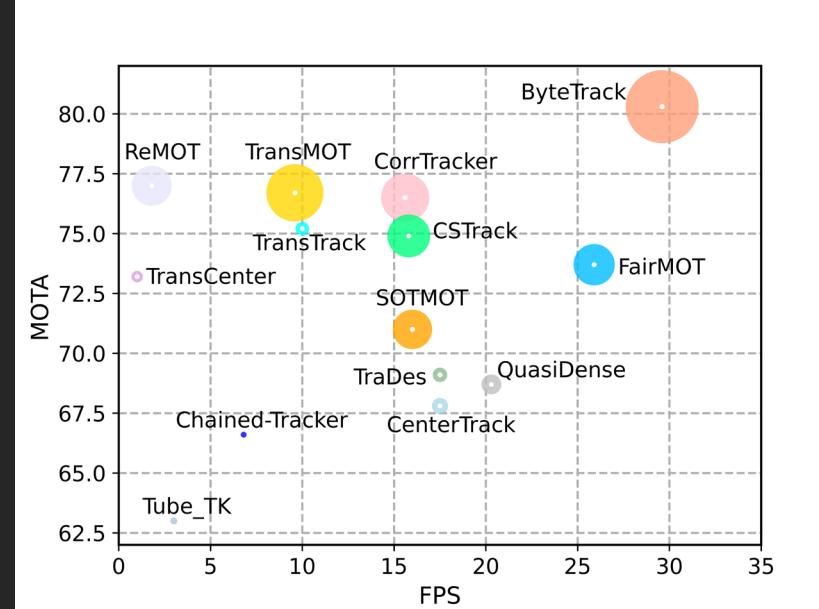


OBJECT REIDENTIFICATION

ByteTrack

Multi-object tracking
(MOT)

