T3_Xgoals_model

February 7, 2022

1 Expected goals model

En este tema vamos a aprender a realizar un modelo básico para el estudio del fútbol, el **expected goals model**, que podríamos traducir algo así como el modelo de goles esperados.

Este va a ser nuestro primer modelo estadístico con el que vamos a tratar de predecir unos resultados, goles, a partir de datos de diferentes eventos, disparos a puerta, utilizando nuestras herramientas de python

1.1 ¿Qué es un expected goals?

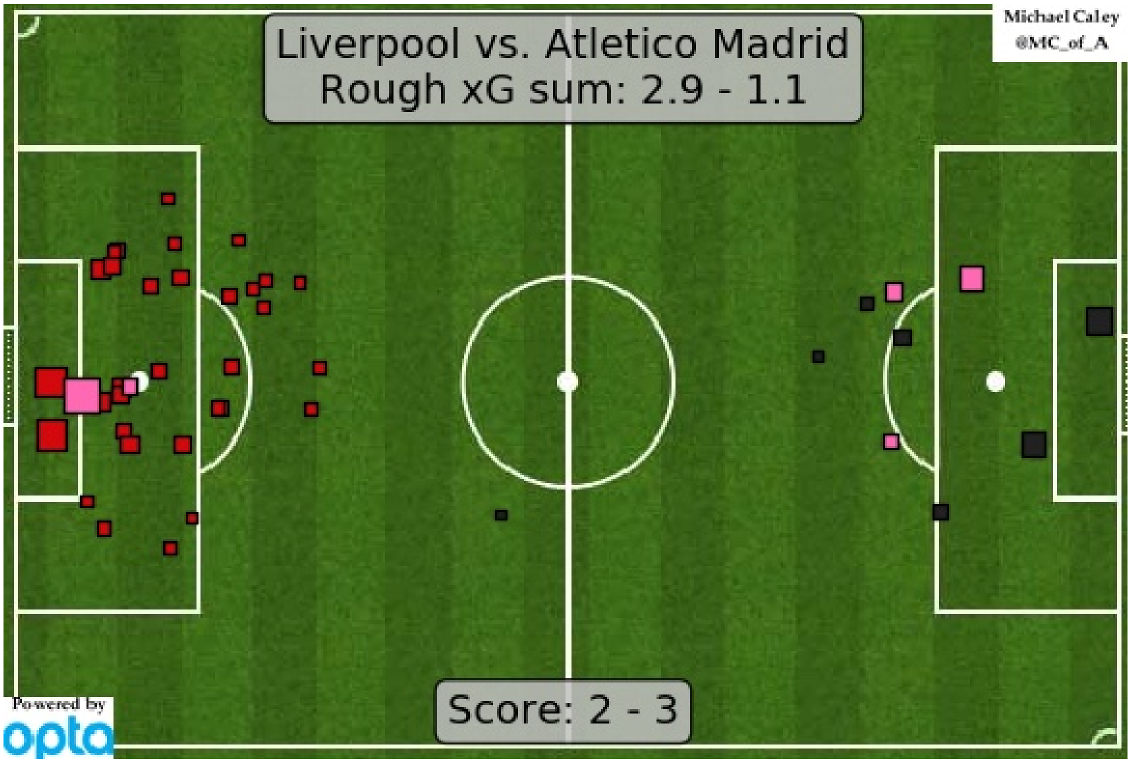
Podráimos definirlo como *la probabilidad de que en un día típico de fútbol un particular disparo a puerta desde una determinada posición acabe siendo gol*, es decir nos da la probabilidad que tiene un disparo a puerta de ser gol.

Esta información la obtenemos analizando una enorme cantidad de partidos con los que *hemos entrenado* a nuestro modelo

1.2 ¿ Por qué son importantes los expected goals?

Hay bastantes razones pero os voy a dar unas pocas:

1. La primera razón es porque nos cuentan una historia sobre un partido que no podemos obtener únicamente del resultado final.
2. La segunda razón es porque pueden usarse como guía para ayudar a jugadores y entrenadores a la hora de tomar decisiones de cara al gol.



1.3 Cargando los datos

Vamos a comenzar importando las librerías que vamos a necesitar. En este problema vamos a trabajar con los datos de yscout para jugar con otros datos. (Wyscout data from https://figshare.com/collections/Soccer_match_event_dataset/4415000/2) Vamos a cargar los datos de la liga inglesa

[1]:
```
#Las librerías básicas
import json
import numpy as np
import pandas as pd
```

[2]:
```
# Cargamos los datos de la liga inglesa en nuestra variable data

with open('Wyscout/events/events_Spain.json') as f:
    data = json.load(f)
```

[3]:
```
#Creamos un DataFrame de pandas

train = pd.DataFrame(data)
train.head()
```

[3]:
```
   eventId subEventName              tags  playerId  \
0        8  Simple pass  [{'id': 1801}]      3542
1        8  Simple pass  [{'id': 1801}]    274435
```

```
2         8  Simple pass  [{'id': 1801}]    364860
3         8  Simple pass  [{'id': 1801}]      3534
4         8  Simple pass  [{'id': 1801}]      3695

                                    positions  matchId eventName  teamId  \
0  [{'y': 61, 'x': 37}, {'y': 50, 'x': 50}]  2565548      Pass     682
1  [{'y': 50, 'x': 50}, {'y': 30, 'x': 45}]  2565548      Pass     682
2  [{'y': 30, 'x': 45}, {'y': 12, 'x': 38}]  2565548      Pass     682
3  [{'y': 12, 'x': 38}, {'y': 69, 'x': 32}]  2565548      Pass     682
4  [{'y': 69, 'x': 32}, {'y': 37, 'x': 31}]  2565548      Pass     682

  matchPeriod   eventSec subEventId         id
0          1H   2.994582         85  180864419
1          1H   3.137020         85  180864418
2          1H   6.709668         85  180864420
3          1H   8.805497         85  180864421
4          1H  14.047492         85  180864422
```

[4]:
```python
# Vemos que la columna que nos interesa es la de subEventName, que dice que␣
 ↪tipo de evento futbolístico tenemos.
# Veamos que tipo de eventos hay usando la función unique()

pd.unique(train['subEventName'])
```

[4]:
```
array(['Simple pass', 'Smart pass', 'Cross', 'Ground defending duel',
       'Acceleration', 'Ground attacking duel', 'Shot', 'Reflexes',
       'Touch', 'Ball out of the field', 'Corner', 'Goal kick',
       'Throw in', 'High pass', 'Head pass', 'Launch',
       'Ground loose ball duel', 'Foul', 'Free Kick', 'Clearance',
       'Air duel', '', 'Free kick cross', 'Hand foul', 'Save attempt',
       'Hand pass', 'Goalkeeper leaving line', 'Penalty',
       'Free kick shot', 'Late card foul', 'Time lost foul', 'Whistle',
       'Simulation', 'Protest', 'Out of game foul', 'Violent Foul'],
      dtype=object)
```

[5]:
```python
# Extraemos entonces los eventos que nos interesan que son los disparos a puerta
shots=train[train['subEventName']=='Shot']

shots.head()
```

