

# 1 Pythagorean expectation and MLB

September 4, 2025

## 1 Getting Started

In this series of MOOCs we aim to introduce participants to methods for analyzing sports data using Python. In this first MOOC we introduce some basic concepts. These can be broken down into three areas:

1. How to code sports data so that you can apply statistical methods
2. The use of statistical methods
3. The interpretation of results

As we go along we will introduce you to the concepts by analyzing data from different sports and generating results. Once you get the hang of how this works, you'll Pythagorean be able to do it for yourself.

In this first week, we're going to go through simple but powerful examples that introduce you to all three elements.

## 2 The Pythagorean Expectation

The Pythagorean expectation is an idea devised by the famous baseball analyst, Bill James, but it can in fact be applied to any sport.

In any sports league, teams win games by accumulating a higher total than opponent. In baseball and cricket the relevant totals are runs, in basketball it is points, and in soccer and hockey it is goals (by "hockey" we mean here what the world outside of the US and Canada usually calls ice hockey, but in fact the same is true in field hockey).

The Pythagorean expectation can be described thus: in any season, the percentage of games won will be proportional to the square of total runs/points/goals scored by the team *squared* divided by the sum of total runs/points/goals scored by the team *squared* plus total runs/points/goals conceded by the team *squared*.

$$\text{or } wpc = TF^2 / (TF^2 + TA^2)$$

Where TF is runs/points/goals scored and TA is runs/points/goals conceded.

This is a concept which can help to explain not only why teams are successful, but also can be used as the basis for predicting results in the future.

In this first week we are going to derive the Pythagorean expectation for five leagues in five different sports:

Major League Baseball The English Premier League (soccer) The Indian Premier League (cricket) The National Basketball Association (NBA) The National Hockey League (NHL)

## 2.1 Coding the data

To derive the Pythagorean Expectation we will need to manipulate the data, which is a core skill that we expect you to obtain from these MOOCs. However, for this first week, we move quite quickly through the code, since our main objective is to show you the kinds of analysis you will be able to produce once you master Python.

## 2.2 The Pythagorean Expectation for baseball

We begin, naturally enough, with baseball. Running code in Python typically involves the following steps:

1. Importing “packages” - these enable to run certain types of commands. The same ones come up over and over again - pandas, numpy, matplotlib.pyplot and so on.
2. Import the raw data - from a csv or excel file - in these MOOCs we will provide the data for you
3. Running commands to shape the data in preparation for running the statistical model
4. Running the statistical model
5. Reviewing the results

With each line of code below, there is a brief explanation of the code. When you are ready, read each line, then place the cursor on the relevant line and press “run” in the toolbar.

```
In [7]: # Here are the packages we need
```

```
import pandas as pd
import numpy as np
import statsmodels.formula.api as smf
import matplotlib.pyplot as plt
import seaborn as sns
```

```
In [8]: # This command imports our data, which is a log of games played in 2018 doenloaded from
#(you can find the data here: https://www.retrosheet.org/)
# the second line of the command prints a list of variable names - there are many more
```

```
MLB = pd.read_excel('../Data/Week 1/Retrosheet MLB game log 2018.xlsx')
print(MLB.columns.tolist())
```

```
['Date', 'DoubleHeader', 'DayOfWeek', 'VisitingTeam', 'VisitingTeamLeague', 'VisitingTeamGameN
```

```
In [9]: # We can see what our dataframe looks like simply by typing its name
```

```
MLB
```

```

Out [9]:
      Date DoubleHeader DayOfWeek VisitingTeam VisitingTeamLeague \
0    20180329          0      Thu          COL              NL
1    20180329          0      Thu          PHI              NL
2    20180329          0      Thu          SFN              NL
3    20180329          0      Thu          CHN              NL
4    20180329          0      Thu          SLN              NL
5    20180329          0      Thu          MIL              NL
6    20180329          0      Thu          MIN              AL
7    20180329          0      Thu          CHA              AL
8    20180329          0      Thu          ANA              AL
9    20180329          0      Thu          CLE              AL
10   20180329          0      Thu          BOS              AL
11   20180329          0      Thu          HOU              AL
12   20180329          0      Thu          NYA              AL
13   20180330          0      Fri          COL              NL
14   20180330          0      Fri          PHI              NL
15   20180330          0      Fri          WAS              NL
16   20180330          0      Fri          SFN              NL
17   20180330          0      Fri          CHN              NL
18   20180330          0      Fri          MIL              NL
19   20180330          0      Fri          PIT              NL
20   20180330          0      Fri          ANA              AL
21   20180330          0      Fri          BOS              AL
22   20180330          0      Fri          HOU              AL
23   20180330          0      Fri          NYA              AL
24   20180331          0      Sat          COL              NL
25   20180331          0      Sat          PHI              NL
26   20180331          0      Sat          WAS              NL
27   20180331          0      Sat          SFN              NL
28   20180331          0      Sat          CHN              NL
29   20180331          0      Sat          SLN              NL
...   ...           ...      ...           ...           ...
2401 20180929          0      Sat          DET              AL
2402 20180929          0      Sat          MIA              NL
2403 20180929          0      Sat          ATL              NL
2404 20180929          0      Sat          ARI              NL
2405 20180929          0      Sat          LAN              NL
2406 20180929          0      Sat          OAK              AL
2407 20180929          1      Sat          HOU              AL
2408 20180929          2      Sat          HOU              AL
2409 20180929          0      Sat          NYA              AL
2410 20180929          0      Sat          CLE              AL
2411 20180929          0      Sat          CHA              AL
2412 20180929          0      Sat          TEX              AL
2413 20180929          0      Sat          TOR              AL
2414 20180930          0      Sun          SLN              NL
2415 20180930          0      Sun          PIT              NL
2416 20180930          0      Sun          WAS              NL

