



Game Changers Python Video Analysis

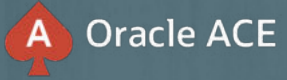
Abi Giles-Haigh

Innovation and Analytics Director



- PhD in ML – Computation Modelling of the human heart
- Oracle DBA for 5 years
- Worked public health care, private banking





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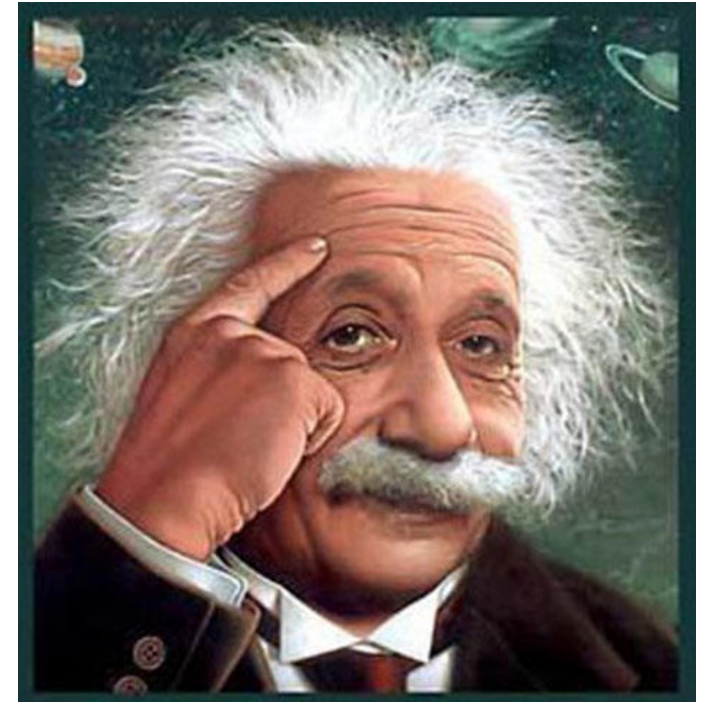


Business problem

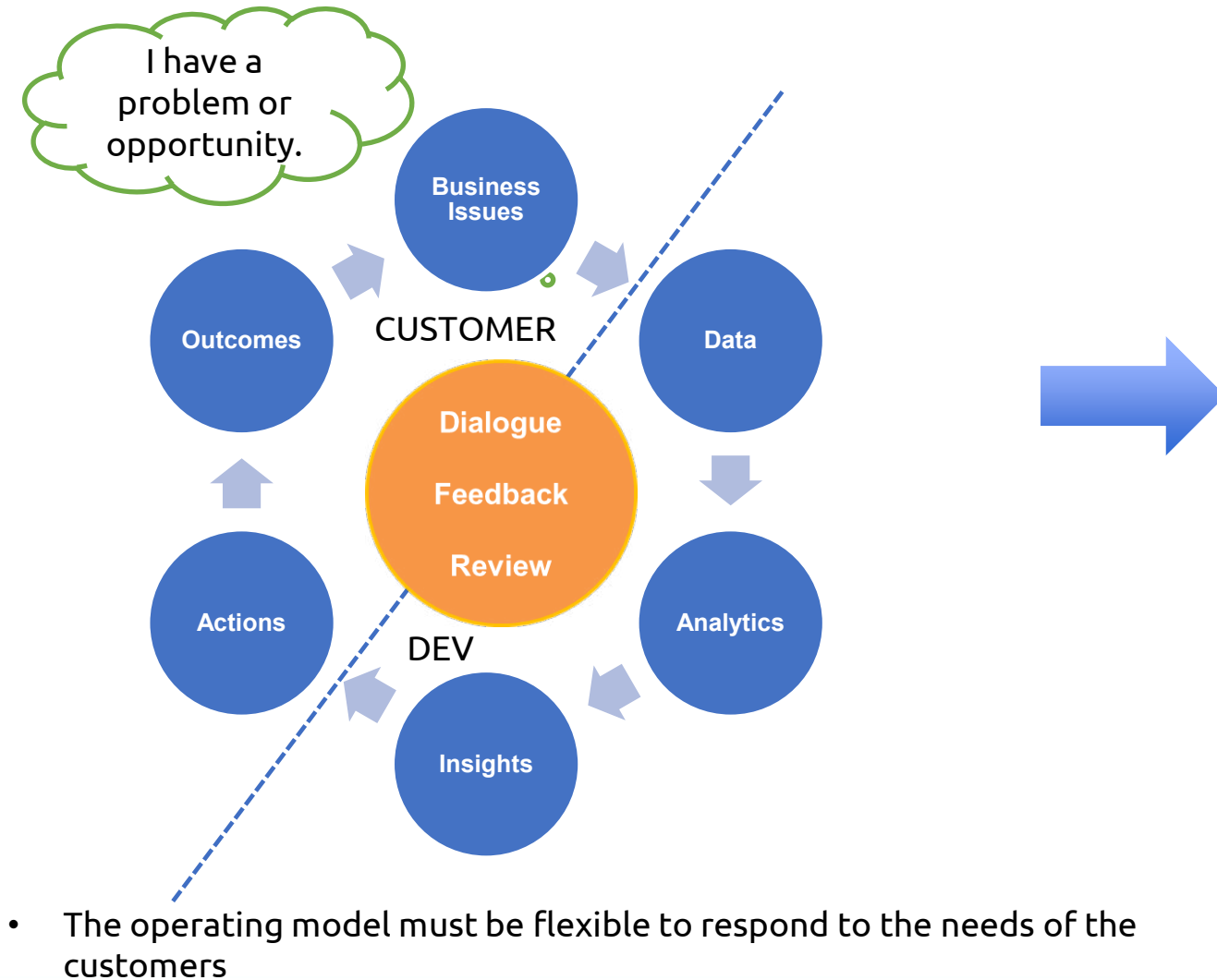
Start with a Well-Defined Business Problem Statement

“If I had an hour to solve a problem, I'd spend 55 minutes thinking about the problem and 5 minutes thinking about solutions.”

— Albert Einstein

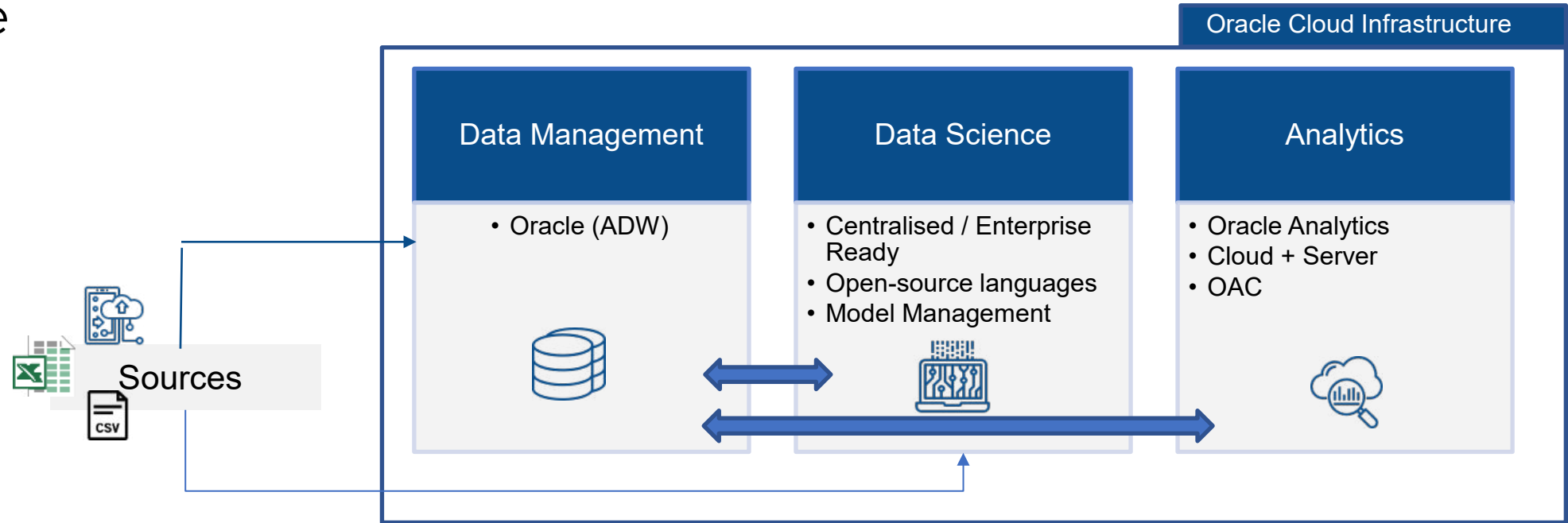


Business need and operational process



- Cross-industry standard process for data mining (CRISP-DM)
- Data mining is a process of extracting and discovering patterns in large data sets