[5]:
```
     eventId subEventName                                               tags  \
20        10         Shot  [{'id': 1901}, {'id': 401}, {'id': 201}, {'id'…
22        10         Shot          [{'id': 402}, {'id': 2101}, {'id': 1802}]
107       10         Shot  [{'id': 402}, {'id': 2101}, {'id': 201}, {'id'…
111       10         Shot  [{'id': 402}, {'id': 201}, {'id': 1216}, {'id'…
228       10         Shot          [{'id': 402}, {'id': 1214}, {'id': 1802}]
```

```
     playerId                                       positions  matchId eventName  \
20     225089      [{'y': 34, 'x': 93}, {'y': 0, 'x': 0}]  2565548      Shot
22     255738      [{'y': 59, 'x': 80}, {'y': 0, 'x': 0}]  2565548      Shot
107     37831  [{'y': 57, 'x': 88}, {'y': 100, 'x': 100}]  2565548      Shot
111     15214  [{'y': 66, 'x': 87}, {'y': 100, 'x': 100}]  2565548      Shot
228    225089      [{'y': 40, 'x': 75}, {'y': 0, 'x': 0}]  2565548      Shot

     teamId matchPeriod    eventSec subEventId         id
20      695          1H   57.771186        100  180865315
22      695          1H   60.727239        100  180864547
107     682          1H  446.986112        100  180864486
111     682          1H  488.929113        100  180864491
228     695          1H  948.872079        100  180864792
```

```
[6]: #Go through the dataframe and calculate X, Y co-ordinates.
#Distance from a line in the centre
#Shot angle.
#Details of tags can be found here: https://apidocs.wyscout.com/
 ↪matches-wyid-events

shots_model=pd.DataFrame(columns=['Goal','X','Y'])
for i,shot in shots.iterrows():

    header=0
    for shottags in shot['tags']:
        if shottags['id']==403:
            header=1
    #Only include non-headers
    if not(header):
        shots_model.at[i,'X']=100-shot['positions'][0]['x']
        shots_model.at[i,'Y']=shot['positions'][0]['y']
        shots_model.at[i,'C']=abs(shot['positions'][0]['y']-50)

        #Distance in metres and shot angle in radians.
        x=shots_model.at[i,'X']*105/100
        y=shots_model.at[i,'C']*65/100
        shots_model.at[i,'Distance']=np.sqrt(x**2 + y**2)
        a = np.arctan(7.32 *x /(x**2 + y**2 - (7.32/2)**2))
        if a<0:
            a=np.pi+a
        shots_model.at[i,'Angle'] =a

        #Was it a goal
        shots_model.at[i,'Goal']=0
        for shottags in shot['tags']:
                #Tags contain that its a goal
                if shottags['id']==101:
```

```
                    shots_model.at[i,'Goal']=1
```

[7]:
```
shots_model
```

[7]:
```
        Goal   X   Y     C   Distance     Angle
20         0   7  34  16.0  12.735089  0.346975
22         0  20  59   9.0  21.799599  0.321317
107        0  12  57   7.0  13.396361  0.506972
111        0  13  66  16.0  17.160492  0.341540
228        0  25  40  10.0  27.042790  0.261520
…        …  ..  ..   …         …         …
628323     0   7  66  16.0  12.735089  0.346975
628374     0  10  32  18.0  15.720687  0.317684
628540     1   8  25  25.0  18.292690  0.189128
628596     0  18  30  20.0  22.939268  0.263508
628637     0  12  43   7.0  13.396361  0.506972

[6608 rows x 6 columns]
```

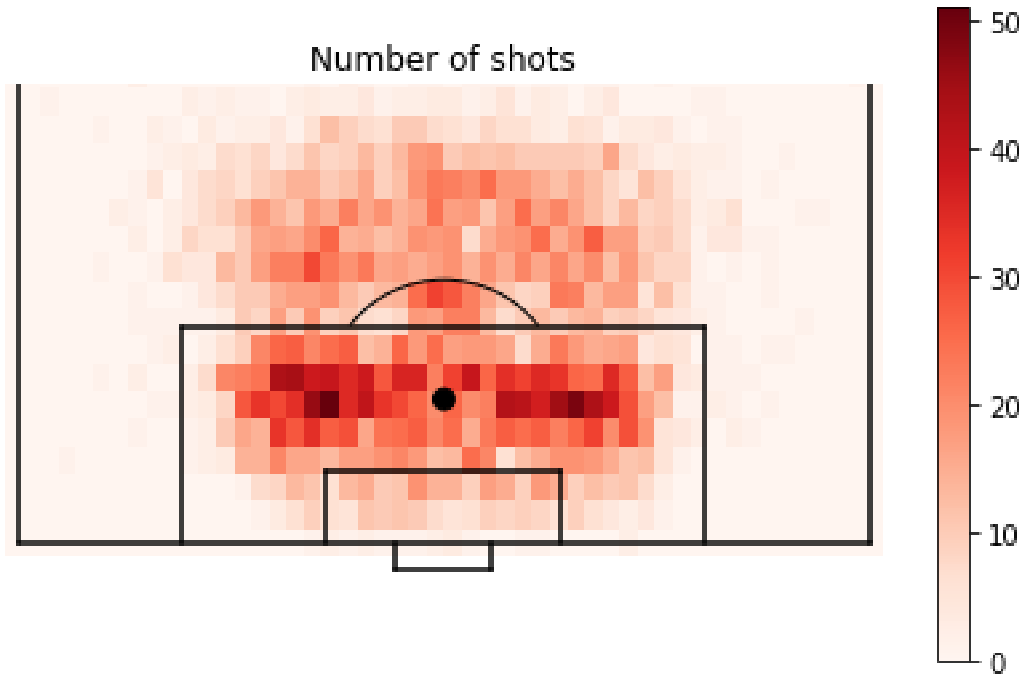
[8]:
```
#Plotting
import matplotlib.pyplot as plt
from matplotlib.patches import Arc
```

[9]:
```
#Two dimensional histogram
H_Shot=np.histogram2d(shots_model['X'], shots_model['Y'],bins=50,range=[[0,␣
↪100],[0, 100]])
goals_only=shots_model[shots_model['Goal']==1]
H_Goal=np.histogram2d(goals_only['X'], goals_only['Y'],bins=50,range=[[0,␣
↪100],[0, 100]])
```

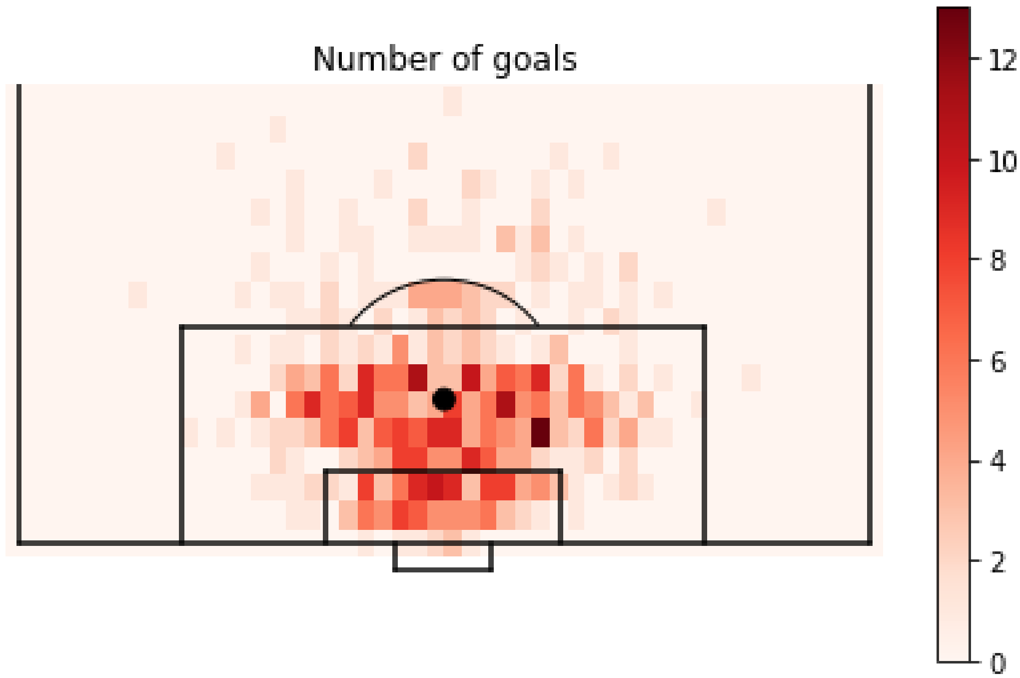
[10]:
```
def createGoalMouth():
    #Adopted from FC Python
    #Create figure
    fig=plt.figure()
    ax=fig.add_subplot(1,1,1)

    linecolor='black'

    #Pitch Outline & Centre Line
    plt.plot([0,65],[0,0], color=linecolor)
    plt.plot([65,65],[50,0], color=linecolor)
    plt.plot([0,0],[50,0], color=linecolor)

    #Left Penalty Area
    plt.plot([12.5,52.5],[16.5,16.5],color=linecolor)
    plt.plot([52.5,52.5],[16.5,0],color=linecolor)
```

```
    plt.plot([12.5,12.5],[0,16.5],color=linecolor)

    #Left 6-yard Box
    plt.plot([41.5,41.5],[5.5,0],color=linecolor)
    plt.plot([23.5,41.5],[5.5,5.5],color=linecolor)
    plt.plot([23.5,23.5],[0,5.5],color=linecolor)

    #Goal
    plt.plot([41.5-5.34,41.5-5.34],[-2,0],color=linecolor)
    plt.plot([23.5+5.34,41.5-5.34],[-2,-2],color=linecolor)
    plt.plot([23.5+5.34,23.5+5.34],[0,-2],color=linecolor)

    #Prepare Circles
    leftPenSpot = plt.Circle((65/2,11),0.8,color=linecolor)

    #Draw Circles
    ax.add_patch(leftPenSpot)

    #Prepare Arcs
    leftArc = Arc((32.5,11),height=18.3,width=18.
↪3,angle=0,theta1=38,theta2=142,color=linecolor)

    #Draw Arcs
    ax.add_patch(leftArc)

    #Tidy Axes
    plt.axis('off')

    return fig,ax
```