144 tracking IDs → 97 tracking IDs



HOMOGRAPHY TRANSFORMATION

3D TO 2D

IMAGE WRAPPING

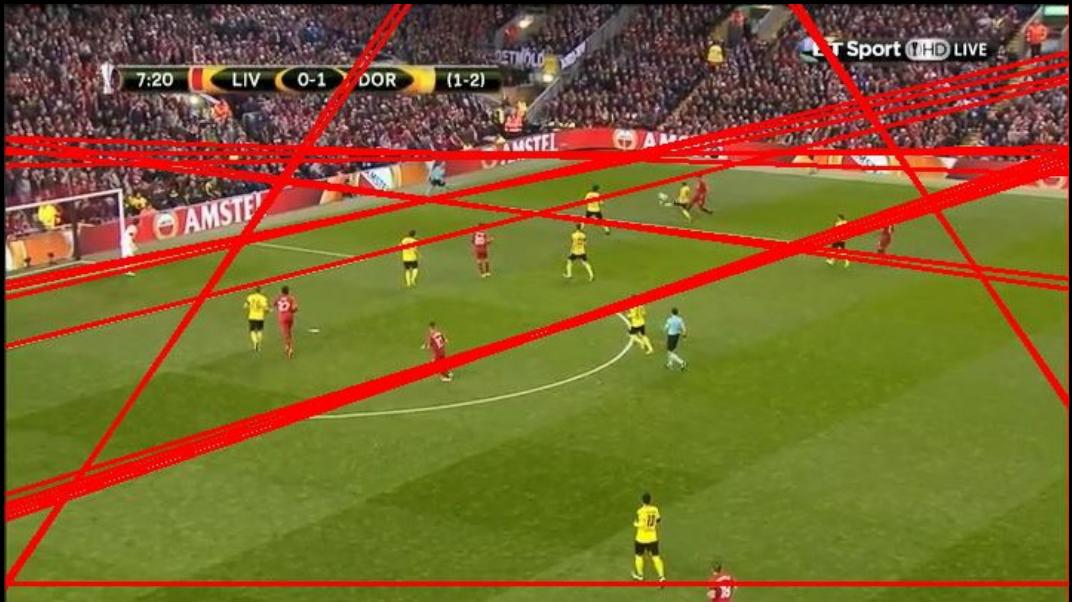


$$\begin{array}{lll}
 & \textbf{2N x 8} & \textbf{8 x 1} & \textbf{2N x 1} \\
 \textbf{Point 1} & \begin{bmatrix} x_1 & y_1 & 1 & 0 & 0 & 0 & -x_1x'_1 & -y_1x'_1 \\ 0 & 0 & 0 & x_1 & y_1 & 1 & -x_1y'_1 & -y_1y'_1 \end{bmatrix} & \begin{bmatrix} h_{11} \\ h_{12} \\ h_{13} \\ h_{21} \\ h_{22} \\ h_{23} \\ h_{31} \\ h_{32} \end{bmatrix} = & \begin{bmatrix} x'_1 \\ y'_1 \\ x'_2 \\ y'_2 \\ x'_3 \\ y'_3 \\ x'_4 \\ y'_4 \end{bmatrix} \\
 \textbf{Point 2} & \begin{bmatrix} x_2 & y_2 & 1 & 0 & 0 & 0 & -x_2x'_2 & -y_2x'_2 \\ 0 & 0 & 0 & x_2 & y_2 & 1 & -x_2y'_2 & -y_2y'_2 \end{bmatrix} & & \\
 \textbf{Point 3} & \begin{bmatrix} x_3 & y_3 & 1 & 0 & 0 & 0 & -x_3x'_3 & -y_3x'_3 \\ 0 & 0 & 0 & x_3 & y_3 & 1 & -x_3y'_3 & -y_3y'_3 \end{bmatrix} & & \\
 \textbf{Point 4} & \begin{bmatrix} x_4 & y_4 & 1 & 0 & 0 & 0 & -x_4x'_4 & -y_4x'_4 \\ 0 & 0 & 0 & x_4 & y_4 & 1 & -x_4y'_4 & -y_4y'_4 \end{bmatrix} & & \\
 \text{additional} & \vdots & & \vdots \\
 \text{points} & \vdots & & \vdots
 \end{array}$$

```

pred_homo = get_perspective_transform(src,dst)
temppoints= np.hstack(track).reshape(-1,1,2).astype(np.float32)[0][0]
track_transformed = track_transformed_history[track_id]
transformed_points = utils.scale_points(temppoints,(st_env.size),(st_env.kp_model_shape))
transformed_points = utils.warp_points([[transformed_points]],pred_homo)
track_transformed.append(transformed_points)

```



ATTEMPT WITH LINE DETECTION

- Picture by [TravelScape](#)



ATTEMPT WITH
SCALE-INVARIANT
FEATURE
TRANSFORM (SIFT)



KEYPOINT MODEL

Convolutional Neural Network (CNN)