```

2417	20180930	0	Sun	DET	AL
2418	20180930	0	Sun	MIA	NL
2419	20180930	0	Sun	ATL	NL
2420	20180930	0	Sun	ARI	NL
2421	20180930	0	Sun	LAN	NL
2422	20180930	0	Sun	OAK	AL
2423	20180930	0	Sun	HOU	AL
2424	20180930	0	Sun	NYA	AL
2425	20180930	0	Sun	CLE	AL
2426	20180930	0	Sun	CHA	AL
2427	20180930	0	Sun	TEX	AL
2428	20180930	0	Sun	TOR	AL
2429	20181001	0	Mon	MIL	NL
2430	20181001	0	Mon	COL	NL

	VisitingTeamGameNumber	HomeTeam	HomeTeamLeague	HomeTeamGameNumber	\
0	1	ARI	NL	1	
1	1	ATL	NL	1	
2	1	LAN	NL	1	
3	1	MIA	NL	1	
4	1	NYN	NL	1	
5	1	SDN	NL	1	
6	1	BAL	AL	1	
7	1	KCA	AL	1	
8	1	OAK	AL	1	
9	1	SEA	AL	1	
10	1	TBA	AL	1	
11	1	TEX	AL	1	
12	1	TOR	AL	1	
13	2	ARI	NL	2	
14	2	ATL	NL	2	
15	1	CIN	NL	1	
16	2	LAN	NL	2	
17	2	MIA	NL	2	
18	2	SDN	NL	2	
19	1	DET	AL	1	
20	2	OAK	AL	2	
21	2	TBA	AL	2	
22	2	TEX	AL	2	
23	2	TOR	AL	2	
24	3	ARI	NL	3	
25	3	ATL	NL	3	
26	2	CIN	NL	2	
27	3	LAN	NL	3	
28	3	MIA	NL	3	
29	2	NYN	NL	2	
...	...	...	...	...	
2401	161	MIL	NL	161	

2402	160	NYN	NL	161
2403	161	PHI	NL	161
2404	161	SDN	NL	161
2405	161	SFN	NL	161
2406	161	ANA	AL	161
2407	160	BAL	AL	160
2408	161	BAL	AL	161
2409	161	BOS	AL	161
2410	161	KCA	AL	161
2411	161	MIN	AL	161
2412	161	SEA	AL	161
2413	161	TBA	AL	161
2414	162	CHN	NL	162
2415	161	CIN	NL	162
2416	162	COL	NL	162
2417	162	MIL	NL	162
2418	161	NYN	NL	162
2419	162	PHI	NL	162
2420	162	SDN	NL	162
2421	162	SFN	NL	162
2422	162	ANA	AL	162
2423	162	BAL	AL	162
2424	162	BOS	AL	162
2425	162	KCA	AL	162
2426	162	MIN	AL	162
2427	162	SEA	AL	162
2428	162	TBA	AL	162
2429	163	CHN	NL	163
2430	163	LAN	NL	163

	VisitorRunsScored	...	HomeBatting7Name	HomeBatting7Position	\
0	2	...	Nick Ahmed	6	
1	5	...	Dansby Swanson	6	
2	1	...	Yasmani Grandal	2	
3	8	...	Miguel Rojas	6	
4	4	...	Kevin Plawecki	2	
5	2	...	Freddy Galvis	6	
6	2	...	Pedro Alvarez	10	
7	14	...	Alex Gordon	8	
8	5	...	Matt Chapman	5	
9	1	...	Ryon Healy	3	
10	4	...	Adeiny Hechavarria	6	
11	4	...	Robinson Chirinos	2	
12	6	...	Russell Martin	2	
13	8	...	Nick Ahmed	6	
14	5	...	Dansby Swanson	6	
15	2	...	Jose Peraza	6	
16	1	...	Chase Utley	4	

17	1	...	Miguel Rojas	6
18	8	...	Cory Spangenberg	5
19	13	...	Mikie Mahtook	7
20	2	...	Matt Chapman	5
21	1	...	Adeiny Hechavarria	6
22	1	...	Robinson Chirinos	2
23	4	...	Russell Martin	2
24	2	...	Nick Ahmed	6
25	2	...	Ryan Flaherty	5
26	13	...	Jose Peraza	6
27	0	...	Austin Barnes	2
28	10	...	Miguel Rojas	6
29	2	...	Juan Lagares	8
...	...	...	...	...
2401	5	...	Jonathan Schoop	4
2402	0	...	Austin Jackson	8
2403	0	...	Scott Kingery	6
2404	5	...	Manuel Margot	8
2405	10	...	Gorkys Hernandez	8
2406	5	...	Taylor Ward	5
2407	4	...	DJ Stewart	9
2408	5	...	John Andreoli	7
2409	8	...	Jackie Bradley	8
2410	4	...	Brian Goodwin	8
2411	3	...	Logan Forsythe	4
2412	1	...	Daniel Vogelbach	3
2413	3	...	Austin Meadows	10
2414	5	...	Kyle Schwarber	7
2415	6	...	Dilson Herrera	4
2416	0	...	Ian Desmond	3
2417	0	...	Manny Pina	2
2418	0	...	Austin Jackson	8
2419	1	...	Scott Kingery	6
2420	3	...	Jose Pirela	4
2421	15	...	Gorkys Hernandez	8
2422	4	...	Kaleb Cowart	6
2423	0	...	DJ Stewart	9
2424	2	...	Ian Kinsler	4
2425	2	...	Alcides Escobar	5
2426	4	...	Logan Forsythe	4
2427	1	...	Kristopher Negron	4
2428	4	...	Austin Meadows	9
2429	3	...	Jason Heyward	8
2430	2	...	Yasiel Puig	9