[11]:
```
#Plot the number of shots from different points
(fig,ax) = createGoalMouth()
pos=ax.imshow(H_Shot[0], extent=[-1,66,104,-1], aspect='auto',cmap=plt.cm.Reds)
fig.colorbar(pos, ax=ax)
ax.set_title('Number of shots')
plt.xlim((-1,66))
plt.ylim((-3,35))
plt.tight_layout()
plt.gca().set_aspect('equal', adjustable='box')
plt.show()
fig.savefig('NumberOfShots.pdf', dpi=None, bbox_inches="tight")
```

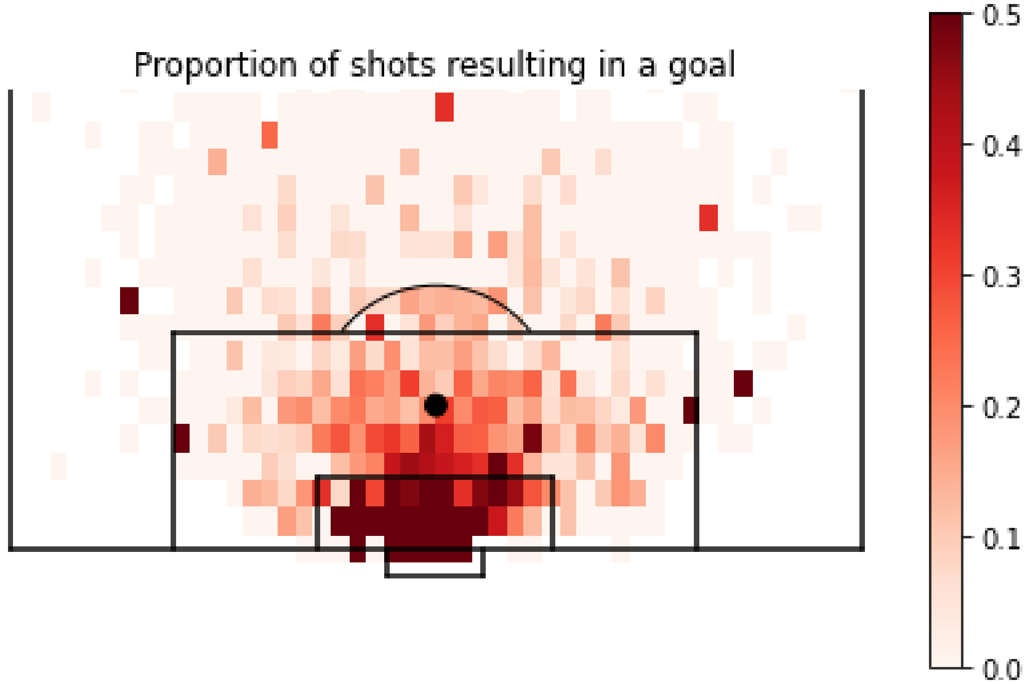



```
[12]: #Plot the number of GOALS from different points
(fig,ax) = createGoalMouth()
pos=ax.imshow(H_Goal[0], extent=[-1,66,104,-1], aspect='auto',cmap=plt.cm.Reds)
fig.colorbar(pos, ax=ax)
ax.set_title('Number of goals')
plt.xlim((-1,66))
plt.ylim((-3,35))
plt.tight_layout()
plt.gca().set_aspect('equal', adjustable='box')
plt.show()
fig.savefig('NumberOfGoals.pdf', dpi=None, bbox_inches="tight")
```



[13]:
```
#Plot the probability of scoring from different points
(fig,ax) = createGoalMouth()
pos=ax.imshow(H_Goal[0]/H_Shot[0], extent=[-1,66,104,-1],␣
↪aspect='auto',cmap=plt.cm.Reds,vmin=0, vmax=0.5)
fig.colorbar(pos, ax=ax)
ax.set_title('Proportion of shots resulting in a goal')
plt.xlim((-1,66))
plt.ylim((-3,35))
plt.tight_layout()
plt.gca().set_aspect('equal', adjustable='box')
plt.show()
fig.savefig('ProbabilityOfScoring.pdf', dpi=None, bbox_inches="tight")
```

```
/var/folders/bp/v78k11s50pdbmf3gy9nync040000gn/T/ipykernel_6596/3280902137.py:3:
RuntimeWarning: invalid value encountered in true_divide
  pos=ax.imshow(H_Goal[0]/H_Shot[0], extent=[-1,66,104,-1],
aspect='auto',cmap=plt.cm.Reds,vmin=0, vmax=0.5)
```



1.4 Ajustando un modelo

Hasta ahora lo que hemos hecho ha sido elegir unas variables y ver sus histogramas para ver que idea nos daban, pero no hemos ajustado ningún modelo matemático. Ajustar un modelo a nuestros datos es lo que nos va a permitir predecir.

[14]:
```
import statsmodels.api as sm
import statsmodels.formula.api as smf
```

1.4.1 Ejemplo de un ajuste lineal

Vamos a ver un ejemplo de un ajuste lineal, que nos puede resultar más fácil de entender. Vamos ajustar los siguientes datos: 1. Número de minutos jugados 2. Número de goles

[15]:
```
#Escribimos unos datos sobre minutos jugados y goles metidos
minutes_played=np.array([120,452,185,708,340,561])
goals_scored=np.array([1,6,3,7,3,5])

#Y lo transformamos en un DataFrame
minutes_model = pd.DataFrame()
minutes_model = minutes_model.assign(minutes=minutes_played)
minutes_model = minutes_model.assign(goals=goals_scored)
```