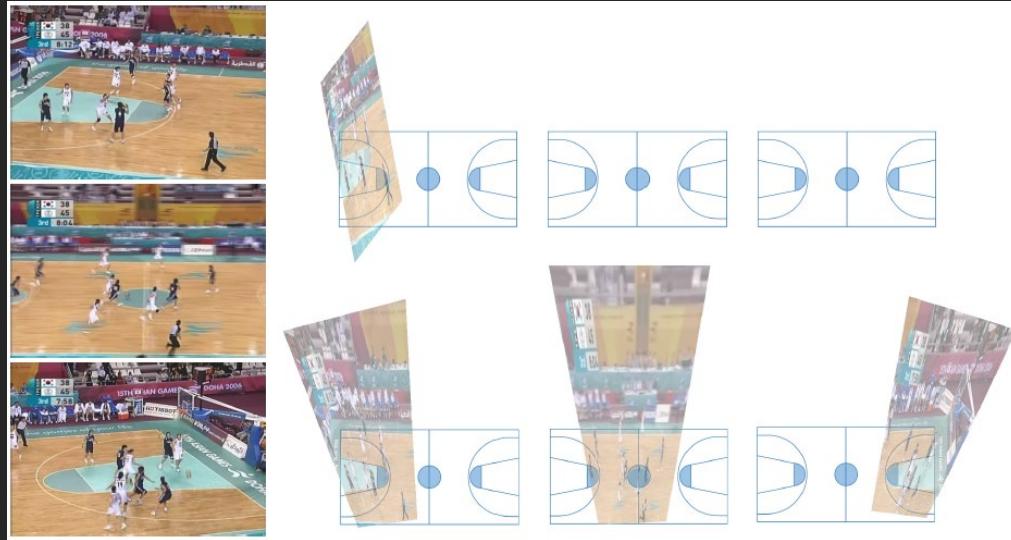
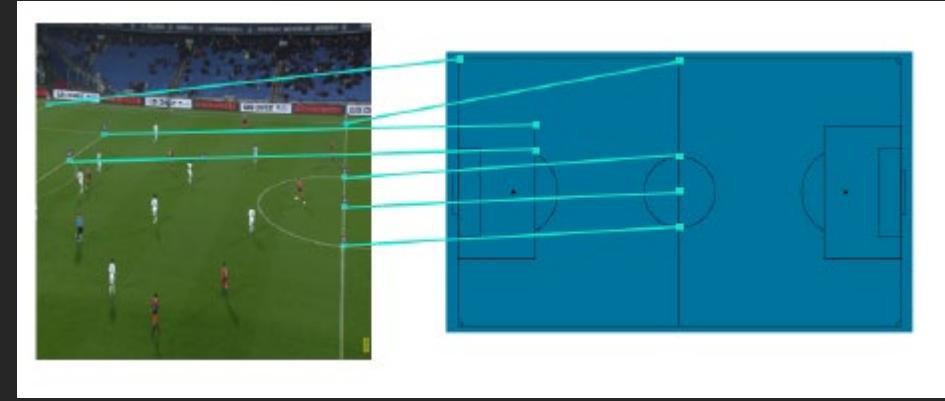
28 key points

