

# Technical and Tactical Football Analysis

How LaLiga uses data to implement novel analytics and metrics in football



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ORGANIZED BY 😂 databricks

### Introduction

- What do we have
- Data Preparation
- Use Cases
- Goal Probability







#### Event Data





#### Event Data





#### **Event Data**

#### <?xml version="1.0" encoding="UTF-8"?>

```
<Game id="943096" away_score="0" away_team_id="178" away_team_name="Barcelona"
competition_id="23" competition_name="Spanish La Liga" game_date="2018-03-31T19:45:00"
home_score="0" home_team_id="179" home_team_name="Sevilla" matchday="30"
period_1_start="2018-03-31T19:45:19" season_id="2017" season_name="Season 2017/2018">
```

```
<Event id="1868950374" event_id="1" type_id="34" period_id="1" min="10" sec="4"
team_id="179" outcome="1" x="0.0" y="0.0" timestamp="2018-03-31T18:57:54.122"
last_modified="2018-03-31T18:57:54">
```

<Q id="1534520812" qualifier\_id="194" value="62991" />

<Q id="2095178222" qualifier\_id="130" value="8" />

<Q id="1878619934" qualifier\_id="197" value="260" />

</Event>

. . .





#### Tracking Data





Player and Ball coordinates sampled at 25Hz



#### Tracking Data

3.6 million rows

1891089:0,1,28,-1112,2770,0.4;1,2,8,834,403,0.2;0,3,3,-913,434,0.00;3,4,1,1643,-3447,0.00;1,5,18,633,-693,0.22;0,6,4,-2159,-1070,0.00;1,7,11,-20,-924,0.3;1,8,20,1359,-1848,0.16;3,9,2,-2199,3428,0.03;1,10,2,1421,1873,0.00;0,11,14,-14,-2541,0.28;0,12,20,40,-8,0.76;1,13,6,1495,-876,0.2;1,14,21,18,956,0.05;1,15,25,4747,7,0.1;1,16,12,-22,1604,0.78;1,17,10,16,-1639,0.09;0,18,25,57,-1169,1.56;0,19,2,-922,-2849,0.06;0,20,31,-3655,-5,0.64;0,21,27,-31,2383,0.28;1,22,4,1682,223,0.00;0,23,17,-2219,436,0.00;0,24,8,-1144,-219,0.19;3,25,0,-333,924,0.07;-1,26,-1,-38,-3483,0.00;4,27,-1,5565,4400,0.00;4,28,-1,5565,4400,0.00;4,29,-1,5565,4400,0.00;:-83,13,30,0,A,Alive,SetAway;:

1891090:0,1,28,-1110,2769,0.4;1,2,8,833,404,0.13;0,3,3,-913,433,0.00;3,4,1,1642,-3447,0.00;1,5,18,632,-695,0.3;0,6,4,-2159,-1069,0.00;1,7,11,-21,-925,0.34;1,8,20,1358,-1850,0.19;3,9,2,-2199,3428,0.03;1,10,2,1421,1874,0.03;0,11,14,-14,-2541,0.28;0,12,20,35,-10,0.84;1,13,6,1495,-877,0.15;1,14,21,13,952,0.09;1,15,25,4747,7,0.07;1,16,12,-23,1605,0.66;1,17,10,16,-1638,0.03;0,18,25,55,-1170,1.52;0,19,2,-922,-2849,0.06;0,20,31,-3653,-4,0.64;0,21,27,-31,2382,0.24;1,22,4,1682,223,0.00;0,23,17,-2219,436,0.00;0,24,8,-1144,-220,0.19;3,25,0,-333,924,0.07;-1,26,-1,-38,-3483,0.00;4,27,-1,5565,4400,0.00;4,28,-1,5565,4400,0.00;4,29,-1,5565,4400,0.00;:-120,1,30,0,A,Alive;:

**1891091**:0,1,28,-1107,2768,0.35;1,2,8,831,406,0.13;0,3,3,-913,433,0.00;3,4,1,1642,-3448,0.00;1,5,18,630,-696,0.35;0,6,4,-2159,-1069,0.00;1,7,11,-21,-928,0.35;1,8,20,1357...