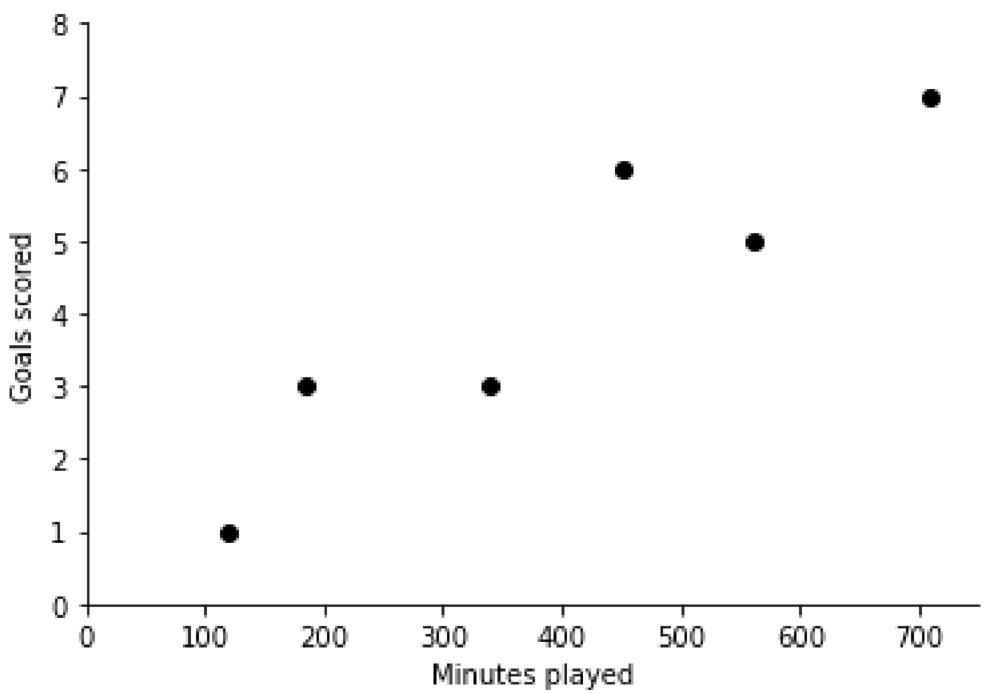
[16]:
```
minutes_model
```

[16]:

	minutes	goals
0	120	1
1	452	6
2	185	3
3	708	7
4	340	3
5	561	5

[17]:

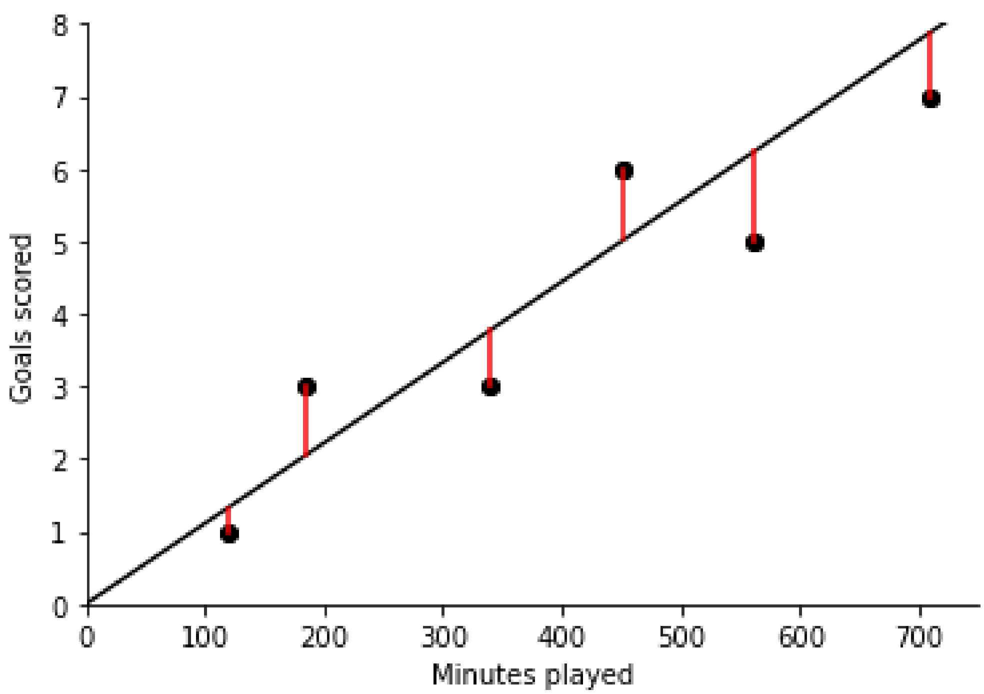
```
fig,ax=plt.subplots(num=1)
ax.plot(minutes_played, goals_scored, linestyle='none', marker= '.',␣
↪markersize= 12, color='black')
ax.set_ylabel('Goals scored')
ax.set_xlabel('Minutes played')
ax.spines['top'].set_visible(False)
ax.spines['right'].set_visible(False)
plt.xlim((0,750))
plt.ylim((0,8));
```



[18]:

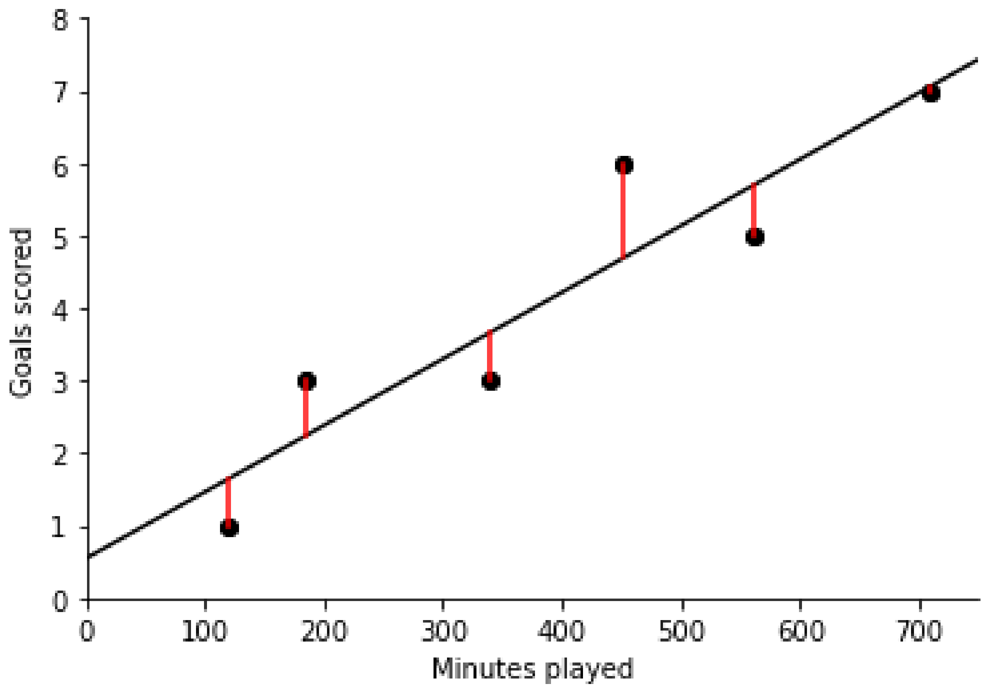
```
fig,ax=plt.subplots(num=1)
ax.plot(minutes_played, goals_scored, linestyle='none', marker= '.',␣
↪markersize= 12, color='black')
ax.set_ylabel('Goals scored')
ax.set_xlabel('Minutes played')
ax.spines['top'].set_visible(False)
```

```
ax.spines['right'].set_visible(False)
plt.xlim((0,750))
plt.ylim((0,8))


#Slope of one goal per 90 played
b=1/90
#Intercept
a=0

x=np.arange(800,step=0.1)
y= a + b*x

ax.plot(minutes_played, goals_scored, linestyle='none', marker= '.',␣
↪markersize= 12, color='black')
ax.plot(x, y, color='black')

#Show distances to line
for i,mp in enumerate(minutes_played):
    ax.plot([mp,mp],[goals_scored[i],a+b*mp], color='red')


plt.show()
```



[19]:

```
fig,ax=plt.subplots(num=1)
ax.plot(minutes_played, goals_scored, linestyle='none', marker= '.',␣
↪markersize= 12, color='black')
ax.set_ylabel('Goals scored')
ax.set_xlabel('Minutes played')
ax.spines['top'].set_visible(False)
ax.spines['right'].set_visible(False)
plt.xlim((0,750))
plt.ylim((0,8))


#Slope determined by linear regression
model_fit=smf.ols(formula='goals_scored ~ minutes_played ', data=minutes_model).
↪fit()
#print(model_fit.summary())
[a,b]=model_fit.params

x=np.arange(800,step=0.1)
y= a + b*x

ax.plot(minutes_played, goals_scored, linestyle='none', marker= '.',␣
↪markersize= 12, color='black')
ax.plot(x, y, color='black')

#Show distances to line
for i,mp in enumerate(minutes_played):
    ax.plot([mp,mp],[goals_scored[i],a+b*mp], color='red')


plt.show()
```