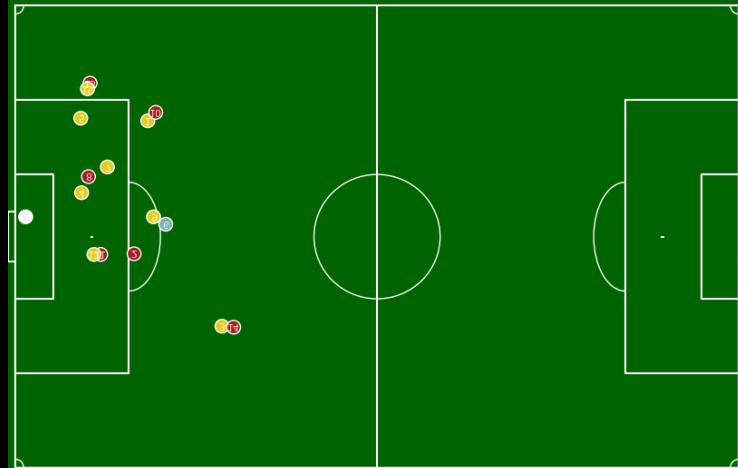
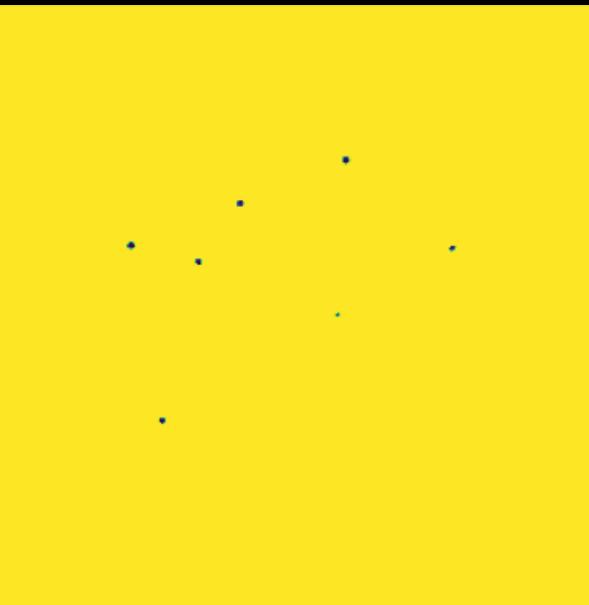
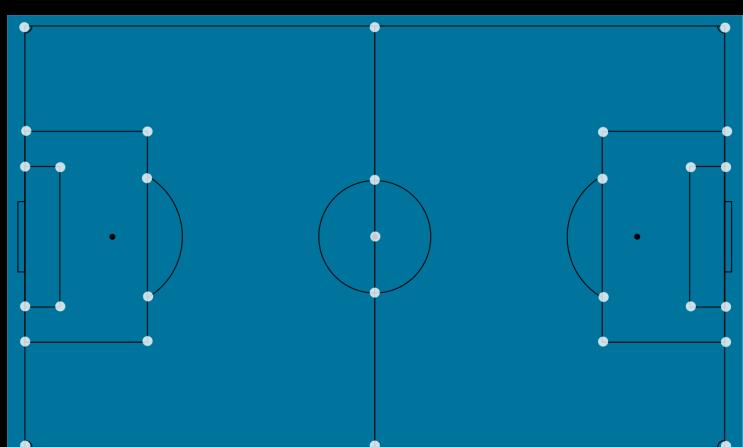
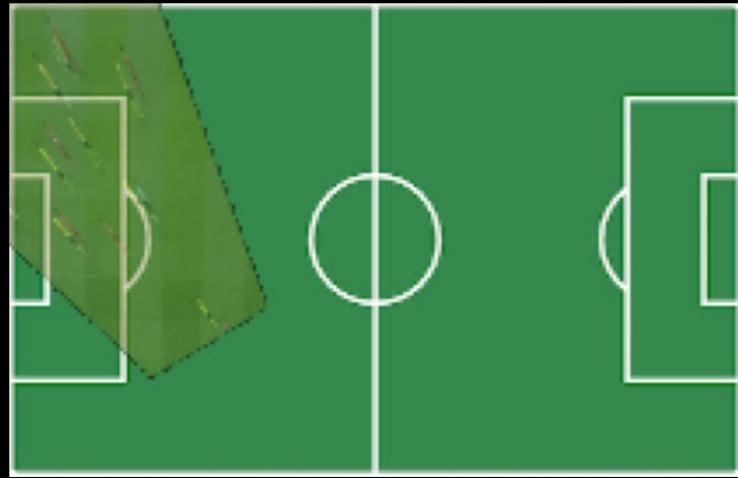
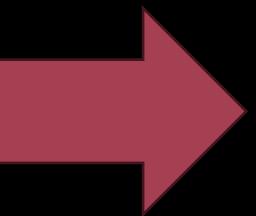
Trained with dataset from Narya paper

~58 images

Reference: Garnier, P., & Gregoir, T. (2021). Evaluating Soccer Player: from Live Camera to Deep Reinforcement Learning. arXiv [Cs.LG]. Retrieved from <http://arxiv.org/abs/2101.05388>

Image: Wen PC, Cheng WC, Wang YS, Chu HK, Tang NC, Liao HM. Court Reconstruction for Camera Calibration in Broadcast Basketball Videos. IEEE Trans Vis Comput Graph. 2016 May;22(5):1517-1526. doi: 10.1109/TVCG.2015.2440236. PMID: 28113142.