Architecture



Oracle OCI: VM.Standard.E2.2 – Data Science

Clone Oracle Database Environment

- Database connection – pull and push statistics from the videos

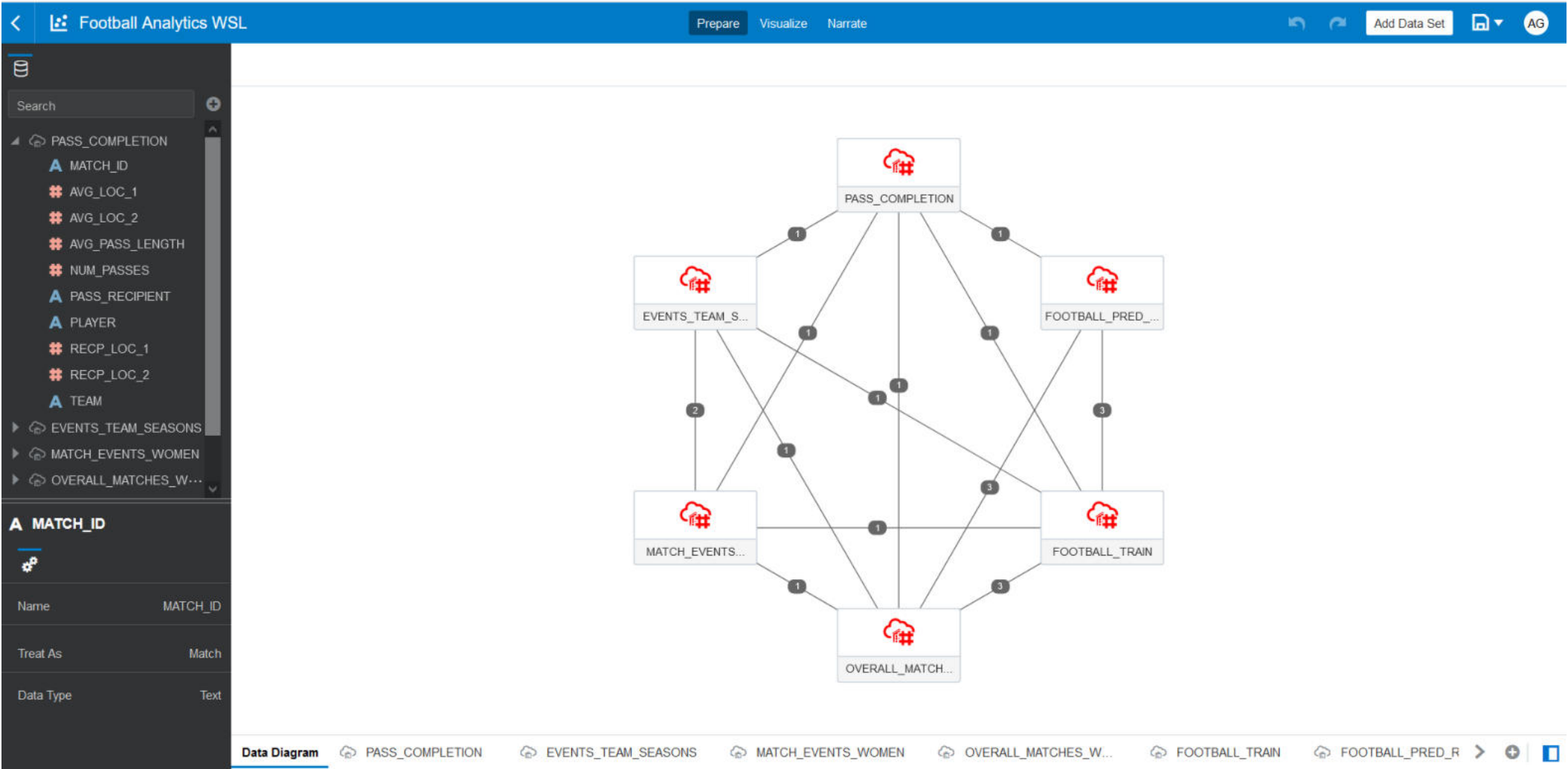
Install Python Packages – Pip Install....

- `sudo yum install freeglut-devel` *#OpenGL Utility Toolkit*
- `pip install opencv-python` *#Read the videos*
- `pip install matplotlib` *#Visualisation tools*
- `pip install pandas` *#Data Processing*

Descriptive analytics



Data Diagrams



Descriptive – Passing Networks

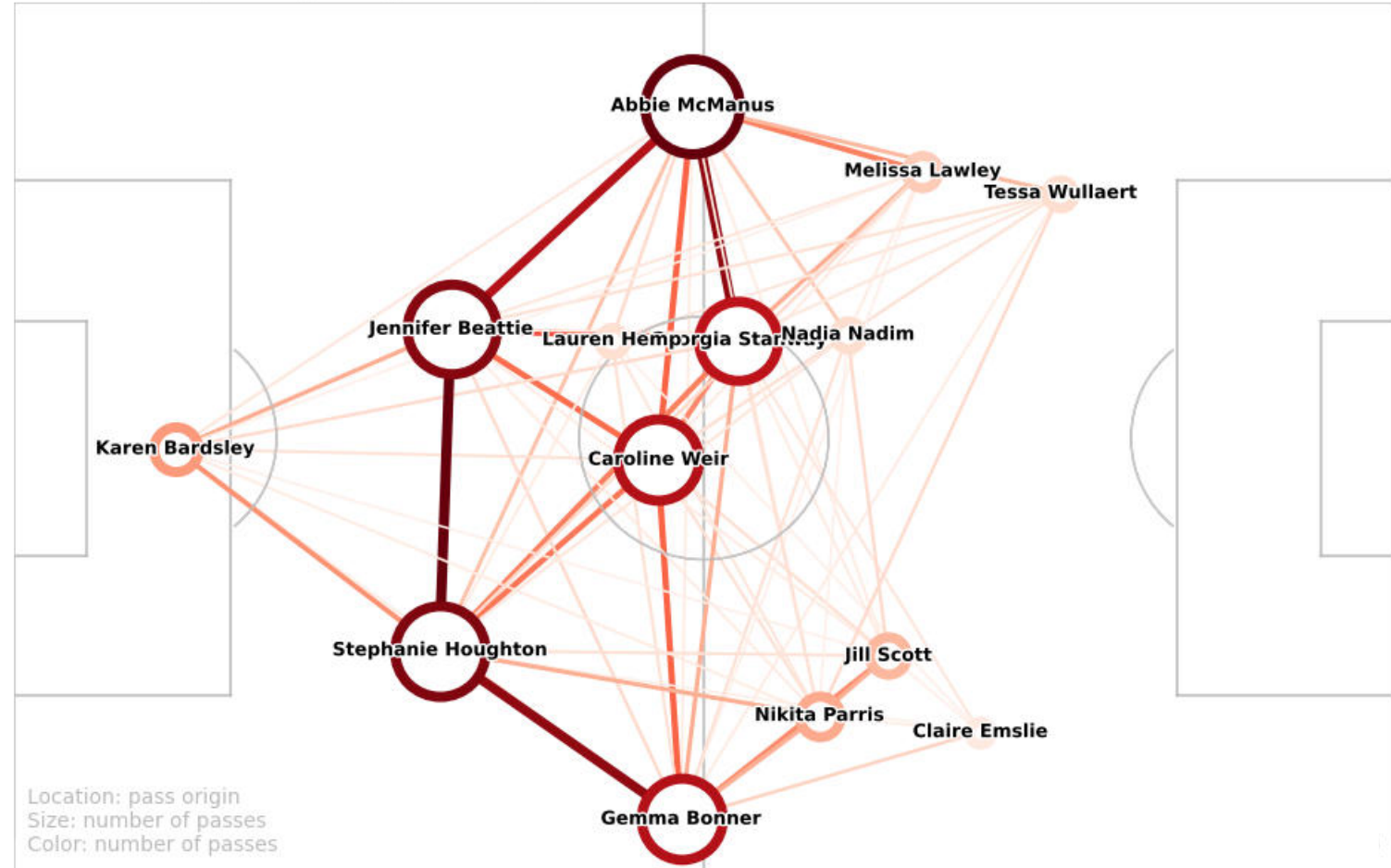
Number of passes completed
from player A to player B

Average location on the pitch

Highlights where they were during
the game as well as potential
threats to deal with

Mapped to a 2D pitch to help
players understand their location

Manchester City WFC's passing network against Everton LFC



Enter OCI & Python....

```
[1]: # Make sure that the path is the root of the project
%cd ..
```

```
/home/datascience/Football Analytics
```

```
[2]: from pandas.io.json import json_normalize
from utils import read_json
```

```
[3]: import cx_Oracle
import logging
import os
import pandas as pd
import warnings
```

```
from ads.database import connection
from ads.database.connection import Connector
from ads.dataset.factory import DatasetFactory
from ads.vault.vault import Vault
import sqlalchemy
from sqlalchemy import create_engine
from sqlalchemy.ext.declarative import declarative_base
from sqlalchemy import Column, Integer, String, Numeric
from sqlalchemy.orm import sessionmaker
from urllib.request import urlopen
```

```
warnings.filterwarnings("ignore", category=DeprecationWarning)
logging.basicConfig(format='%(levelname)s:%(message)s', level=logging.INFO)
```

```
[2]: # Sample credentials that are going to be stored.
credential = {'database_name': 'db202004201349_high',
```

Step 2: Set text information

```
[13]: plot_name = "statsbomb_match{0}_{1}".format(match_id, team_name)

opponent_team = [x for x in df_events.team_name.unique() if x != team_name][0]
plot_title = "{0}'s passing network against {1} ".format(team_name, opponent_team)

plot_legend = "Location: pass origin\nSize: number of passes\nColor: number of passes"
```