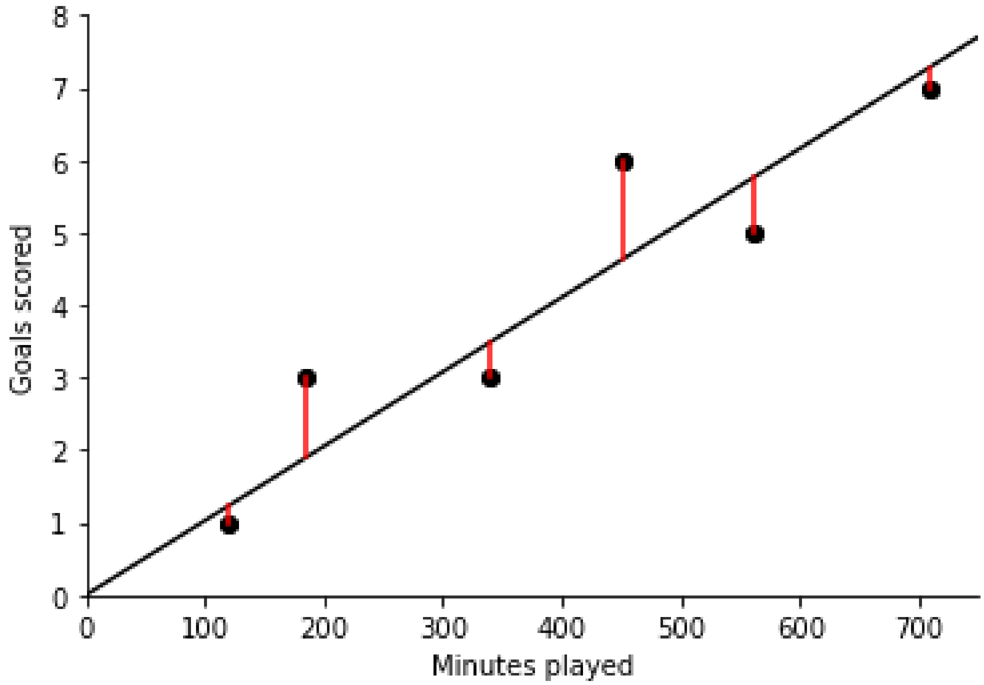


[20]:
```
fig,ax=plt.subplots(num=1)
ax.plot(minutes_played, goals_scored, linestyle='none', marker= '.',␣
↪markersize= 12, color='black')
ax.set_ylabel('Goals scored')
ax.set_xlabel('Minutes played')
ax.spines['top'].set_visible(False)
ax.spines['right'].set_visible(False)
plt.xlim((0,750))
plt.ylim((0,8))


#Slope determined by linear regression
model_fit=smf.ols(formula='goals_scored ~ minutes_played -1',␣
↪data=minutes_model).fit()
print(model_fit.summary())
[b]=model_fit.params

a=0
x=np.arange(800,step=0.1)
y= a + b*x

ax.plot(minutes_played, goals_scored, linestyle='none', marker= '.',␣
↪markersize= 12, color='black')
ax.plot(x, y, color='black')
```

```
#Show distances to line
for i,mp in enumerate(minutes_played):
    ax.plot([mp,mp],[goals_scored[i],a+b*mp], color='red')


plt.show()
```

```
/Users/galeanojav/opt/anaconda3/lib/python3.8/site-
packages/statsmodels/stats/stattools.py:74: ValueWarning: omni_normtest is not
valid with less than 8 observations; 6 samples were given.
  warn("omni_normtest is not valid with less than 8 observations; %i "

                                 OLS Regression Results
================================================================================
=======
Dep. Variable:           goals_scored   R-squared (uncentered):
0.969
Model:                            OLS   Adj. R-squared (uncentered):
0.963
Method:                 Least Squares   F-statistic:
156.1
Date:                Mon, 07 Feb 2022   Prob (F-statistic):
5.83e-05
Time:                        12:44:32   Log-Likelihood:
-7.2998
No. Observations:                   6   AIC:
16.60
Df Residuals:                       5   BIC:
16.39
Df Model:                           1
Covariance Type:            nonrobust
================================================================================
==
                     coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
--
minutes_played     0.0103      0.001     12.495      0.000       0.008
0.012
==============================================================================
Omnibus:                          nan   Durbin-Watson:                   1.148
Prob(Omnibus):                    nan   Jarque-Bera (JB):                0.840
Skew:                           0.586   Prob(JB):                        0.657
Kurtosis:                       1.590   Cond. No.                         1.00
==============================================================================

Notes:
```

```
[1] R² is computed without centering (uncentered) since the model does not
contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
```



[21]:
```
1/b
```

[21]: 97.3466469428008

1.4.2 Logistic curve

Pero en nuestro caso parece que un ajuste lineal no va a ir bien. Primero porque queremos ajustar probabilidades que van a ir de 0 a 1, y va a llegar un momento que se tienen que suavizar al llegar a los límites.

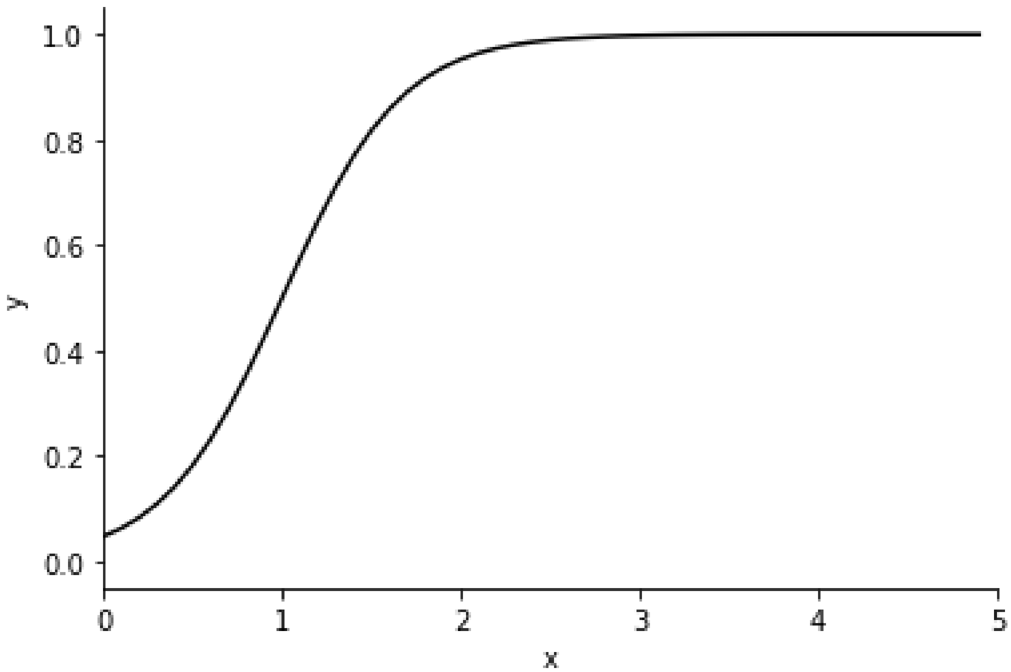
Para eso en los años 50 se inventó la ecuación logística, que tiene la forma:

$$y = \frac{1}{1 + e^{b_0 + b_1 x}}$$

démonos cuenta que en realidad la idea es la misma tenemos que encontrar los parámetros b_0 y b_1 que mejor se ajusten a nustros datos.