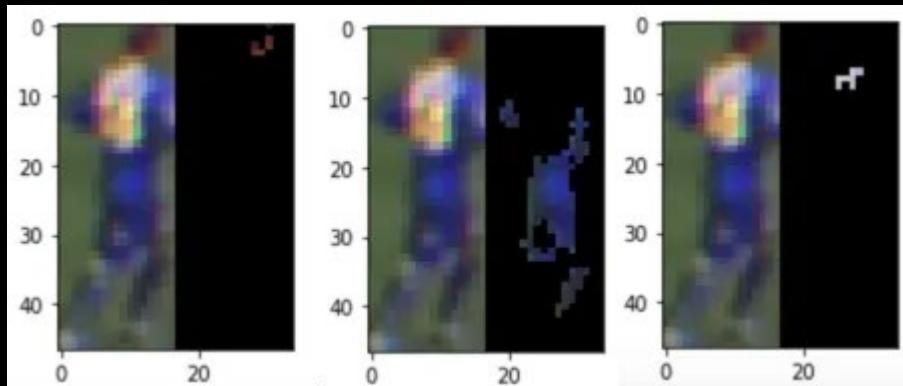






SAMPLE FRAME

TEAM IDENTIFICATION



COLOR MASK BASED ON RGB BOUNDARY
RANGE

$$Ratio = \frac{\text{Non-black pixels}}{\text{total pixels}}$$

Threshold ~ 20-30%



SAMPLE DETECTIONS

```

for team,color in bgrteamcolorlist.items():
    tempframe=frame
    crop_img = tempframe[int(y1):int(y2),int(x1):int(x2)]
    mask = cv2.inRange(crop_img, color[1],color[2])
    # get nonblack vs total pixel ratio
    colorpixelratio=cv2.countNonZero(mask)/(w*h)
    if colorpixelratio > 0.3:
        box_color=color[0]
        label = team + label
        team_name = team_history[track_id]
        team_name.append(team)
        break
    
```

Target Video file: 0a2d9b_0.mp4



[Use another frame](#)

Choose Team

Your Team GK

Pick your team color



Your team color is (131, 56, 75)

Pick your opponent team color



Your opponent team color is (128, 112, 54)

Pick your team GK color



Your team GK color is (111, 109, 125)

Pick your opponent team GK color



Your opponent team GK color is (80, 59, 118)

Pick referee color



Referee color is (55, 46, 54)

[Submit & Run](#)