	HomeBatting8PlayerID	HomeBatting8Name	HomeBatting8Position	\
0	dysoj001	Jarrod Dyson	9	
1	flahr001	Ryan Flaherty	5	

2	forsl001	Logan Forsythe	5
3	wallc001	Chad Wallach	2
4	syndn001	Noah Syndergaard	1
5	hedga001	Austin Hedges	2
6	gentc001	Craig Gentry	9
7	escoa003	Alcides Escobar	6
8	lucrj001	Jonathan Lucroy	2
9	marjm001	Mike Marjama	2
10	robed004	Daniel Robertson	4
11	odorr001	Rougned Odor	4
12	pillk001	Kevin Pillar	8
13	murpj001	John Ryan Murphy	2
14	flahr001	Ryan Flaherty	5
15	bailh001	Homer Bailey	1
16	forsl001	Logan Forsythe	5
17	wallc001	Chad Wallach	2
18	hedga001	Austin Hedges	2
19	iglej001	Jose Iglesias	6
20	lucrj001	Jonathan Lucroy	2
21	robed004	Daniel Robertson	4
22	odorr001	Rougned Odor	4
23	pillk001	Kevin Pillar	8
24	mathj001	Jeff Mathis	2
25	stewc001	Chris Stewart	2
26	barnt001	Tucker Barnhart	2
27	farmk001	Kyle Farmer	5
28	holab001	Bryan Holaday	2
29	degrj001	Jacob deGrom	1
...	...	...	...
2401	crate001	Erik Kratz	2
2402	plawk001	Kevin Plawecki	2
2403	alfaj002	Jorge Alfaro	2
2404	guerj004	Javy Guerra	6
2405	blang001	Gregor Blanco	7
2406	cowak001	Kaleb Cowart	4
2407	rickj001	Joey Rickard	7
2408	wynna001	Austin Wynns	2
2409	swihb001	Blake Swihart	9
2410	escoa003	Alcides Escobar	5
2411	fielj003	Johnny Field	7
2412	zunim001	Mike Zunino	2
2413	sucrj001	Jesus Sucre	2
2414	contw001	Willson Contreras	2
2415	fedet001	Tim Federowicz	2
2416	iannc001	Chris Iannetta	2
2417	arcio002	Orlando Arcia	6
2418	nidot001	Tomas Nido	2
2419	knapa001	Andrew Knapp	2

2420	margm001	Manuel Margot	8
2421	blang001	Gregor Blanco	7
2422	hudsj002	Joe Hudson	2
2423	wilks001	Steve Wilkerson	4
2424	leons001	Sandy Leon	2
2425	philb002	Brett Phillips	7
2426	astuw001	Willians Astudillo	5
2427	freid001	David Freitas	2
2428	bauej001	Jake Bauers	3
2429	quinj001	Jose Quintana	1
2430	herne001	Enrique Hernandez	4

	HomeBatting9PlayerID	HomeBatting9Name	HomeBatting9Position \
0	corbp001	Patrick Corbin	1
1	tehej001	Julio Teheran	1
2	kersc001	Clayton Kershaw	1
3	urenj001	Jose Urena	1
4	rosaa003	Amed Rosario	6
5	richc002	Clayton Richard	1
6	josec002	Caleb Joseph	2
7	buted001	Drew Butera	2
8	poweb002	Boog Powell	8
9	suzui001	Ichiro Suzuki	7
10	refsr001	Rob Refsnyder	10
11	rua-r001	Ryan Rua	7
12	diaza003	Aledmys Diaz	6
13	ray-r002	Robbie Ray	1
14	foltm001	Mike Foltynewicz	1
15	hamib001	Billy Hamilton	8
16	wooda002	Alex Wood	1
17	smitc006	Caleb Smith	1
18	luccj001	Joey Lucchesi	1
19	machd001	Dixon Machado	4
20	pindc001	Chad Pinder	7
21	refsr001	Rob Refsnyder	7
22	rua-r001	Ryan Rua	7
23	diaza003	Aledmys Diaz	6
24	greiz001	Zack Greinke	1
25	mccab001	Brandon McCarthy	1
26	castl003	Luis Castillo	1
27	maedk001	Kenta Maeda	1
28	despo001	Odrisamer Despaigne	1
29	rosaa003	Amed Rosario	6
...	...	...	...
2401	milew001	Wade Miley	1
2402	matzs001	Steven Matz	1
2403	nolaa001	Aaron Nola	1
2404	nix-j002	Jacob Nix	1



2405	rodrrd001	Dereck Rodriguez	1
2406	bricj001	Jose Briceno	2
2407	josec002	Caleb Joseph	2
2408	wilks001	Steve Wilkerson	4
2409	vazqc001	Christian Vazquez	2
2410	vilom001	Meibrys Vilorio	2
2411	gimec001	Chris Gimenez	2
2412	gordd002	Dee Gordon	8
2413	velaa001	Andrew Velazquez	5
2414	montm002	Mike Montgomery	1
2415	romas001	Sal Romano	1
2416	andet002	Tyler Anderson	1
2417	gonzg003	Gio Gonzalez	1
2418	syndn001	Noah Syndergaard	1
2419	suarrr001	Ranger Suarez	1
2420	luccj001	Joey Lucchesi	1
2421	suara002	Andrew Suarez	1
2422	johns002	Sherman Johnson	4
2423	josec002	Caleb Joseph	2
2424	bradj001	Jackie Bradley	8
2425	vilom001	Meibrys Vilorio	2
2426	gratj001	Juan Graterol	2
2427	romia001	Andrew Romine	6
2428	ciufn001	Nick Ciuffo	2
2429	contw001	Willson Contreras	2
2430	buehw001	Walker Buehler	1