Step 3: Prepare data

```
[14]: def _statsbomb_to_point(location, max_width=120, max_height=80):
    ...
    Convert a point's coordinates from a StatsBomb's range to 0-1 range.
    ...
    return location[0] / max_width, 1-(location[1] / max_height)

[15]: df_passes = df_events[(df_events.type_name == "Pass") &
                          (df_events.pass_outcome_name.isna()) &
                          (df_events.team_name == team_name)].copy()

# If available, use player's nickname instead of full name to optimize space in plot
df_passes["pass_recipient_name"] = df_passes.pass_recipient_name.apply(lambda x: names_dict[x] if names_dict[x] else x)
df_passes["player_name"] = df_passes.player_name.apply(lambda x: names_dict[x] if names_dict[x] else x)

df_passes.head()
```

Enter OCI & Python....

```
[16]: df_passes["origin_pos_x"] = df_passes.location.apply(lambda x: _statsbomb_to_point(x)[0])
df_passes["origin_pos_y"] = df_passes.location.apply(lambda x: _statsbomb_to_point(x)[1])
player_position = df_passes.groupby("player_name").agg({"origin_pos_x": "median", "origin_pos_y": "median"})
```

```
[16]:
```

	origin_pos_x	origin_pos_y
player_name		
Abbie McManus	0.491667	0.88125
Caroline Weir	0.466667	0.47500
Claire Emslie	0.700000	0.16250
Gemma Bonner	0.483333	0.06250
Georgia Stanway	0.525000	0.61250
Jennifer Beattie	0.316667	0.62500
Jill Scott	0.633333	0.25000
Karen Bardsley	0.116667	0.48750
Lauren Hemp	0.433333	0.61250
Melissa Lawley	0.658333	0.80625
Nadia Nadim	0.604167	0.61875
Nikita Parris	0.583333	0.18125
Stephanie Houghton	0.308333	0.25625

```
[10]: df_passes["pair_key"] = df_passes.apply(lambda x: "_".join(sorted([x["player_name"], x["pass_recipient_name"]])), axis=1)
pair_pass_count = df_passes.groupby("pair_key").size().to_frame("num_passes")
pair_pass_value = df_passes.groupby("pair_key").size().to_frame("pass_value")

pair_pass_count.head(10)
```

```
[10]:
```

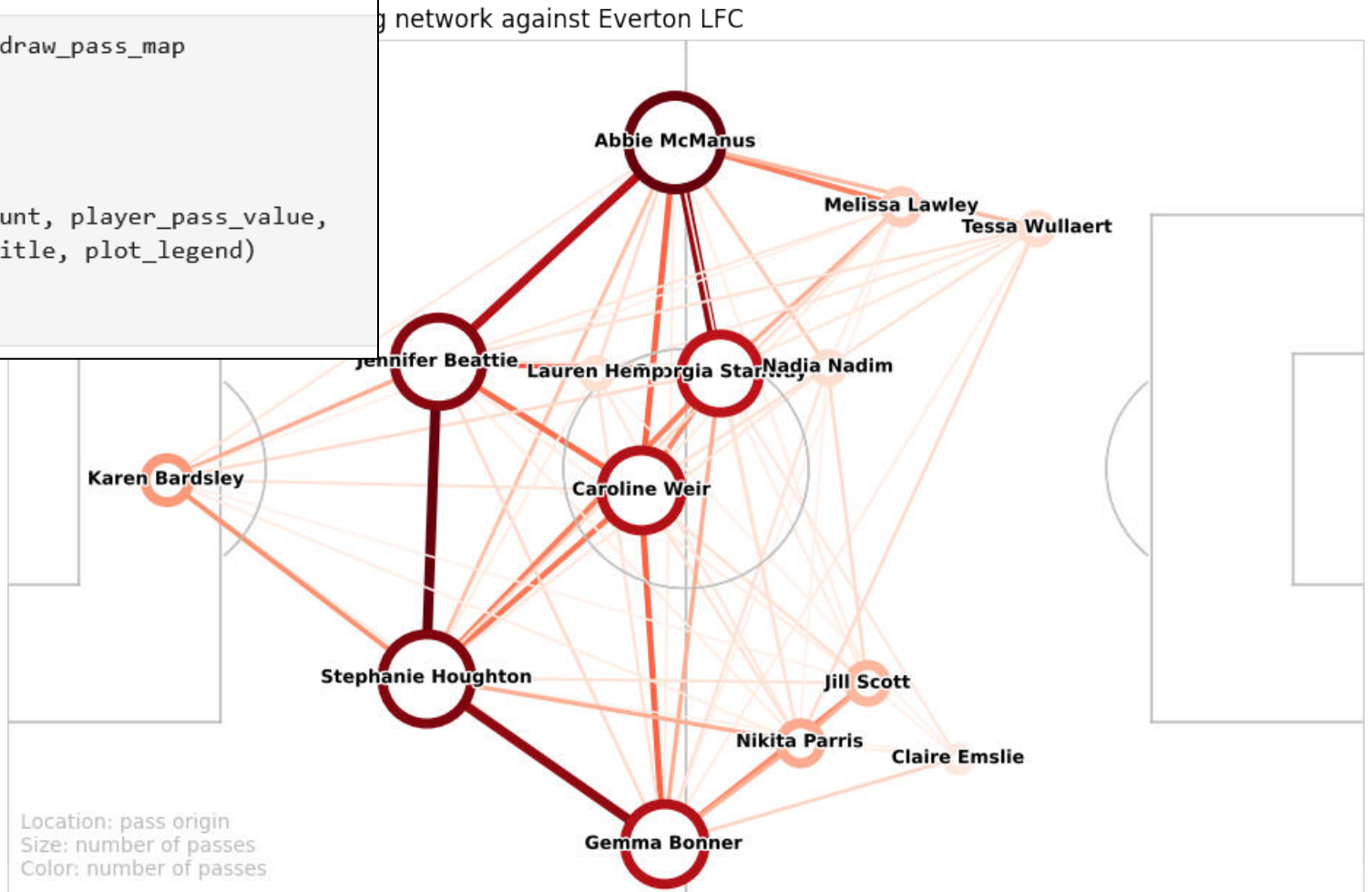
	num_passes
pair_key	
Abbie McManus_Caroline Weir	18
Abbie McManus_Gemma Bonner	2
Abbie McManus_Georgia Stanway	32
Abbie McManus_Jennifer Beattie	29
Abbie McManus_Jill Scott	2
Abbie McManus_Karen Bardsley	3
Abbie McManus_Lauren Hemp	5
Abbie McManus_Melissa Lawley	15
Abbie McManus_Nadia Nadim	7
Abbie McManus_Nikita Parris	2

Step 4: Plot passing network

```
[19]: from visualization.passing_network import draw_pitch, draw_pass_map
import matplotlib.pyplot as plt

ax = draw_pitch()
ax = draw_pass_map(ax, player_position, player_pass_count, player_pass_value,
                  pair_pass_count, pair_pass_value, plot_title, plot_legend)

plt.savefig("demo/{0}.png".format(plot_name))
```



Augment Analytics: Machine Learning

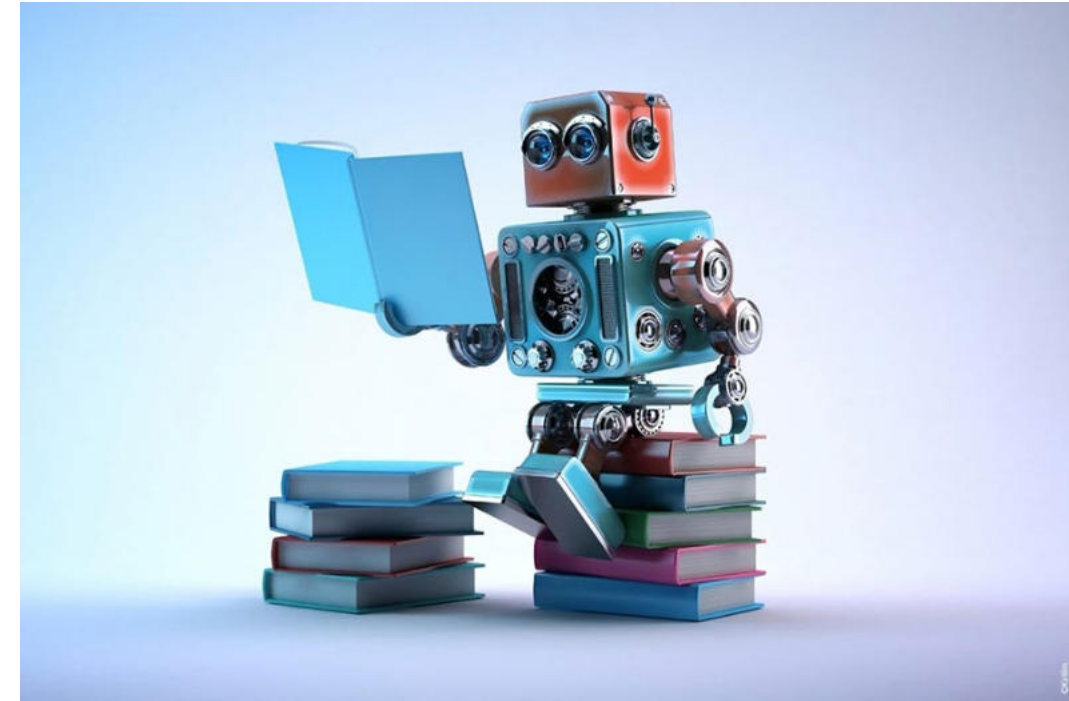
Present historic data to a machine
Identify patterns within the data