COLOR PICKER WIDGET

DEMO

APPLICATION



Scouting talents

Identifying players that suits the team's playstyle

Opponent analysis

Identify opponent weakness and exploit them

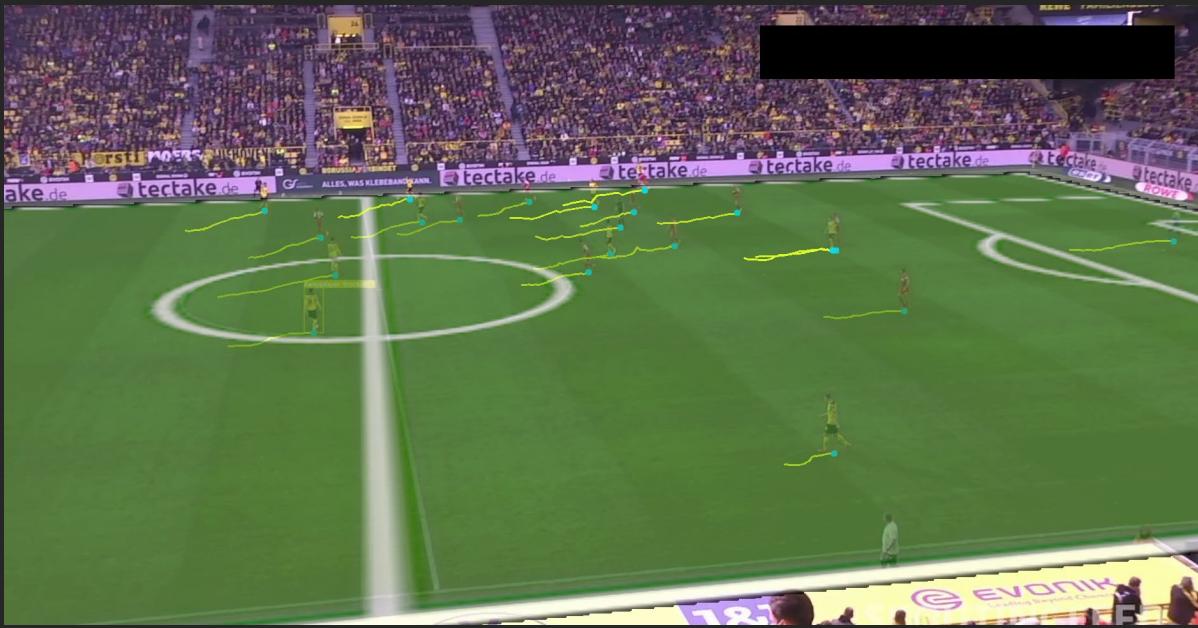
Training analysis

Analyze player strengths and weaknesses

Team dynamics

Analyze players that play well together

NEXT STEPS



Update Team Identification System

Teams with more than one color on their jersey

Upgrade Classification Model

Have better detections on players as well as on the ball

Upgrade Keypoint Model

Refine homography estimation

Pose Model

Identify body language



Implement AI in analytics

Prompt to visualization with LLM



Source: Manuel Stein at FC Barcelona Sports Tomorrow



Metrics

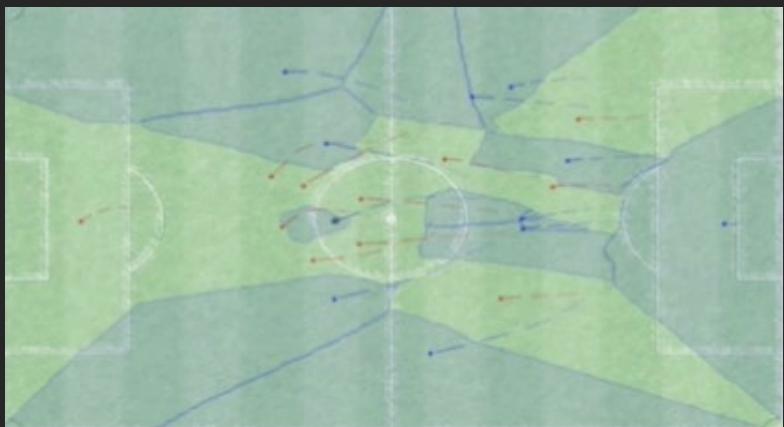
- Identify passes and shots
- Find best passing option and best time to shoot

xGs and xAs

- Predict game results

Identify spaces

- Free space on the pitch
- Dominant zones and cover shadows



THANK YOU



thealexfok



thisisalexfok@gmail.com

SOURCES

Images

<https://www.sofascore.com/player/andre-onana/787498>

<https://www.sofascore.com/player/jan-oblak/69768>

<https://www.sofascore.com/player/manuel-neuer/8959>

<https://www.amazon.com/STATSports-Activity-Football-Performance-Technology/dp/B07NYYP1RC?th=1>

<https://yolov8.com/>

<https://soccer-coaches.com/importance-space-pep-guardiola/>

<https://www.sportperformanceanalysis.com/article/automating-data-collection-and-match-analysis-from-video>

SOURCES

Datasource:

<https://universe.roboflow.com/roboflow-jvuqo/football-players-detection-3zvbc>

Paper references:

Garnier, P., & Gregoir, T. (2021). Evaluating Soccer Player: from Live Camera to Deep Reinforcement Learning. arXiv [Cs.LG].
Retrieved from <http://arxiv.org/abs/2101.05388>