DAT



#### First Step: Transform files into tables





First Step: Transform files into tables



				Tracking				
IdFrame	NuJersey	Speed	XPlayer	YPlayer	XBall	YBall	ZBall	IdGame
1891089	10	1.9	-1042	2617	-1022	241	0	12233
1891090	9	2.4	1922	2312	-1021	242	0	12233



Then, combine event and tracking



Frame correction





Combine event and tracking into a data model



### Use Cases





1. OPPONENTS PASSED BY A PASS







#### 2. BALL CARRIES LEADING TO SHOT

A player carries the ball and finishes with a shot on target







### 3. DISTANCE COVERED AFTER LOOSING POSSESSION

Distance covered during the 5 seconds after loosing possession







#### 4. PASSES INTO DOUBLE PRESSURE

The player who gives the pass and the player who receives it are under pressure (less than 2 meters)





### Goal Probability



### What is it?

**Goal Probability** is a metric that evaluates the chances of a player scoring a goal based on his position and the position of his opponents. Powered by

Goal probability

**11 ASENSIO** 

4%

It can be applied to any player, regardless of whether he is in possession of the ball or not. In this way, every player has an associate goal probability at each moment of the match



#### 1. We receive the position of the players and the ball 25 times per second in real time

Team	Jersev	X	Υ
Team	Jersey	X	Y
Team	n Jersey	X	Y
FCB	1	31.18	33.21
FCB	3	67.20	40.44
FCB	4	63.09	29.13
FCB	5	81.46	28.55
FCB	7	91.61	17.13
FCB	8	76.32	18.41
FCB	16	84.81	32.55
FCB	18	93.36	47.40
FCB	19	93.44	40.30
FCB	21	91.11	27.25
FCB	25	92.29	34.41
SEV	4	92.56	26.53
SEV	5	81.18	17.52
SEV	6	92.64	28.81
SEV	8	91.39	32.40
SEV	9	90.06	44.34
SEV	10	85.11	37.44
SEV	13	103.94	33.41
SEV	16	95.60	42.41
SEV	20	87.28	33.68
SEV	22	71.23	39.44
SEV	23	93.21	37.11
		70.00	
Ball	85.17	32.09	

DATA+AI SUMMIT 2022 Frame = 2028093 Frame = 2028094

Frame = 2028092

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2. This data is processed in order to calculate the **input variables** to the model

- Distance to goal 18.45
- Distance to goalkeeper 16.42
- Angle to goal 20.4
- Number of opponents in the cone of vision 2.5
- Distance to the nearest opponent 0.3
- Angle to the nearest opponent 25
- 💿 One-on-one 🏾 0
- Angle to goalkeeper 1.5
- Quality of the player 1





3. The model returns the goal probability

- Distance to goal 18.45
- Distance to goalkeeper 16.42
- Angle to goal 20.4
- Number of opponents in the cone of vision 2.5
- Distance to the nearest opponent 0.3
- Angle to the nearest opponent 25
- One-on-one O
- Angle to goalkeeper 1.5
- Quality of the player



For every frame and every player



Frame

4. We send the results to a web front-end via API

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5. Goal probability graphic is included in the broadcast



1. We receive the position of the players and the ball 25 times per second in real time

< 30 sec.