Unsupervised:

- Identify unusual patterns

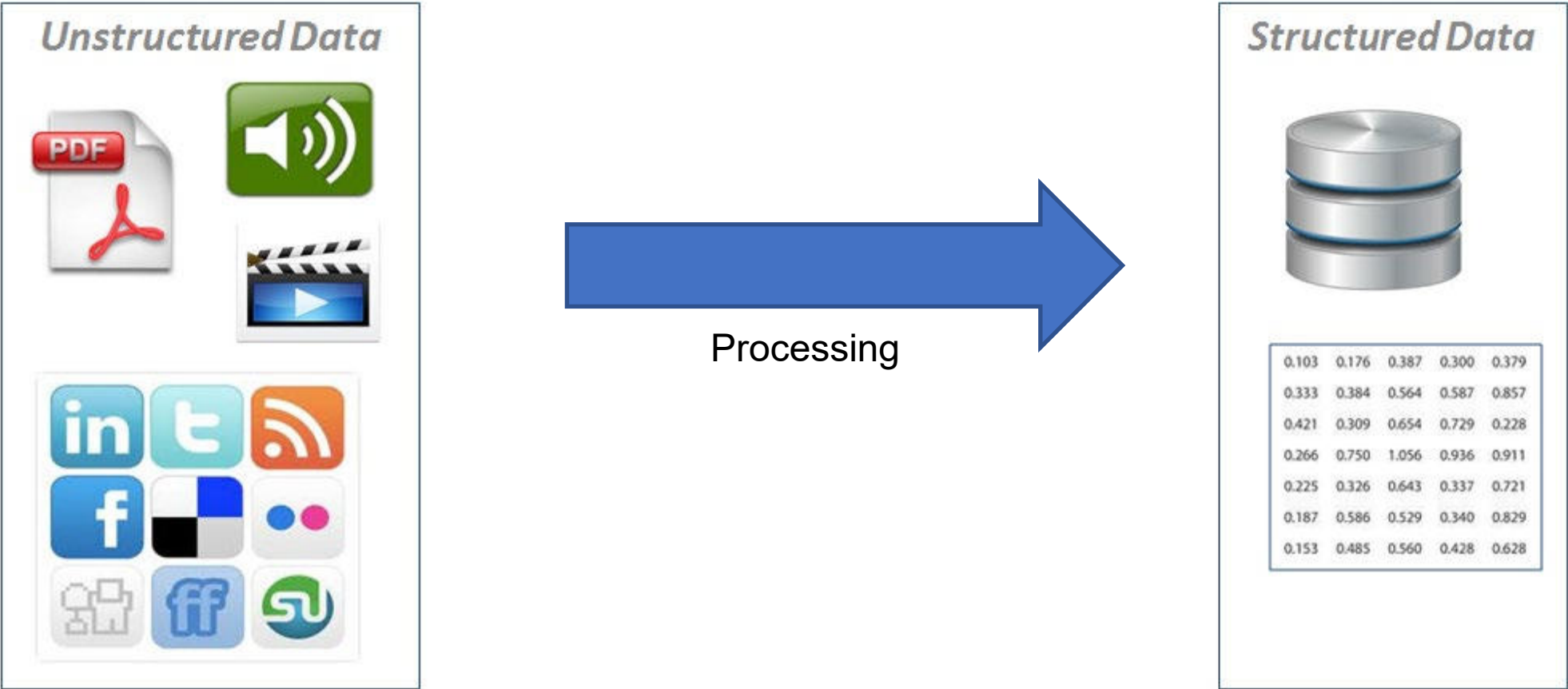
Supervised:

- Learning from a particular target



Bad Data + Machine Learning = Really Big Problem!

From Video to Stats.....



How its traditionally captured

Human labelling of data

Utilising gaming theory – reward/ games consoles

Requires time/ training

Still used by betting companies etc to provide a live feedback from the game



How its currently captured

Fixed cameras around the arena/ stadium

Players/ equipment have GPS trackers on/
match with the visual input - cameras

Location vs pitch location enabling basic
trigonometry to be used in combination with
GPS

Then utilises AI / ML to detect different players
and equipment/ areas



Deep learning – Image Processing

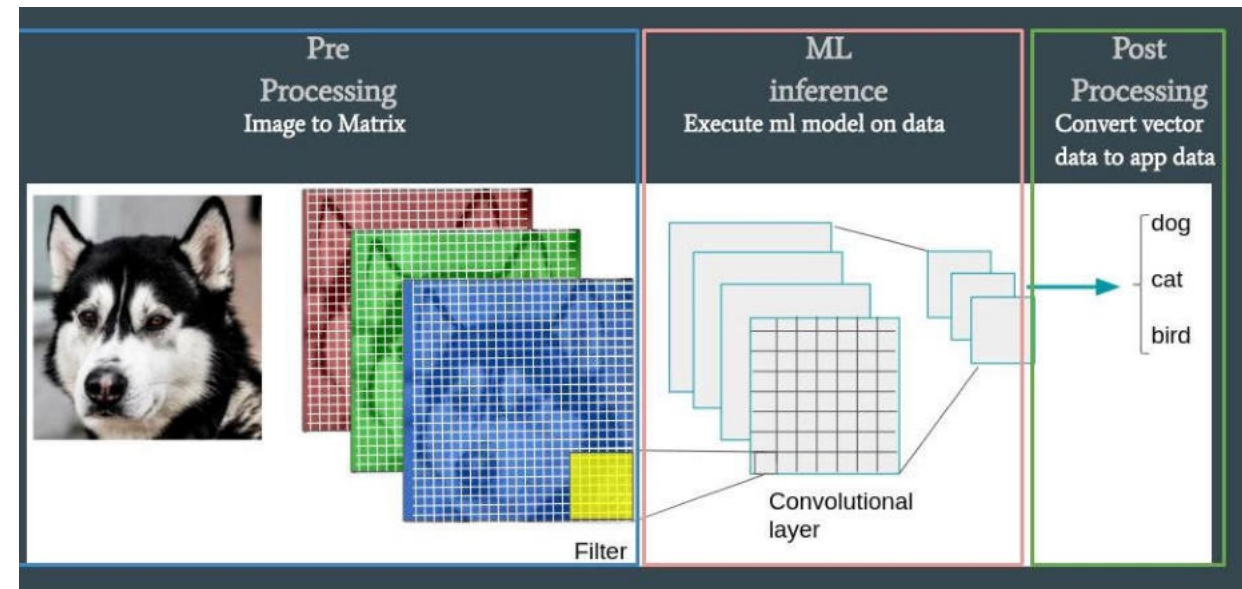
Videos are simply lots of images together

Decide how often to extract frames

Train the ML model

Apply the model to the video

Extract the results



How to detect players

Difference between team 1 and 2

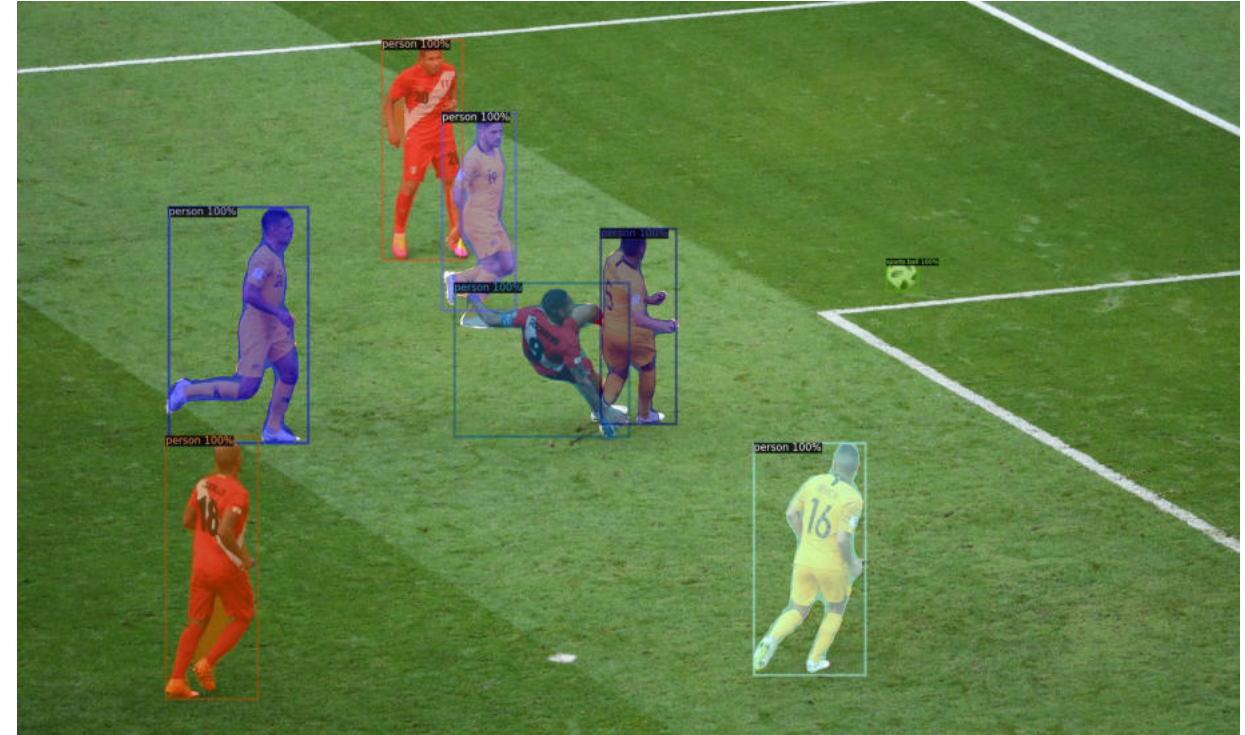
- Red or Blue

Ball

- Colour and size

Pitch

- White lines on the pitch
- Extrapolate to a 2D pitch



Original Video: England v USA Women 2019



```

1  #Import libraries
2  import cv2
3  import os
4  import numpy as np
5
6  #Reading the video
7  vidcap = cv2.VideoCapture('USA_Womens.mp4')
8  success,image = vidcap.read()
9  count = 0
10 success = True
11 idx = 0
12 print('we start')