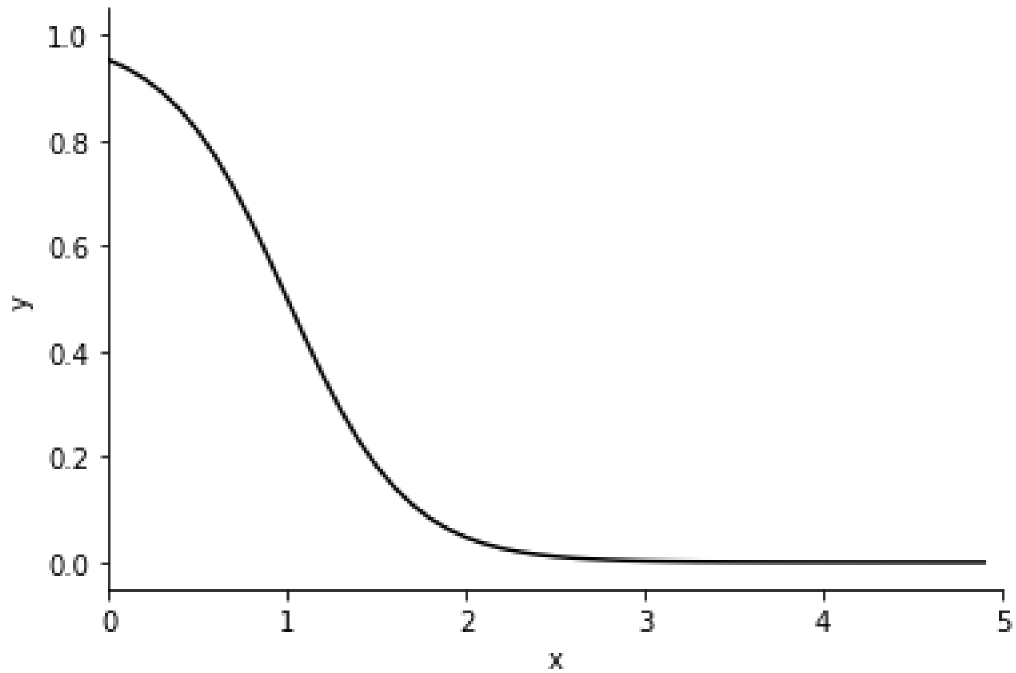
En realidad esto es uno de los problemas clásicos en Machine Learning que es el problema de regresión.

[22]:
```
#Plot a logistic curve
b=[3, -3]
x=np.arange(5,step=0.1)
y=1/(1+np.exp(+b[0]+b[1]*x))
fig,ax=plt.subplots(num=1)
plt.ylim((-0.05,1.05))
plt.xlim((0,5))
ax.set_ylabel('y')
ax.set_xlabel("x")
ax.plot(x, y, linestyle='solid', color='black')
ax.spines['top'].set_visible(False)
ax.spines['right'].set_visible(False)
plt.show()
```



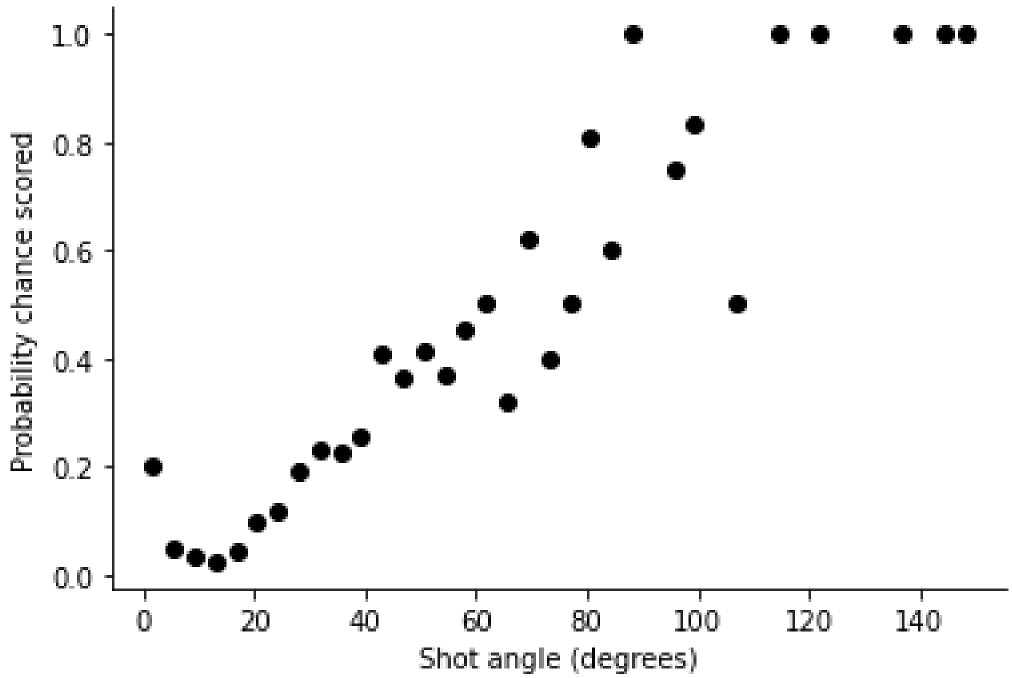
[23]:
```
#Plot a logistic curve
b=[3, -3]
x=np.arange(5,step=0.1)
y=1/(1+np.exp(-b[0]-b[1]*x))
fig,ax=plt.subplots(num=1)
plt.ylim((-0.05,1.05))
plt.xlim((0,5))
ax.set_ylabel('y')
ax.set_xlabel("x")
ax.plot(x, y, linestyle='solid', color='black')
ax.spines['top'].set_visible(False)
```

```
ax.spines['right'].set_visible(False)
plt.show()
```



[24]:
```
#Show empirically how goal angle predicts probability of scoring
shotcount_dist=np.histogram(shots_model['Angle']*180/np.pi,bins=40,range=[0,␣
↪150])
goalcount_dist=np.histogram(goals_only['Angle']*180/np.pi,bins=40,range=[0,␣
↪150])
prob_goal=np.divide(goalcount_dist[0],shotcount_dist[0])
angle=shotcount_dist[1]
midangle= (angle[:-1] + angle[1:])/2
fig,ax=plt.subplots(num=2)
ax.plot(midangle, prob_goal, linestyle='none', marker= '.', markersize= 12,␣
↪color='black')
ax.set_ylabel('Probability chance scored')
ax.set_xlabel("Shot angle (degrees)")
ax.spines['top'].set_visible(False)
ax.spines['right'].set_visible(False)
```

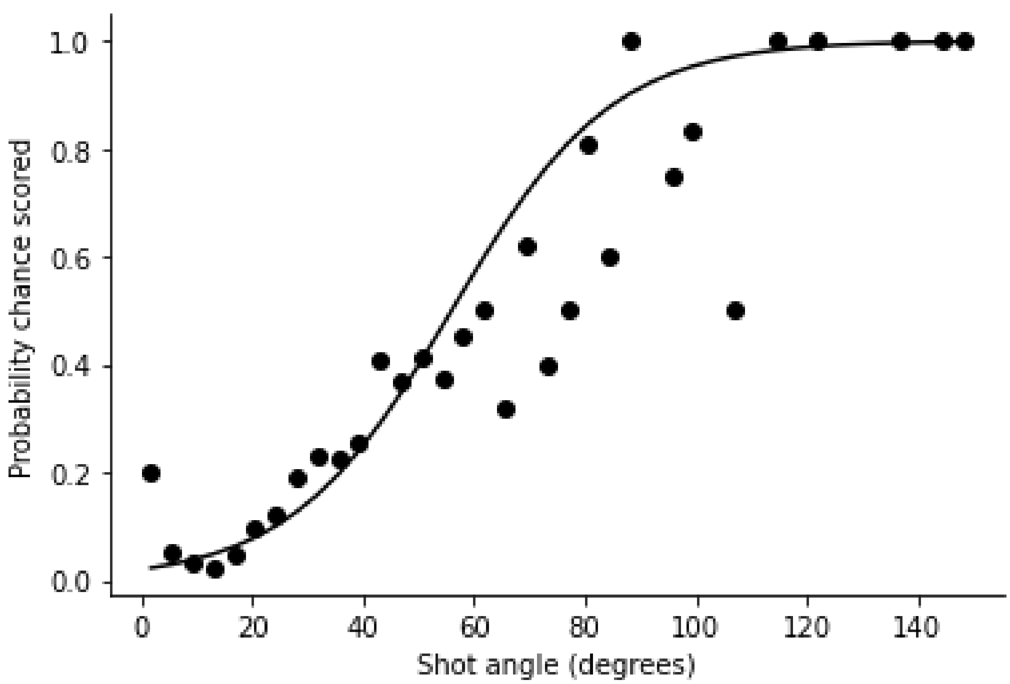
```
/var/folders/bp/v78k11s50pdbmf3gy9nync040000gn/T/ipykernel_6596/1294969170.py:4:
RuntimeWarning: invalid value encountered in true_divide
  prob_goal=np.divide(goalcount_dist[0],shotcount_dist[0])
```



[25]:
```
test_model = smf.glm(formula="Goal ~ Angle" , data=shots_model,
                           family=sm.families.Binomial()).fit()
print(test_model.summary())
b=test_model.params


xGprob=1/(1+np.exp(b[0]+b[1]*midangle*np.pi/180))
fig,ax=plt.subplots(num=1)
ax.plot(midangle, prob_goal, linestyle='none', marker= '.', markersize= 12,␣
 ↪color='black')
ax.plot(midangle, xGprob, linestyle='solid', color='black')
ax.set_ylabel('Probability chance scored')
ax.set_xlabel("Shot angle (degrees)")
ax.spines['top'].set_visible(False)
ax.spines['right'].set_visible(False)
plt.show()
fig.savefig('ProbabilityOfScoringAngleFit.pdf', dpi=None, bbox_inches="tight")
```

```
                 Generalized Linear Model Regression Results
================================================================================
==
Dep. Variable:      ['Goal[0]', 'Goal[1]']   No. Observations:
6608
Model:                                 GLM   Df Residuals:
6606
```

```
Model Family:                     Binomial   Df Model:
1
Link Function:                       logit   Scale:
1.0000
Method:                               IRLS   Log-Likelihood:
-1908.7
Date:                     Mon, 07 Feb 2022   Deviance:
3817.4
Time:                             12:44:53   Pearson chi2:
6.12e+03
No. Iterations:                          6   Pseudo R-squ. (CS):
0.09699
Covariance Type:                 nonrobust
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept      3.8730      0.093     41.854      0.000       3.692       4.054
Angle         -3.9638      0.171    -23.228      0.000      -4.298      -3.629
==============================================================================
```

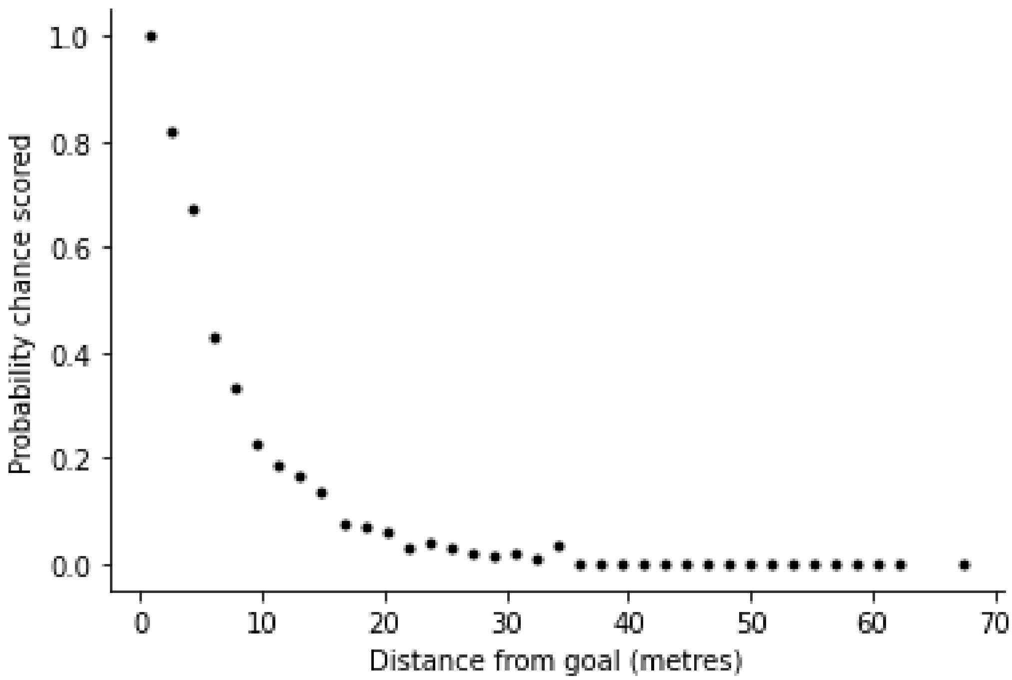


[26]:

```
shotcount_dist=np.histogram(shots_model['Distance'],bins=40,range=[0, 70])
goalcount_dist=np.histogram(goals_only['Distance'],bins=40,range=[0, 70])
prob_goal=np.divide(goalcount_dist[0],shotcount_dist[0])
distance=shotcount_dist[1]
middistance= (distance[:-1] + distance[1:])/2
```

```
fig,ax=plt.subplots(num=1)
ax.plot(middistance, prob_goal, linestyle='none', marker= '.', color='black')
ax.set_ylabel('Probability chance scored')
ax.set_xlabel("Distance from goal (metres)")
ax.spines['top'].set_visible(False)
ax.spines['right'].set_visible(False)
```

```
/var/folders/bp/v78k11s50pdbmf3gy9nync040000gn/T/ipykernel_6596/83466701.py:3:
RuntimeWarning: invalid value encountered in true_divide
  prob_goal=np.divide(goalcount_dist[0],shotcount_dist[0])
```



[27]:
```
#Make single variable model of distance
test_model = smf.glm(formula="Goal ~ Distance" , data=shots_model,
                           family=sm.families.Binomial()).fit()
print(test_model.summary())
b=test_model.params
xGprob=1/(1+np.exp(b[0]+b[1]*middistance))
ax.plot(middistance, xGprob, linestyle='solid', color='black')
plt.show()
fig.savefig('ProbabilityOfScoringDistance.pdf', dpi=None, bbox_inches="tight")
```

```
                 Generalized Linear Model Regression Results
================================================================================
==
Dep. Variable:     ['Goal[0]', 'Goal[1]']   No. Observations:
```

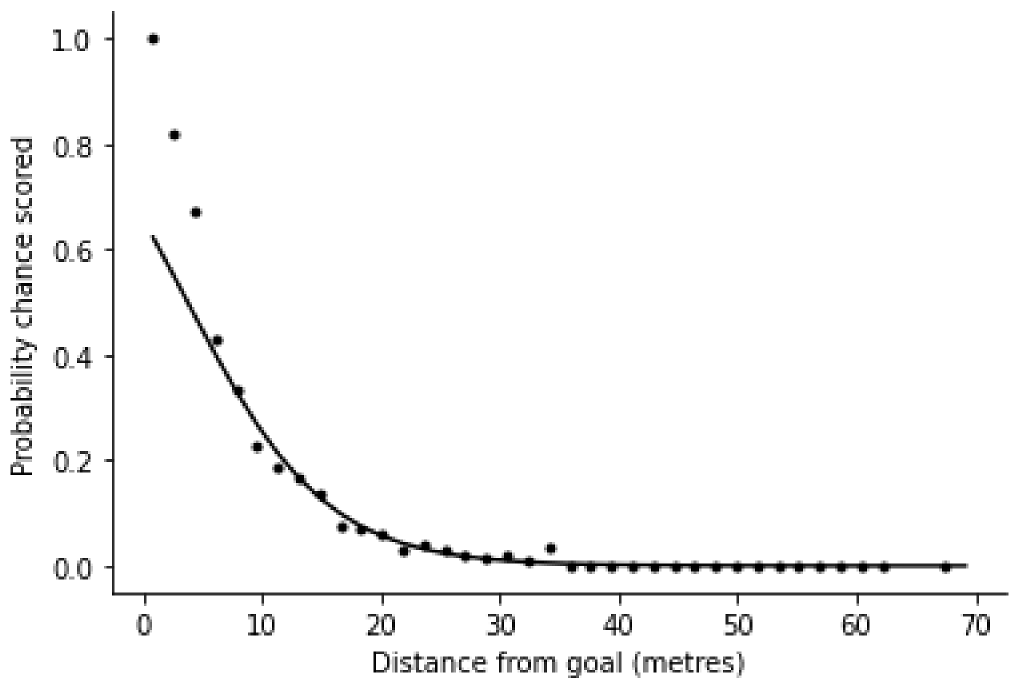
```
6608
Model:                            GLM   Df Residuals:
6606
Model Family:                Binomial   Df Model:
1
Link Function:                  logit   Scale:
1.0000
Method:                          IRLS   Log-Likelihood:
-1891.9
Date:                Mon, 07 Feb 2022   Deviance:
3783.8
Time:                        12:45:08   Pearson chi2:
3.10e+07
No. Iterations:                     7   Pseudo R-squ. (CS):
0.1016
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept     -0.6505      0.113     -5.764      0.000      -0.872      -0.429
Distance       0.1722      0.008     22.397      0.000       0.157       0.187
==============================================================================
```