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2. This data is processed in order to calculate the input variables to the model

3. The model returns the goal probability

4. We send the results to a web front-end via API

3.4%

18.45 16.42 20.4 2.5 0.3 25 0



0 540 5404 222222 00078 🔶 5504 550 44554

5. Goal probability graphic is included in the broadcast

1.5 1



#### **Amount of Data**

3 million data for every game30 million data for every matchdayHigh processing capacity

#### **Multidisciplinary Team**

Data Scientists, Data Engineers, Data Arquitects, Audiovisual and Football experts make up the work team

#### Partnership

Partnership with Microsoft and its software tools helped develop the solution



### **Technology's Arquitecture**



### About the quality of the player

Players are grouped into 4 groups, based on the **number of goals per game** and **the number of goals per shot** 



More likely to score



Less likely to score

- We use historical data to collect examples of shots
- For every shot, we calculate and store the variables along with the output (goal/no-goal)





	Eve	ent					
	VARIABLES						
Distance to goal	Distance to GK		OUTPUT				
4	2	•••	1				
5	6	•••	0				
5	4		0				
25	6		1				
12	4	•••	0				
•••	•••	•••	•••	38			

Tracking



Imbalanced dataset (~20% of shots on target are goals) ()

Need for explainability



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Imbalanced dataset (~20% of shots on target are goals)



Goal distance	GK distance	Goal Angle	Opp. In cone	Dist. nearest	Angle nearest	One-on- one	GK Angle	Player Quality	Goal
5	6	30	0	1	10	0	10	1	1
15	10	20	2	3	55	0	15	3	1
				Synt	hetic new san	nple			
10	8	25	1	2	30	0	12	2	1
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Logistic regression is a traditional statistics technique that models the probabilities for classification problems

Let's consider the angle to goal as the only explanatory variable for scoring

Sigmoid function  $Probability = \theta(w_0 + w_1 \cdot angle)$ 

We don't have access to the actual probability

We can only observe the occurrence of an event and try to infer that probability

Angle	Goal
5	1
35	0
21	0
10	1



$$Probability = \theta(w_0 + w_1 \cdot angle)$$

 $\theta(s) =$ 

Angle	Goal scored	$w_0 = 1.2$ $w_1 = -0.07$ Probability	$w_0 = 2.3$ $w_1 = -0.15$ Probability		Maximum likelihood estimation
5	1	70%	82%		Soloot the percenters we have
35	0	22%	5%	Which one is better?	that maximiza this likelihood
21	0	43%	3%		that maximize this likelihood
10	1	62%	69%		







Using all our variables:

 $Probability = \theta(w_0 + w_1 \cdot distance + w_2 \cdot angle + w_3 \cdot opp in cone + \cdots)$ 

O However, this model doesn't give real probabilities, since we trained it with a balanced dataset





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+3191:32 CAD 0 0 CEL	<u> </u>	
	crosoft	MEDIACOACH
Goal probe	Variable	Value
Y LOZA	Goal distar	nce 6.4
	GK distance	e 5.2
	Goal Angle	57.7
	Opp. in cor	ne 1.5
	Dist. neare	st 1.3
	Angle near	est 138
	One-on-on	e 0
	GK angle	5.8
	Player Qua	lity 1

8.8% Goal probability 35 LOBETE		
Variable	Value	
Goal distance	22.3	
GK distance	18	
Goal Angle	15.9	1
Opp. in cone	1	
Dist. nearest	3.1	
Angle nearest	54	
One-on-one	0	
GK angle	0.1	Males MAQ IMC
Player Quality	1	18 .



onte Circulation Ci		euskalter(s
Variable	Value	
Goal distance	16.9	
GK distance	11.9	
Goal Angle	21.7	1-
Opp. in cone	2	
Dist. nearest	2.1	
Angle nearest	25	all a la
One-on-one	0	
GK angle	1.4	MQ
Player Quality	1	A A



		ni a Gipuzkoe	LaLiga Saltander EALE SEGUROS
ander Santander	Santander Santander	Sontonde	er Sontander
	Variable	Value	
i e	Goal distance	5.2	
1	GK distance	4.8	Euuros de
	Goal Angle	38.5	
	Opp. in cone	0.5	Powered by Microsoft
	Dist. nearest	3.8	72.6% Goal probability
	Angle nearest	119	23 Sørloth
	One-on-one	1	
	GK angle	15	
	Player Quality	1	



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# Thank you



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