```



```

→ #Red range
→ lower_red = np.array([0,31,255])
→ upper_red = np.array([176,255,255])

→ #white range
→ lower_white = np.array([0,0,0])
→ upper_white = np.array([0,0,255])

```



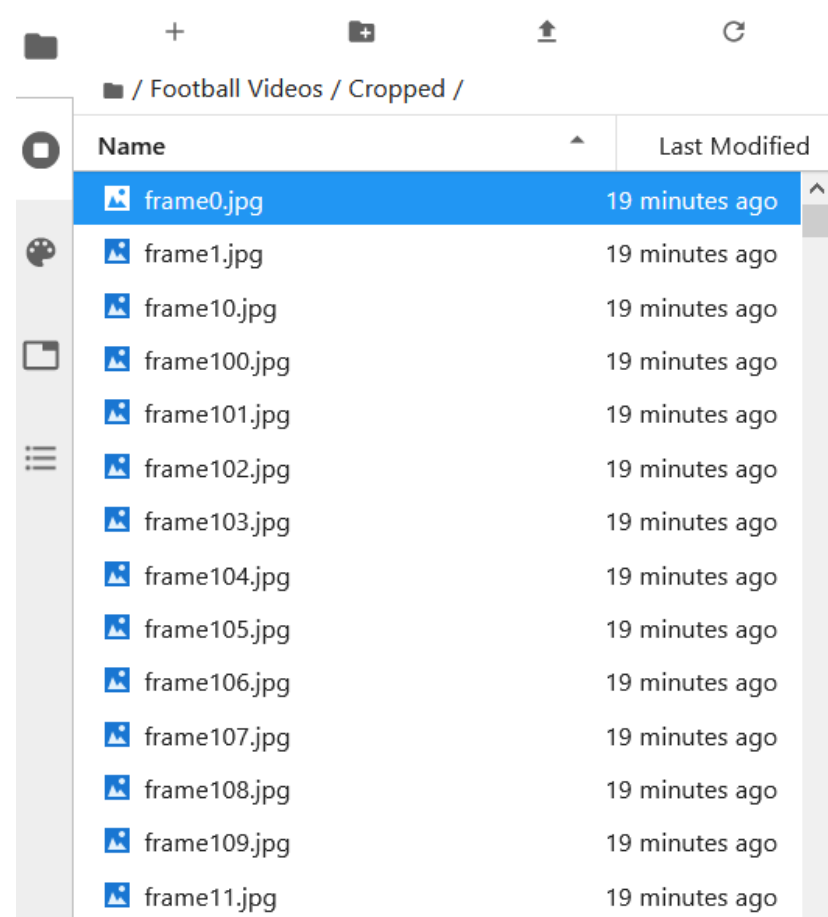
```

→ #Detect players
→ if(h>=(1.5)*w):
→     if(w>15 and h>= 15):
→         idx = idx+1
→         player_img = image[y:y+h,x:x+w]
→         player_hsv = cv2.cvtColor(player_img,cv2.COLOR_BGR2HSV)
→         #If player has white jersey
→         mask1 = cv2.inRange(player_hsv, lower_white, upper_white)
→         res1 = cv2.bitwise_and(player_img, player_img, mask=mask1)
→         res1 = cv2.cvtColor(res1,cv2.COLOR_HSV2BGR)
→         res1 = cv2.cvtColor(res1,cv2.COLOR_BGR2GRAY)
→         nzCount = cv2.countNonZero(res1)

```

```
→cv2.imwrite("./Cropped/frame%d.jpg" % count, image)
→print('Read a new frame: ', success)      # save frame as JPEG file→
→count += 1
    #cv2.startWindowThread()
    #cv2.namedWindow("preview")
→#cv2.imshow('Match Detection',image)
→#if cv2.waitKey(1) & 0xFF == ord('q'):
→→#break
→success,image = vidcap.read()

vidcap.release()
cv2.destroyAllWindows()
```



/ Football Videos / Cropped /	
Name	Last Modified
frame0.jpg	19 minutes ago
frame1.jpg	19 minutes ago
frame10.jpg	19 minutes ago
frame100.jpg	19 minutes ago
frame101.jpg	19 minutes ago
frame102.jpg	19 minutes ago
frame103.jpg	19 minutes ago
frame104.jpg	19 minutes ago
frame105.jpg	19 minutes ago
frame106.jpg	19 minutes ago
frame107.jpg	19 minutes ago
frame108.jpg	19 minutes ago
frame109.jpg	19 minutes ago
frame11.jpg	19 minutes ago

Processed: England v USA Women 2019

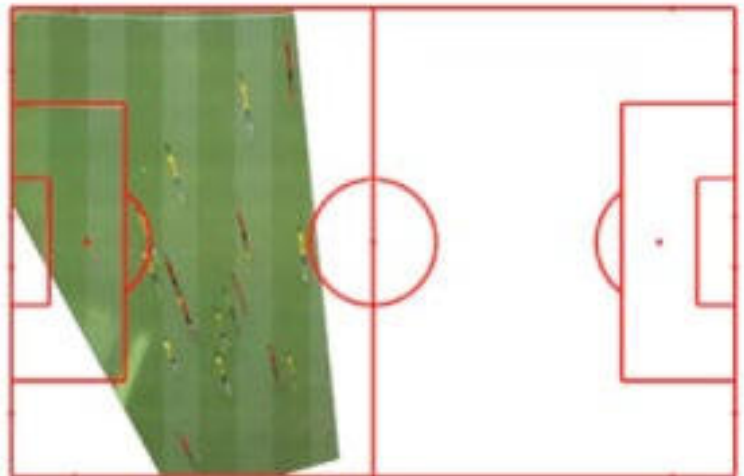


Location, Location, Location...



Teach the machine to look for edge of the pitch

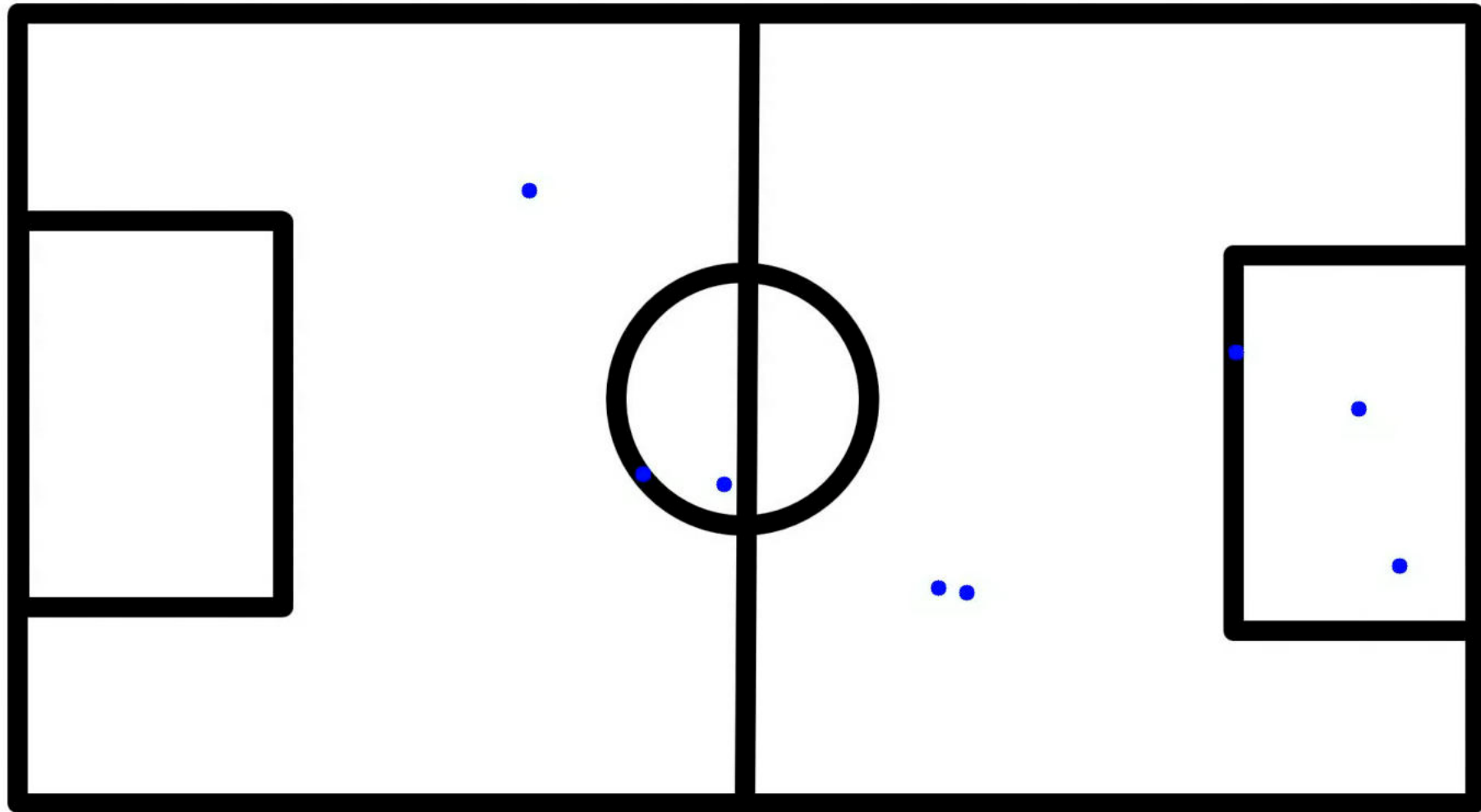
Use the lines detected to map to a 2D pitch