	AdditionalInfo	AcquisitionInfo
0	NaN	Y
1	NaN	Y
2	NaN	Y
3	NaN	Y
4	NaN	Y
5	NaN	Y
6	NaN	Y
7	NaN	Y
8	NaN	Y
9	NaN	Y
10	NaN	Y
11	NaN	Y
12	NaN	Y
13	NaN	Y
14	NaN	Y
15	NaN	Y
16	NaN	Y
17	NaN	Y
18	NaN	Y
19	umpchange,8,umphone,randt901,8,ump2b,(None)	Y

20	NaN	Y
21	NaN	Y
22	NaN	Y
23	NaN	Y
24	NaN	Y
25	NaN	Y
26	NaN	Y
27	NaN	Y
28	NaN	Y
29	NaN	Y
...	...	...
2401	NaN	Y
2402	NaN	Y
2403	NaN	Y
2404	NaN	Y
2405	NaN	Y
2406	NaN	Y
2407	NaN	Y
2408	NaN	Y
2409	NaN	Y
2410	NaN	Y
2411	NaN	Y
2412	NaN	Y
2413	NaN	Y
2414	NaN	Y
2415	NaN	Y
2416	NaN	Y
2417	NaN	Y
2418	NaN	Y
2419	NaN	Y
2420	NaN	Y
2421	NaN	Y
2422	NaN	Y
2423	NaN	Y
2424	NaN	Y
2425	NaN	Y
2426	NaN	Y
2427	NaN	Y
2428	NaN	Y
2429	NaN	Y
2430	NaN	Y

[2431 rows x 161 columns]

```
In [10]: # For the Pythagorean Expectation we need only runs scored and conceded. Of course, w
# and the date will also be useful. We put these into a new dataframe (df) which we c
# The variable names are rather lengthy, so to make life easier we can rename columns
# If we want to see what the data looks like, we can just type the name of the df.
```

```

MLB18 = MLB[['VisitingTeam', 'HomeTeam', 'VisitorRunsScored', 'HomeRunsScore', 'Date']]
MLB18 = MLB18.rename(columns={'VisitorRunsScored': 'VisR', 'HomeRunsScore': 'HomR'})
MLB18

```

```

Out[10]:

```

	VisitingTeam	HomeTeam	VisR	HomR	Date
0	COL	ARI	2	8	20180329
1	PHI	ATL	5	8	20180329
2	SFN	LAN	1	0	20180329
3	CHN	MIA	8	4	20180329
4	SLN	NYN	4	9	20180329
5	MIL	SDN	2	1	20180329
6	MIN	BAL	2	3	20180329
7	CHA	KCA	14	7	20180329
8	ANA	OAK	5	6	20180329
9	CLE	SEA	1	2	20180329
10	BOS	TBA	4	6	20180329
11	HOU	TEX	4	1	20180329
12	NYA	TOR	6	1	20180329
13	COL	ARI	8	9	20180330
14	PHI	ATL	5	4	20180330
15	WAS	CIN	2	0	20180330
16	SFN	LAN	1	0	20180330
17	CHN	MIA	1	2	20180330
18	MIL	SDN	8	6	20180330
19	PIT	DET	13	10	20180330
20	ANA	OAK	2	1	20180330
21	BOS	TBA	1	0	20180330
22	HOU	TEX	1	5	20180330
23	NYA	TOR	4	2	20180330
24	COL	ARI	2	1	20180331
25	PHI	ATL	2	15	20180331
26	WAS	CIN	13	7	20180331
27	SFN	LAN	0	5	20180331
28	CHN	MIA	10	6	20180331
29	SLN	NYN	2	6	20180331
...	...	...	...	...	...
2401	DET	MIL	5	6	20180929
2402	MIA	NYN	0	1	20180929
2403	ATL	PHI	0	3	20180929
2404	ARI	SDN	5	4	20180929
2405	LAN	SFN	10	6	20180929
2406	OAK	ANA	5	2	20180929
2407	HOU	BAL	4	3	20180929
2408	HOU	BAL	5	2	20180929
2409	NYA	BOS	8	5	20180929
2410	CLE	KCA	4	9	20180929
2411	CHA	MIN	3	8	20180929

2412	TEX	SEA	1	4	20180929
2413	TOR	TBA	3	4	20180929
2414	SLN	CHN	5	10	20180930
2415	PIT	CIN	6	5	20180930
2416	WAS	COL	0	12	20180930
2417	DET	MIL	0	11	20180930
2418	MIA	NYN	0	1	20180930
2419	ATL	PHI	1	3	20180930
2420	ARI	SDN	3	4	20180930
2421	LAN	SFN	15	0	20180930
2422	OAK	ANA	4	5	20180930
2423	HOU	BAL	0	4	20180930
2424	NYA	BOS	2	10	20180930
2425	CLE	KCA	2	1	20180930
2426	CHA	MIN	4	5	20180930
2427	TEX	SEA	1	3	20180930
2428	TOR	TBA	4	9	20180930
2429	MIL	CHN	3	1	20181001
2430	COL	LAN	2	5	20181001