[28]:

```
#Adding distance squared
#squaredD = shots_model['Distance']**2
#shots_model = shots_model.assign(D2=squaredD)
test_model = smf.glm(formula="Goal ~ Distance " , data=shots_model,
                           family=sm.families.Binomial()).fit()
print(test_model.summary())
b=test_model.params
xGprob=1/(1+np.exp(b[0]+b[1]*middistance) )
fig,ax=plt.subplots(num=1)
ax.plot(middistance, prob_goal, linestyle='none', marker= '.', color='black')
ax.set_ylabel('Probability chance scored')
ax.set_xlabel("Distance from goal (metres)")
ax.spines['top'].set_visible(False)
ax.spines['right'].set_visible(False)
ax.plot(middistance, xGprob, linestyle='solid', color='black')
plt.show()
fig.savefig('ProbabilityOfScoringDistanceSquared.pdf', dpi=None,␣
 ↪bbox_inches="tight")
```

```
                 Generalized Linear Model Regression Results
================================================================================
==
Dep. Variable:     ['Goal[0]', 'Goal[1]']   No. Observations:
6608
Model:                            GLM   Df Residuals:
```

```
6606
Model Family:                      Binomial   Df Model:
1
Link Function:                        logit   Scale:
1.0000
Method:                                IRLS   Log-Likelihood:
-1891.9
Date:                      Mon, 07 Feb 2022   Deviance:
3783.8
Time:                              12:45:12   Pearson chi2:
3.10e+07
No. Iterations:                           7   Pseudo R-squ. (CS):
0.1016
Covariance Type:                  nonrobust
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept     -0.6505      0.113     -5.764      0.000      -0.872      -0.429
Distance       0.1722      0.008     22.397      0.000       0.157       0.187
==============================================================================
```



[29]:
```
# A general model for fitting goal probability
# List the model variables you want here
model_variables = ['Angle','Distance']
model=''
```

```
for v in model_variables[:-1]:
    model = model  + v + ' + '
model = model + model_variables[-1]

model
```

[29]: 'Angle + Distance'

[30]:
```
#Fit the model
test_model = smf.glm(formula="Goal ~ " + model, data=shots_model,
                           family=sm.families.Binomial()).fit()
print(test_model.summary())
b=test_model.params
```

```
                 Generalized Linear Model Regression Results
================================================================================
==
Dep. Variable:     ['Goal[0]', 'Goal[1]']   No. Observations:
6608
Model:                                GLM   Df Residuals:
6605
Model Family:                    Binomial   Df Model:
2
Link Function:                      logit   Scale:
1.0000
Method:                              IRLS   Log-Likelihood:
-1859.4
Date:                    Mon, 07 Feb 2022   Deviance:
3718.8
Time:                            12:45:19   Pearson chi2:
1.52e+05
No. Iterations:                         7   Pseudo R-squ. (CS):
0.1104
Covariance Type:                nonrobust
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept      1.2693      0.269      4.711      0.000       0.741       1.797
Angle         -1.8692      0.248     -7.536      0.000      -2.355      -1.383
Distance       0.1034      0.011      9.410      0.000       0.082       0.125
==============================================================================
```

[31]:
```
#Return xG value for more general model
def calculate_xG(sh):
    bsum=b[0]
    for i,v in enumerate(model_variables):
        bsum=bsum+b[i+1]*sh[v]
```

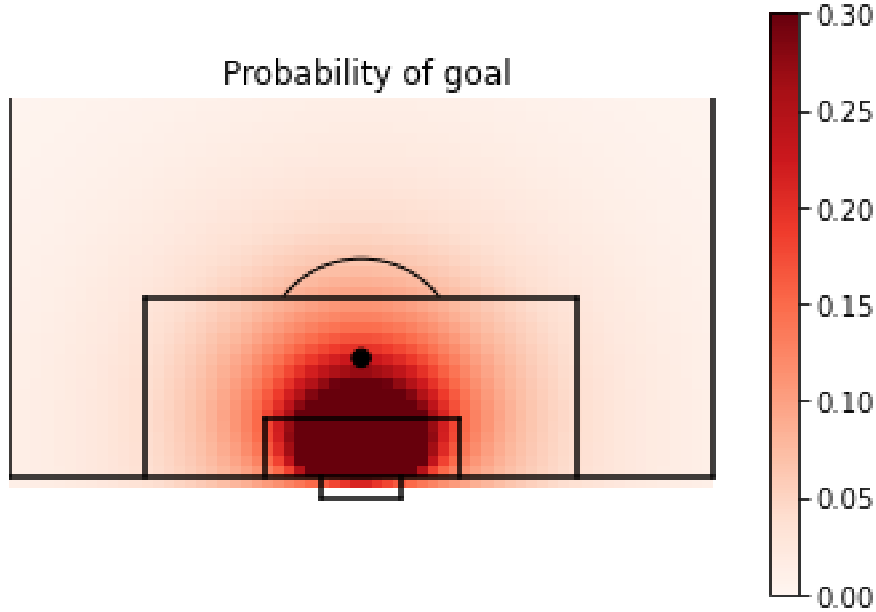
```
    xG = 1/(1+np.exp(bsum))
    return xG

#Add an xG to my dataframe
xG=shots_model.apply(calculate_xG, axis=1)
shots_model = shots_model.assign(xG=xG)
```

[32]:
```
shots_model.head()
```

[32]:

	Goal	X	Y	C	Distance	Angle	xG
20	0	7	34	16.0	12.735089	0.346975	0.125891
22	0	20	59	9.0	21.799599	0.321317	0.051017
107	0	12	57	7.0	13.396361	0.506972	0.153539
111	0	13	66	16.0	17.160492	0.341540	0.082743
228	0	25	40	10.0	27.042790	0.261520	0.027191

[33]:
```
#Create a 2D map of xG
pgoal_2d=np.zeros((65,65))
for x in range(65):
    for y in range(65):
        sh=dict()
        a = np.arctan(7.32 *x /(x**2 + abs(y-65/2)**2 - (7.32/2)**2))
        if a<0:
            a = np.pi + a
        sh['Angle'] = a
        sh['Distance'] = np.sqrt(x**2 + abs(y-65/2)**2)

        pgoal_2d[x,y] =  calculate_xG(sh)

(fig,ax) = createGoalMouth()
pos=ax.imshow(pgoal_2d, extent=[-1,65,65,-1], aspect='auto',cmap=plt.cm.
 ↪Reds,vmin=0, vmax=0.3)
fig.colorbar(pos, ax=ax)
ax.set_title('Probability of goal')
plt.xlim((0,66))
plt.ylim((-3,35))
plt.gca().set_aspect('equal', adjustable='box')
plt.show()
fig.savefig('goalprobfor_' + model  + '.pdf', dpi=None, bbox_inches="tight")
```


Probability of goal
0.30
0.25
0.20
0.15
0.10
0.05
0.00

```
[ ]:
```