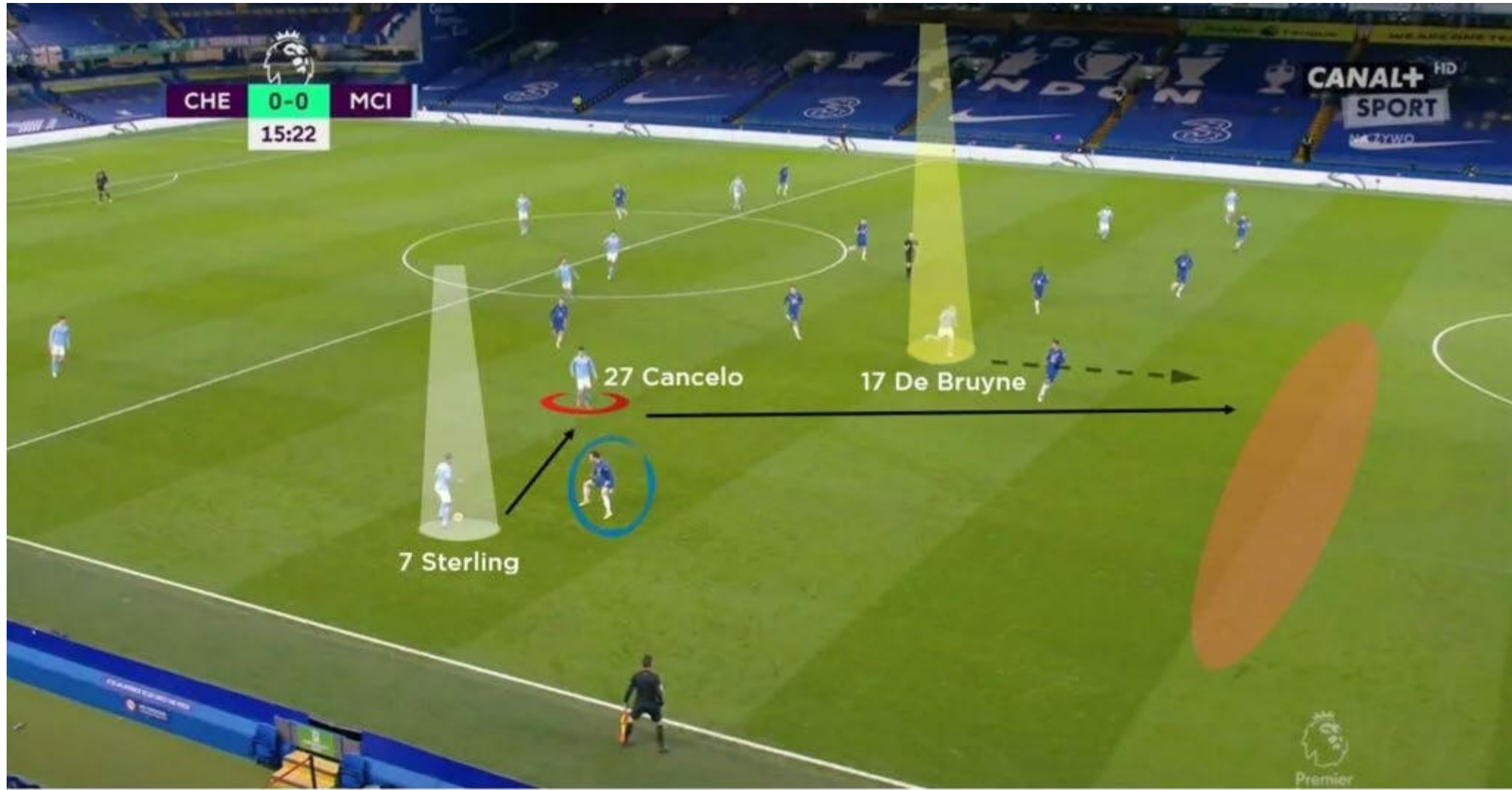
Use some clever maths (Homography matrices) to figure out the location on the pitch

Plot the player each frame of the video

Piecing it all together

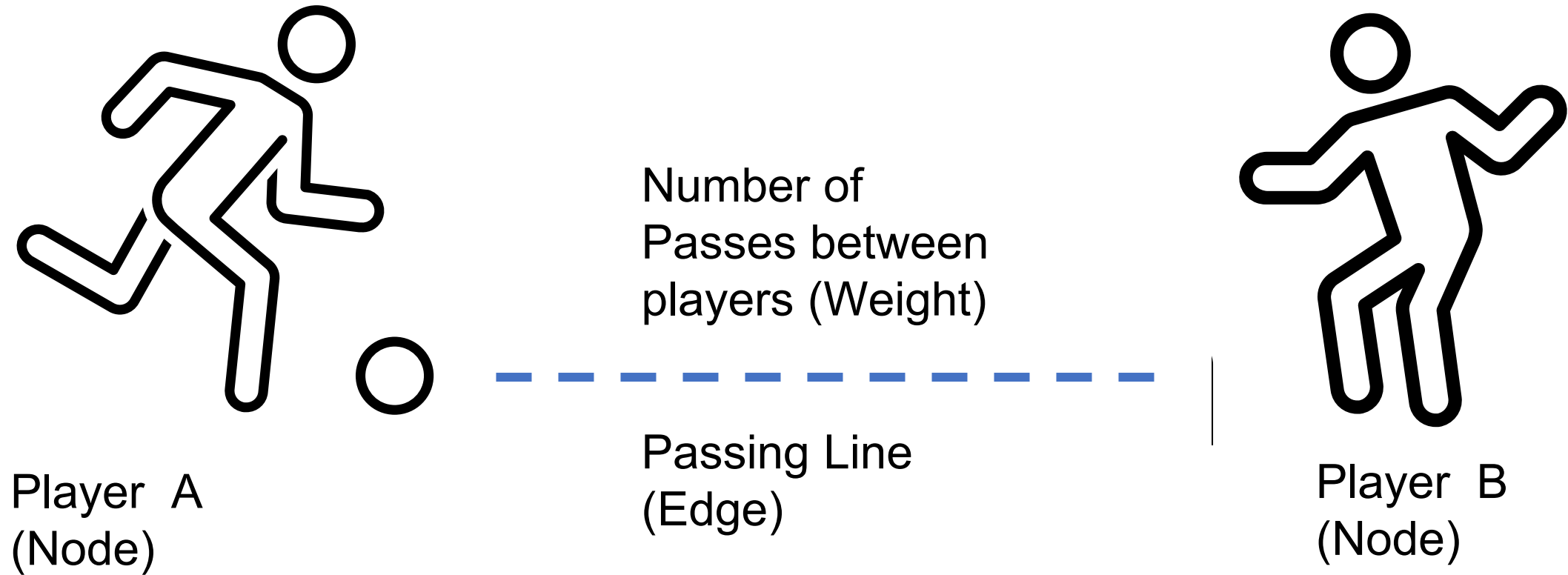






Powered by **wyscout**

What does the property graph look like



Put the passes together

Nodes for each player

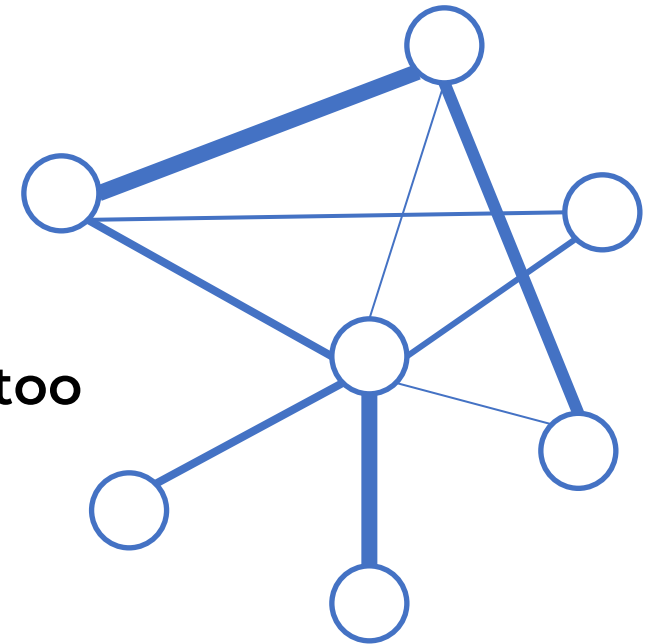
Edges for each pass

Weights for the edges:

- number of passes between players
- Distance of the pass

Degrees for the number of players a player receives or passes too

All combined, it makes a passing graph



```
SELECT match_id,player_id, player, team, COUNT(1) AS Num_Passes_Recieved
FROM graph_table ( WWC23_Passing_Graph
MATCH (src is WWC23_Players) –
[e IS WWC23_Pass_Transactions] -> (dst is WWC23_Players)
COLUMNS (dst.player_id, dst.player, dst.team, e.match_id)
) GROUP BY match_id, player_id, player, team
ORDER BY Num_Passes_Recieved DESC
FETCH FIRST 10 ROWS ONLY;
```

MATCH_ID	PLAYER_ID	PLAYER	TEAM	NUM_PASSES_RECIEVED
3893799	10261	Sara Doorsoun-Khajeh	Germany Women's	113
3893799	10399	Kathrin Julia Hendrich	Germany Women's	103
3893799	32355	Felicitas Rauch	Germany Women's	90
3901797	4999	Lindsey Michelle Horan	United States Women's	88
3904628	10161	María Francesca Caldentey Oliver	Spain Women's	85
3893828	4642	Millie Bright	England Women's	84
3893828	10252	Alex Greenwood	England Women's	82
3901734	25638	Moeka Minami	Japan Women's	81
3893820	10395	Maren Nævdal Mjelde	Norway Women's	81
3893833	10399	Kathrin Julia Hendrich	Germany Women's	79

You can find players involved in a chain of passes

```
SELECT player_id, player, team, COUNT(1) AS Num_In_Middle
FROM graph_table (WWC23_Passing_Graph
MATCH (src is WWC23_Players) - [e IS WWC23_Pass_Transactions] ->
      (via is WWC23_Players) - [e2 IS WWC23_Pass_Transactions] ->
      (dst is WWC23_Players)
where e.match_id = 3904629
      and e.match_id = e2.match_id
      and (e2.event_index - e.event_index) < 4
COLUMNS ( via.player_id, via.player, via.team)
)
GROUP BY player_id, player, team
ORDER BY Num_In_Middle
DESC FETCH FIRST 10 ROWS ONLY;
```

You can find players involved in a chain of passes

where `e.match_id = 3904629`



Specific Match

and `e.match_id = e2.match_id`



Ensure the passes
are the same match

and `(e2.event_index - e.event_index) < 4`



The events happen
close to each other

You can find players involved in a chain of passes

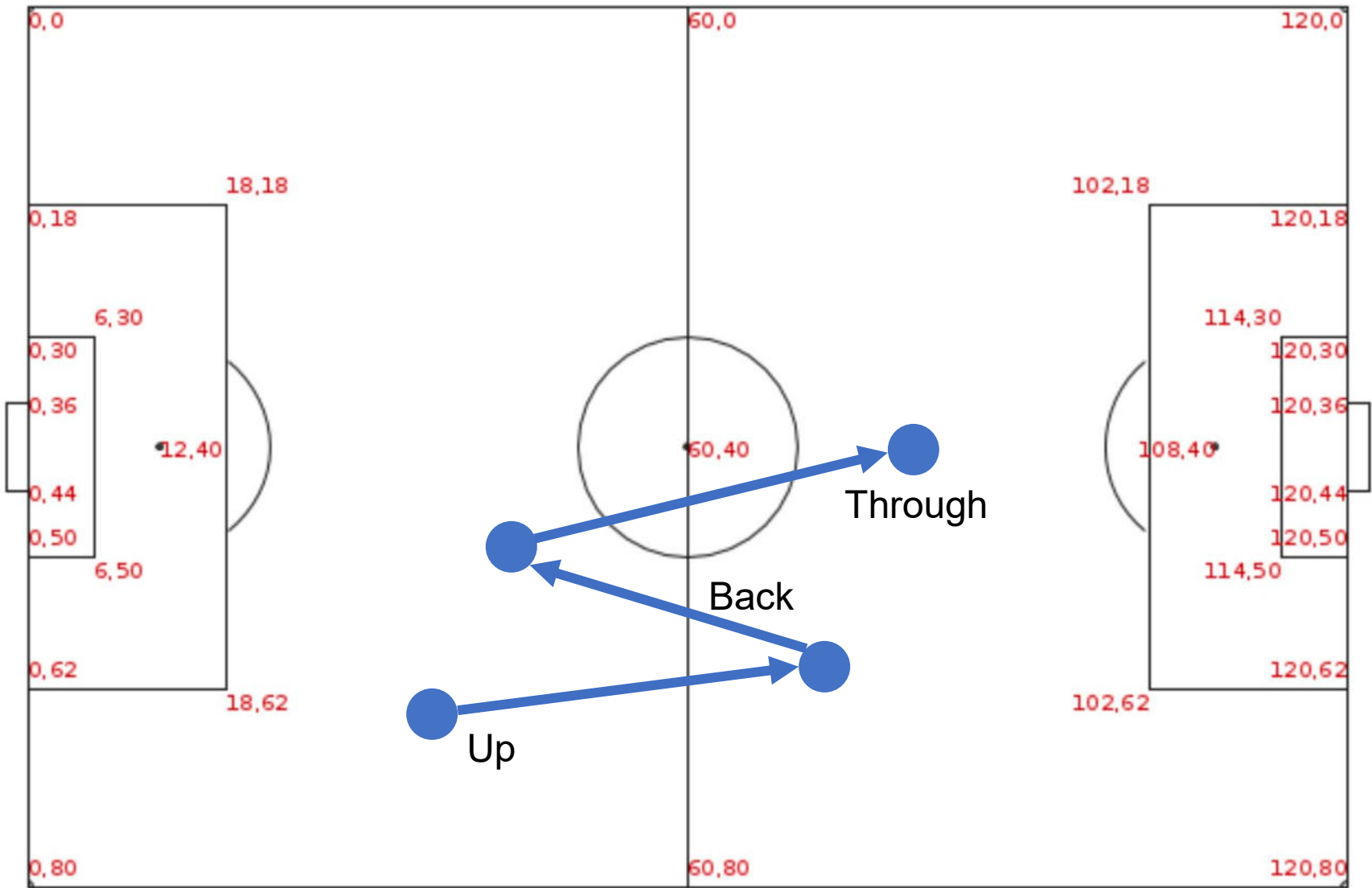
```
SELECT player_id, player, team, COUNT(1) AS Num_In_Middle  
FROM graph_table (...)  
) GROUP BY player_id, player, team ORDER BY Num_In_Middle DESC FETCH  
FIRST 10 ROWS ONLY;
```

PLAYER_ID	PLAYER	TEAM	NUM_IN_MIDDLE
10252	Alex Greenwood	England Women's	2578
4642	Millie Bright	England Women's	2401
4658	Keira Walsh	England Women's	1712
5000	Stephanie-Elise Catley	Australia Women's	1508
19422	Jessica Carter	England Women's	1182
4643	Georgia Stanway	England Women's	997
5058	Rachel Daly	England Women's	944
5095	Ellie Madison Carpenter	Australia Women's	819
47521	Alessia Russo	England Women's	687
10178	Lucy Bronze	England Women's	676

Passing pattern: Up, Back, through



Defining an “up, back, through”



Find it in our graph

```
SELECT distinct ev_id, ev_id2, ev_id3, period, minute, second, team,  
               srcID, srcplayer, x1, viaID, viaPlayer, x2 dstID, dstPlayer, x3 dstID2, dstPlayer2, x4, (x4-x1) as total_distance  
FROM graph_table ( WWC23_Passing_Graph  
MATCH (src is WWC23_Players) - [e IS WWC23_Pass_Transactions] -> (via is WWC23_Players) - [e2 IS WWC23_Pass_Transactions] -> (dst is  
WWC23_Players) - [e3 IS WWC23_Pass_Transactions] -> (dst2 is WWC23_Players)  
  where e.match_id = 3904629 and e.loc_x < e.end_loc_x  
  and e.pass_recipient_id = e2.player_id and e2.pass_recipient_id = e3.player_id  
  and e.period = e2.period and e.period = e3.period  
  and e.match_id = e2.match_id and e.match_id = e3.match_id  
  and e.event_index < e2.event_index and e2.event_index < e3.event_index  
  and (e3.event_index - e.event_index) < 10  
COLUMNS (e.event_index as ev_id, e.period, e.minute, e.second,  
          src.player_id as srcID, src.player as srcplayer, src.team as team,  
          e.loc_x as x1, e.end_loc_x as x2,  
          via.player_id as viaID, via.player as viaPlayer,  
          dst.player_id as dstID, dst.player as dstPlayer,  
          e2.event_index as ev_id2, e2.end_loc_x as x3,  
          dst2.player_id as dstID2, dst2.player as dstPlayer2,  
          e3.event_index as ev_id3, e3.end_loc_x as x4  
          )  
) order by minute, second asc;
```

Find it in our graph

and e.loc_x < e.end_loc_x
and e2.end_loc_x < e.end_loc_x



"Up, Back..."