[2431 rows x 5 columns]

```
In [11]: # We will need to know who won the game - which we can tell by who scored the more runs
#(there are no ties in baseball)
# The variable 'hwin' is defined here as equaling 1 if the home team scored more runs
# The variable 'awin' is defined in a similar way for the away team.
# we also create a 'counter' variable = 1 for each row.
```

```
MLB18['hwin'] = np.where(MLB18['HomR'] > MLB18['VisR'], 1, 0)
MLB18['awin'] = np.where(MLB18['HomR'] < MLB18['VisR'], 1, 0)
MLB18['count'] = 1
MLB18
```

```
Out[11]:
```

	VisitingTeam	HomeTeam	VisR	HomR	Date	hwin	awin	count
0	COL	ARI	2	8	20180329	1	0	1
1	PHI	ATL	5	8	20180329	1	0	1
2	SFN	LAN	1	0	20180329	0	1	1
3	CHN	MIA	8	4	20180329	0	1	1
4	SLN	NYN	4	9	20180329	1	0	1
5	MIL	SDN	2	1	20180329	0	1	1
6	MIN	BAL	2	3	20180329	1	0	1
7	CHA	KCA	14	7	20180329	0	1	1
8	ANA	OAK	5	6	20180329	1	0	1
9	CLE	SEA	1	2	20180329	1	0	1
10	BOS	TBA	4	6	20180329	1	0	1
11	HOU	TEX	4	1	20180329	0	1	1
12	NYA	TOR	6	1	20180329	0	1	1
13	COL	ARI	8	9	20180330	1	0	1

14	PHI	ATL	5	4	20180330	0	1	1
15	WAS	CIN	2	0	20180330	0	1	1
16	SFN	LAN	1	0	20180330	0	1	1
17	CHN	MIA	1	2	20180330	1	0	1
18	MIL	SDN	8	6	20180330	0	1	1
19	PIT	DET	13	10	20180330	0	1	1
20	ANA	OAK	2	1	20180330	0	1	1
21	BOS	TBA	1	0	20180330	0	1	1
22	HOU	TEX	1	5	20180330	1	0	1
23	NYA	TOR	4	2	20180330	0	1	1
24	COL	ARI	2	1	20180331	0	1	1
25	PHI	ATL	2	15	20180331	1	0	1
26	WAS	CIN	13	7	20180331	0	1	1
27	SFN	LAN	0	5	20180331	1	0	1
28	CHN	MIA	10	6	20180331	0	1	1
29	SLN	NYN	2	6	20180331	1	0	1
...	...	...	...	...	...	...	...	...
2401	DET	MIL	5	6	20180929	1	0	1
2402	MIA	NYN	0	1	20180929	1	0	1
2403	ATL	PHI	0	3	20180929	1	0	1
2404	ARI	SDN	5	4	20180929	0	1	1
2405	LAN	SFN	10	6	20180929	0	1	1
2406	OAK	ANA	5	2	20180929	0	1	1
2407	HOU	BAL	4	3	20180929	0	1	1
2408	HOU	BAL	5	2	20180929	0	1	1
2409	NYA	BOS	8	5	20180929	0	1	1
2410	CLE	KCA	4	9	20180929	1	0	1
2411	CHA	MIN	3	8	20180929	1	0	1
2412	TEX	SEA	1	4	20180929	1	0	1
2413	TOR	TBA	3	4	20180929	1	0	1
2414	SLN	CHN	5	10	20180930	1	0	1
2415	PIT	CIN	6	5	20180930	0	1	1
2416	WAS	COL	0	12	20180930	1	0	1
2417	DET	MIL	0	11	20180930	1	0	1
2418	MIA	NYN	0	1	20180930	1	0	1
2419	ATL	PHI	1	3	20180930	1	0	1
2420	ARI	SDN	3	4	20180930	1	0	1
2421	LAN	SFN	15	0	20180930	0	1	1
2422	OAK	ANA	4	5	20180930	1	0	1
2423	HOU	BAL	0	4	20180930	1	0	1
2424	NYA	BOS	2	10	20180930	1	0	1
2425	CLE	KCA	2	1	20180930	0	1	1
2426	CHA	MIN	4	5	20180930	1	0	1
2427	TEX	SEA	1	3	20180930	1	0	1
2428	TOR	TBA	4	9	20180930	1	0	1
2429	MIL	CHN	3	1	20181001	0	1	1
2430	COL	LAN	2	5	20181001	1	0	1

[2431 rows x 8 columns]

```
In [13]: # Since our data refers to games, for each game there are two teams, but what we want
# by each team and its win percentage.
# To create this we are going to define two dfs, one for home teams and one for away
# the stats for the entire season.
# Here we define a df for home teams. The command is called ".groupby" and we will use
# to obtain the sum of wins and runs (scored and conceded) and also the counter variable
# (in MLB the teams do not necessarily play the same number of games in the regular season)
# Finally we rename the columns.

MLBhome = MLB18.groupby('HomeTeam')['hwin', 'HomR', 'VisR', 'count'].sum().reset_index()
MLBhome = MLBhome.rename(columns={'HomeTeam': 'team', 'VisR': 'VisRh', 'HomR': 'HomRh', 'count': 'Gh'})
MLBhome
```

```
Out[13]:
```

	team	hwin	HomRh	VisRh	Gh
0	ANA	42	355	355	81
1	ARI	40	359	328	81
2	ATL	43	391	357	81
3	BAL	28	339	411	81
4	BOS	57	468	322	81
5	CHA	30	321	409	81
6	CHN	51	385	349	82
7	CIN	37	385	418	81
8	CLE	49	443	334	81
9	COL	47	445	404	81
10	DET	38	330	363	81
11	HOU	46	373	288	81
12	KCA	32	333	424	81
13	LAN	45	366	297	82
14	MIA	38	279	323	81
15	MIL	51	384	322	81
16	MIN	49	397	361	81
17	NYA	53	453	352	81
18	NYN	37	274	310	81
19	OAK	50	369	310	81
20	PHI	49	370	347	81
21	PIT	44	326	318	80
22	SDN	31	313	390	81
23	SEA	45	299	337	81
24	SFN	42	321	334	81
25	SLN	43	351	346	81
26	TBA	51	371	284	81
27	TEX	34	432	479	81
28	TOR	40	361	393	81
29	WAS	41	409	363	81

```
In [ ]: #Your Code Here
```

### 3 Self test - 1

Sometimes the code you write doesn't produce the result you want, and you need to go back and re-do it. Frequently it makes sense to go back to the beginning, rather than try to amend a df which isn't working the way you want it to. Re-starting is easy- just click on "Kernel" in the toolbar and then click "Restart and Clear Output". You can now begin again.

Copy the previous cell (first use "Insert" to add a extra cell, and then use copy and paste), and then delete ".reset\_index()" and then run the code to see what happens differently. The extra headings would be a problem later on, which makes ".reset\_index()" very useful in many situations.

```
In [14]: # Now we create a similar df for teams playing as visitors - To write this code all y
# the previous cell and then change any reference to the home team into a reference t
```

```
MLBaway = MLB18.groupby('VisitingTeam')['awin','HomR','VisR','count'].sum().reset_ind
MLBaway = MLBaway.rename(columns={'VisitingTeam':'team','VisR':'VisRa','HomR':'HomRa'
MLBaway
```

```
Out[14]:
```

	team	awin	HomRa	VisRa	Ga
0	ANA	38	367	366	81
1	ARI	42	316	334	81
2	ATL	47	300	368	81
3	BAL	19	481	283	81
4	BOS	51	325	408	81
5	CHA	32	439	335	81
6	CHN	44	296	376	81
7	CIN	30	401	311	81
8	CLE	42	314	375	81
9	COL	44	341	335	82
10	DET	26	433	300	81
11	HOU	57	246	424	81
12	KCA	26	409	305	81
13	LAN	47	313	438	81
14	MIA	25	486	310	80
15	MIL	45	337	370	82
16	MIN	29	414	341	81
17	NYA	47	317	398	81
18	NYN	40	397	402	81
19	OAK	47	364	444	81
20	PHI	31	381	307	81
21	PIT	38	375	366	81
22	SDN	35	377	304	81
23	SEA	44	374	378	81
24	SFN	31	365	282	81
25	SLN	45	345	408	81
26	TBA	39	362	345	81
27	TEX	33	369	305	81
28	TOR	33	439	348	81
29	WAS	41	319	362	81

```
In [15]: # We now merge MLBhome and MLBaway so that we have a list of all the clubs with home
# We will be using pd.merge frequently during the course to combine dfs
# Note that we've called this new df "MLB18", which is name we had already used for e
# overwriting the old MLB18 - which is fine in this case since we don't need the data
# If we did want to retain the daat in the old MLB18 df, we should have given this ne
```

```
MLB18 = pd.merge(MLBhome,MLBaway,on='team')
MLB18
```

```
Out[15]:
```

	team	hwin	HomRh	VisRh	Gh	awin	HomRa	VisRa	Ga
0	ANA	42	355	355	81	38	367	366	81
1	ARI	40	359	328	81	42	316	334	81
2	ATL	43	391	357	81	47	300	368	81
3	BAL	28	339	411	81	19	481	283	81
4	BOS	57	468	322	81	51	325	408	81
5	CHA	30	321	409	81	32	439	335	81
6	CHN	51	385	349	82	44	296	376	81
7	CIN	37	385	418	81	30	401	311	81
8	CLE	49	443	334	81	42	314	375	81
9	COL	47	445	404	81	44	341	335	82
10	DET	38	330	363	81	26	433	300	81
11	HOU	46	373	288	81	57	246	424	81
12	KCA	32	333	424	81	26	409	305	81
13	LAN	45	366	297	82	47	313	438	81
14	MIA	38	279	323	81	25	486	310	80
15	MIL	51	384	322	81	45	337	370	82
16	MIN	49	397	361	81	29	414	341	81
17	NYA	53	453	352	81	47	317	398	81
18	NYN	37	274	310	81	40	397	402	81
19	OAK	50	369	310	81	47	364	444	81
20	PHI	49	370	347	81	31	381	307	81
21	PIT	44	326	318	80	38	375	366	81
22	SDN	31	313	390	81	35	377	304	81
23	SEA	45	299	337	81	44	374	378	81
24	SFN	42	321	334	81	31	365	282	81
25	SLN	43	351	346	81	45	345	408	81
26	TBA	51	371	284	81	39	362	345	81
27	TEX	34	432	479	81	33	369	305	81
28	TOR	40	361	393	81	33	439	348	81
29	WAS	41	409	363	81	41	319	362	81

## 4 Self test - 2

When creating MLBhome and MLBaway we we renamed the variables using “.rename(columns=‘oldname’:‘newname’)”. Copy and paste these cells and then re-run the code and see how the merge looks. Note that when Python encounters two variables with the same name in a merge it relabels the names with \_x and \_y.



Sometimes we can work with the data in this way, but usually renaming makes it easier to follow.