and e3.end_loc_x > e2.end_loc_x
and src.player_id != dst.player_id



"...through"

and (e2.event_index -
e.event_index) < 10



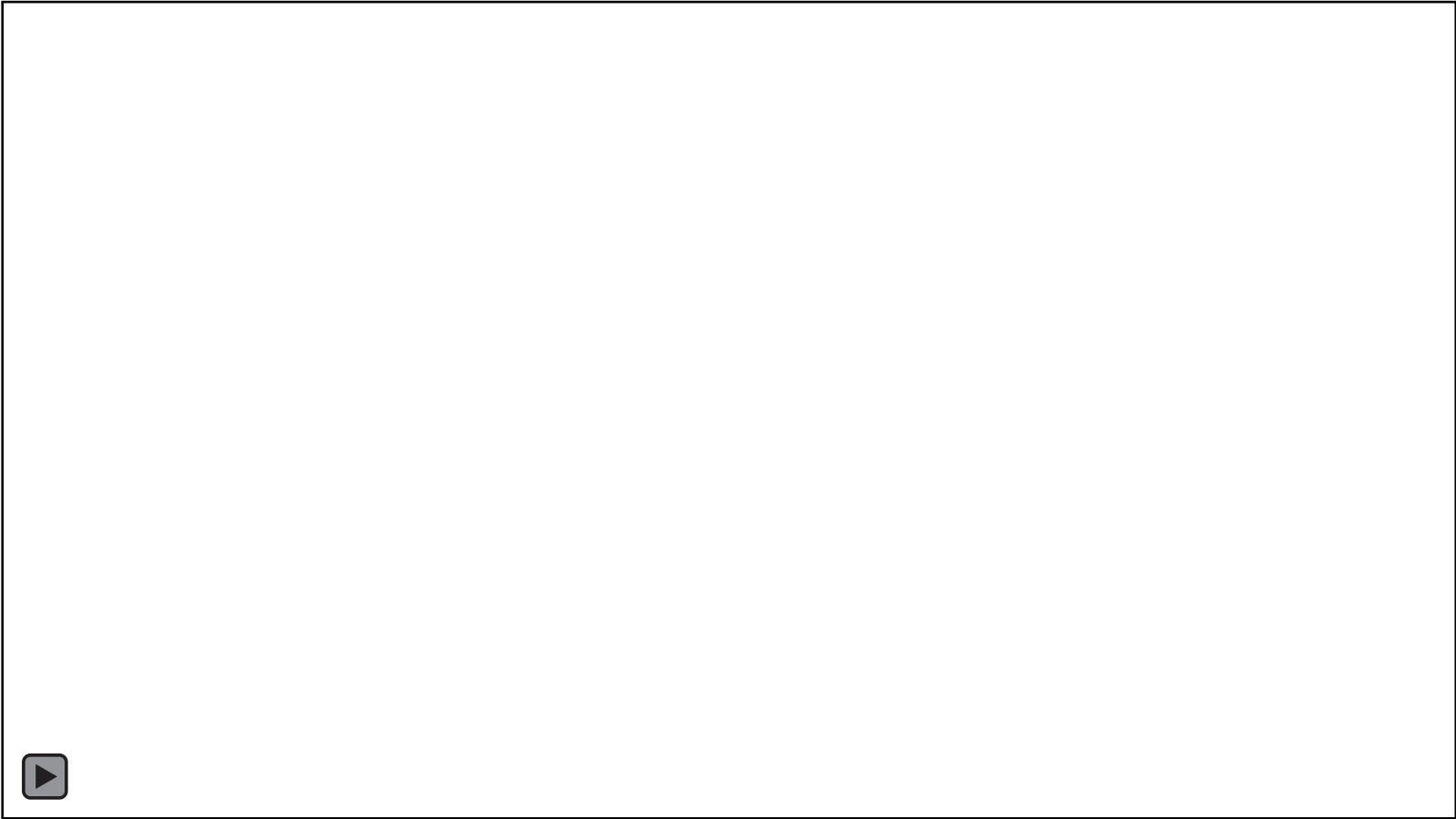
...that are linked passes

What we found: up, back, through

	EV_ID	EV_ID2	EV_ID3	PERIOD	MINUTE	SECOND	TEAM	SRCID	SRCPLAYER	X1	VIAID	VIAPLAYER	DSTID	DSTPLAYER	DSTID2	DSTPLAYER2	X4
1	24	27	30	1	0		19 England Women's	31538	Mary Alexandra Earps	15.9	10252	Alex Greenwood	21.2	Millie Bright	24.5	Lauren Hemp	87.
2	45	47	49	1	1		9 Australia Women's	401635	Clare Hunt	58.4	4979	Katrina Gorry	67.9	Clare Hunt	53.6	Clare Elizabeth Polkinghorne	45.
3	84	86	88	1	2		41 Australia Women's	401635	Clare Hunt	20.4	5095	Ellie Madison Carpenter	27.8	Katrina Gorry	29.3	Hayley Emma Raso	41.
4	86	88	90	1	2		41 Australia Women's	5095	Ellie Madison Carpenter	28.4	4979	Katrina Gorry	29.3	Hayley Emma Raso	41.5	Ellie Madison Carpenter	38.
5	88	90	96	1	2		43 Australia Women's	4979	Katrina Gorry	29.5	6818	Hayley Emma Raso	41.5	Ellie Madison Carpenter	38.9	Mary Boio Fowler	58.
6	96	98	100	1	3		7 Australia Women's	5095	Ellie Madison Carpenter	50.3	35693	Mary Boio Fowler	58.9	Ellie Madison Carpenter	51.2	Hayley Emma Raso	68.
7	113	116	119	1	3		25 England Women's	4642	Millie Bright	26.5	4643	Georgia Stanway	44.8	Jessica Carter	27.9	Millie Bright	34.
8	122	125	128	1	3		37 England Women's	4642	Millie Bright	38.9	19422	Jessica Carter	44.4	Millie Bright	38.3	Alex Greenwood	39.
9	128	131	134	1	3		44 England Women's	4642	Millie Bright	39	10252	Alex Greenwood	39.5	Ella Toone	62.6	Rachel Daly	57.
10	131	134	136	1	3		47 England Women's	10252	Alex Greenwood	43.1	31534	Ella Toone	62.6	Rachel Daly	57.5	Lauren Hemp	75.
11	141	145	149	1	4		5 Australia Women's	5095	Ellie Madison Carpenter	45.7	4961	Samantha May Kerr	66.2	Katrina Gorry	60.7	Hayley Emma Raso	69.
12	156	159	161	1	4		14 Australia Women's	401635	Clare Hunt	33.7	131586	Kyra Lillee Cooney-Cross	42	Stephanie-Elise Catley	38.6	Caitlin Jade Foord	72.
13	167	169	172	1	4		31 England Women's	4643	Georgia Stanway	39	10178	Lucy Bronze	51.2	Jessica Carter	36.4	Millie Bright	33.
14	175	178	180	1	4		38 England Women's	4642	Millie Bright	34.4	19422	Jessica Carter	39.8	Alessia Russo	87.3	Lauren Hemp	10
15	184	188	191	1	4		53 Australia Women's	42787	Mackenzie Arnold	12	401635	Clare Hunt	20.3	Mackenzie Arnold	7.8	Hayley Emma Raso	64.
16	193	197	200	1	5		2 England Women's	10252	Alex Greenwood	55.3	31534	Ella Toone	69.7	Rachel Daly	63.9	Ella Toone	55.
17	211	214	217	1	5		16 England Women's	19422	Jessica Carter	22.6	4642	Millie Bright	26.7	Jessica Carter	35.6	Millie Bright	34.
18	214	217	220	1	5		20 England Women's	4642	Millie Bright	29.8	19422	Jessica Carter	35.6	Millie Bright	34.8	Alex Greenwood	3
19	220	224	227	1	5		27 England Women's	4642	Millie Bright	36.2	10252	Alex Greenwood	39	Millie Bright	32.9	Rachel Daly	51.
20	247	250	254	1	5		48 England Women's	31538	Mary Alexandra Earps	16.7	4642	Millie Bright	26.4	Jessica Carter	31.1	Mary Alexandra Earps	9.

What we found: up, back, through

EV_ID	EV_ID2	EV_ID3	PERIOD	MINUTE	SECOND	TEAM	SRCPLAYER	X1	VIAPLAYER	X2	DSTPLAYER	X3	DSTPLAYER2	X4	TOTAL_DISTANCE
131	134	136	1	3	47	England Women's	Alex Greenwood	43.1	Ella Toone	62.6	Rachel Daly	57.5	Lauren Hemp	75.8	32.7



What we found: up, back, through

```
select team, count(*) as num_UPBACKTHROUGH
From (SELECT distinct ev_id, ev_id2, ev_id3, period, minute, second, team,
      srcID, srcplayer, x1, viaID, viaPlayer, x2 dstID.....
```

```
) group by team;
```

	TEAM	NUM_UPBACKTHROUGH
1	Australia Women's	30
2	England Women's	49

Key takeaways

- There is hidden value in unstructured data, but you mind need to think outside the box to get it
- Data-informed is good - but ensure you add your context
- It's one element of the picture – don't just rely on it!
- It's being used across the sports industry, but equally can be used in business, supply chain and finance

Ideas and Questions always welcome....

Dr. Abi Giles-Haigh

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