In [16]: *# Now we create the total wins, games, played, runs scored and run conceded by summing*

```
MLB18['W']=MLB18['hwin']+MLB18['awin']
MLB18['G']=MLB18['Gh']+MLB18['Ga']
MLB18['R']=MLB18['HomRh']+MLB18['VisRa']
MLB18['RA']=MLB18['VisRh']+MLB18['HomRa']
MLB18
```

```
Out[16]:
```

	team	hwin	HomRh	VisRh	Gh	awin	HomRa	VisRa	Ga	W	G	R	RA
0	ANA	42	355	355	81	38	367	366	81	80	162	721	722
1	ARI	40	359	328	81	42	316	334	81	82	162	693	644
2	ATL	43	391	357	81	47	300	368	81	90	162	759	657
3	BAL	28	339	411	81	19	481	283	81	47	162	622	892
4	BOS	57	468	322	81	51	325	408	81	108	162	876	647
5	CHA	30	321	409	81	32	439	335	81	62	162	656	848
6	CHN	51	385	349	82	44	296	376	81	95	163	761	645
7	CIN	37	385	418	81	30	401	311	81	67	162	696	819
8	CLE	49	443	334	81	42	314	375	81	91	162	818	648
9	COL	47	445	404	81	44	341	335	82	91	163	780	745
10	DET	38	330	363	81	26	433	300	81	64	162	630	796
11	HOU	46	373	288	81	57	246	424	81	103	162	797	534
12	KCA	32	333	424	81	26	409	305	81	58	162	638	833
13	LAN	45	366	297	82	47	313	438	81	92	163	804	610
14	MIA	38	279	323	81	25	486	310	80	63	161	589	809
15	MIL	51	384	322	81	45	337	370	82	96	163	754	659
16	MIN	49	397	361	81	29	414	341	81	78	162	738	775
17	NYA	53	453	352	81	47	317	398	81	100	162	851	669
18	NYN	37	274	310	81	40	397	402	81	77	162	676	707
19	OAK	50	369	310	81	47	364	444	81	97	162	813	674
20	PHI	49	370	347	81	31	381	307	81	80	162	677	728
21	PIT	44	326	318	80	38	375	366	81	82	161	692	693
22	SDN	31	313	390	81	35	377	304	81	66	162	617	767
23	SEA	45	299	337	81	44	374	378	81	89	162	677	711
24	SFN	42	321	334	81	31	365	282	81	73	162	603	699
25	SLN	43	351	346	81	45	345	408	81	88	162	759	691
26	TBA	51	371	284	81	39	362	345	81	90	162	716	646
27	TEX	34	432	479	81	33	369	305	81	67	162	737	848
28	TOR	40	361	393	81	33	439	348	81	73	162	709	832
29	WAS	41	409	363	81	41	319	362	81	82	162	771	682

In [17]: *# The last step in preparing the data is to define win percentage and the Pythagorean*

```
MLB18['wpc'] = MLB18['W']/MLB18['G']
MLB18['pyth'] = MLB18['R']**2/(MLB18['R']**2 + MLB18['RA']**2)
MLB18
```

```

Out[17]:
  team hwin HomRh VisRh Gh awin HomRa VisRa Ga W G R RA \
0 ANA 42 355 355 81 38 367 366 81 80 162 721 722
1 ARI 40 359 328 81 42 316 334 81 82 162 693 644
2 ATL 43 391 357 81 47 300 368 81 90 162 759 657
3 BAL 28 339 411 81 19 481 283 81 47 162 622 892
4 BOS 57 468 322 81 51 325 408 81 108 162 876 647
5 CHA 30 321 409 81 32 439 335 81 62 162 656 848
6 CHN 51 385 349 82 44 296 376 81 95 163 761 645
7 CIN 37 385 418 81 30 401 311 81 67 162 696 819
8 CLE 49 443 334 81 42 314 375 81 91 162 818 648
9 COL 47 445 404 81 44 341 335 82 91 163 780 745
10 DET 38 330 363 81 26 433 300 81 64 162 630 796
11 HOU 46 373 288 81 57 246 424 81 103 162 797 534
12 KCA 32 333 424 81 26 409 305 81 58 162 638 833
13 LAN 45 366 297 82 47 313 438 81 92 163 804 610
14 MIA 38 279 323 81 25 486 310 80 63 161 589 809
15 MIL 51 384 322 81 45 337 370 82 96 163 754 659
16 MIN 49 397 361 81 29 414 341 81 78 162 738 775
17 NYA 53 453 352 81 47 317 398 81 100 162 851 669
18 NYN 37 274 310 81 40 397 402 81 77 162 676 707
19 OAK 50 369 310 81 47 364 444 81 97 162 813 674
20 PHI 49 370 347 81 31 381 307 81 80 162 677 728
21 PIT 44 326 318 80 38 375 366 81 82 161 692 693
22 SDN 31 313 390 81 35 377 304 81 66 162 617 767
23 SEA 45 299 337 81 44 374 378 81 89 162 677 711
24 SFN 42 321 334 81 31 365 282 81 73 162 603 699
25 SLN 43 351 346 81 45 345 408 81 88 162 759 691
26 TBA 51 371 284 81 39 362 345 81 90 162 716 646
27 TEX 34 432 479 81 33 369 305 81 67 162 737 848
28 TOR 40 361 393 81 33 439 348 81 73 162 709 832
29 WAS 41 409 363 81 41 319 362 81 82 162 771 682

      wpc      pyth
0 0.493827 0.499307
1 0.506173 0.536600
2 0.555556 0.571662
3 0.290123 0.327161
4 0.666667 0.647037
5 0.382716 0.374388
6 0.582822 0.581946
7 0.413580 0.419344
8 0.561728 0.614423
9 0.558282 0.522939
10 0.395062 0.385147
11 0.635802 0.690171
12 0.358025 0.369726
13 0.564417 0.634665
14 0.391304 0.346435

```

```

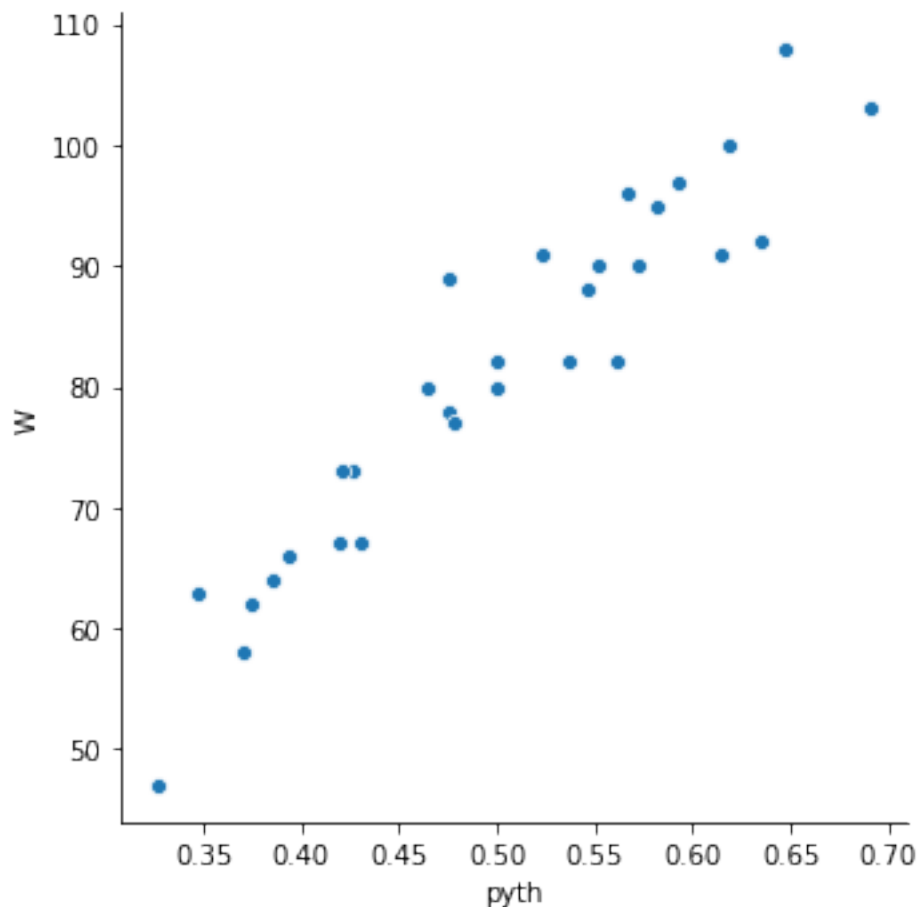
15  0.588957  0.566930
16  0.481481  0.475560
17  0.617284  0.618044
18  0.475309  0.477596
19  0.598765  0.592667
20  0.493827  0.463749
21  0.509317  0.499278
22  0.407407  0.392877
23  0.549383  0.475519
24  0.450617  0.426666
25  0.543210  0.546794
26  0.555556  0.551260
27  0.413580  0.430310
28  0.450617  0.420687
29  0.506173  0.561024

```

In [18]: *# Having prepared the data, we are now ready to examine it. First, we generate and xy*  
*# This illustrates nicely the close correlation between win percentage and the Pythag*

```
sns.relplot(x="pyth", y="wpc", data = MLB18)
```

Out[18]: <seaborn.axisgrid.FacetGrid at 0x7fcd94e0dac8>



## 4.1 Self test - 3

run `sns.relplot` again, but this time write `y="W"` instead of `y="wpc"`. What do you find? Does it make a difference?

## 5 Finally we generate a regression.

The regression output tells you many things about the fitted relationship between win percentage and the Pythagorean Expectation. Regression is a method for identifying an equation which best fits the data. In this case that relationship is

$$\text{wpc} = \text{Intercept} + \text{coef} \times \text{pyth}$$

You can see the value of Intercept is 0.0609 and coef is .8770. It's this latter value we're interested in. It means that for every one unit increase in `pyth`, the value of `wpc` goes up by 0.887.

Two other points to note:

- (i) The standard error (std err) gives us an idea of the precision of the estimate. The ratio of the coefficient (coef) to the standard error is called the t statistic (t) and its value informs us about statistical significance. This is illustrated by the p-value ( $P > |t|$ ) - this is the probability that we would observe the value .8770 by chance, if the true value were really zero. This probability here is 0.000 - (this is not exactly zero, but the table doesn't include enough decimal places to show this) which means we can be confident it is not zero. By convention, it is usual to conclude that we cannot be confident that the value of the coefficient is not zero if the p-value is greater than .05
- (ii) in the top right hand corner of the table is the R-squared. This statistic tells you the percentage of variation in the y-variable (`wpc`) which can be accounted for by the variation in the x variables (`pyth`). R-squared can be thought of as a percentage - here the Pythagorean Expectation can account for 89.4% of the variation in win percentage.

In [ ]: *# Finally we generate a regression.*

```
pyth_lm = smf.ols(formula = 'wpc ~ pyth', data=MLB18).fit()
pyth_lm.summary()
```

## 5.1 Self test - 4

Run the regression above but instead write '`wpc ~ W`' instead of '`wpc ~ pyth`' in the line starting `pyth_lm`. What difference does this make?

## 6 Conclusion

This example was intended to get you started- don't worry if some things seem unclear - we're now going to conduct the same analysis for cricket, basketball, soccer and hockey. This will extend your understanding and help to make clear what we have just looked at.

A Useful Tip: when working in Python you will often come across problems that can be solved using methods you have encountered previously. It is often a good idea to return to an old notebook at a later stage to remind yourself how to code a particular problem.

In [ ]: