

# MagIC\_workshop\_example

May 13, 2014

## 1 Example notebook

This simple example notebook accompanies a short talk given at the 2014 MagIC science and database workshop. The PDF of the slides is available here: [https://github.com/Swanson-Hysell/PmagPy\\_IPython/raw/master/2014\\_MagIC\\_workshop/Swanson-Hysell\\_MagIC2014.pdf](https://github.com/Swanson-Hysell/PmagPy_IPython/raw/master/2014_MagIC_workshop/Swanson-Hysell_MagIC2014.pdf)

### 1.1 Import function libraries

IPmag.py is a function library for paleomagnetic data analysis and plotting developed for interactive use within IPython notebooks. The IPmag.py library relies on the pmag.py and pmagplotlib.py libraries of the PmagPy project (<https://github.com/ltauxe/PmagPy>) and adds new functions and modifies stand alone PmagPy programs for use in the interactive IPython environment. The pmag.py library is included in the IPmag.py repository as a very slightly modified version from that available in the main PmagPy repository. The version of pmag.py being used here from pmagpy-2.206.

```
In [1]: import pmag, pmagplotlib, IPmag
        import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        from IPython.core.display import Image
        %matplotlib inline

In [2]: Image(filename='2014_MagIC_workshop/MagIC2014.png')
```

Out[2]:

# Open and reproducible paleomagnetic data analysis using IPython

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**Calculate and graphically display the confidence interval on the minimum rate estimate implied by the Monte Carlo sampled pairs of sampled ages and paleolatitudes from the two poles**

The pairs of sampled ages and poles can be used to calculate rates (with the total number of rates being set by `sample_size` in the input box above). The rate calculated above of 24.0 cm/year can now be given confidence bounds by taking 2.5 percentile and 97.5 percentile of the Monte Carlo simulated rates.

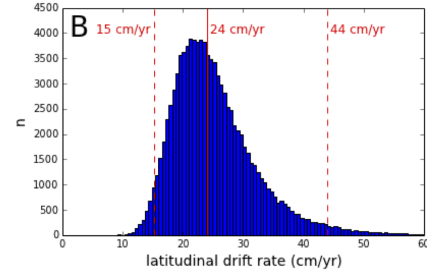
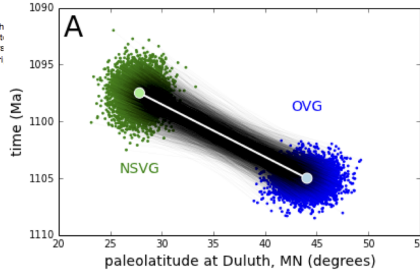
```
In [32]: #calculating the change in paleolatitude between the Monte Carlo pairs
pole1_pole2_Delta_degrees=[]
pole1_pole2_Delta_Kilometers=[]
pole1_pole2_Delta_Myr=[]
pole1_pole2_degrees_per_Myr=[]
pole1_pole2_cm_per_Yr=[]

for n in range(sample_size):
    Delta_degrees=pole1_McPaleolat[n]-pole2_McPaleolat[n]
    Delta_Myr=pole1_McAge[n]-pole2_McAge[n]
    pole1_pole2_Delta_degrees.append(Delta_degrees)
    degrees_per_Myr=Delta_degrees/Delta_Myr
    cm_per_Yr=(Delta_degrees*111)*100000/(Delta_Myr*1000000)
    pole1_pole2_degrees_per_Myr.append(degrees_per_Myr)
    pole1_pole2_cm_per_Yr.append(cm_per_Yr)

In [33]: twopointfive_percentile=stats.scoreatpercentile(pole1_pole2_cm_per_Yr,2.5)
fifty_percentile=stats.scoreatpercentile(pole1_pole2_cm_per_Yr,50)
ninetysevenpointfive_percentile=stats.scoreatpercentile(pole1_pole2_cm_per_Yr,97.5)
print "2.5th percentile is: " + str(twopointfive_percentile)
print "50th percentile is: " + str(fifty_percentile)
print "97.5th percentile is: " + str(ninetysevenpointfive_percentile)

2.5th percentile is: 15.1860289306
50th percentile is: 23.983375899
97.5th percentile is: 44.0180724854
```

We can see here that the 50th percentile from the percentile give a 95% confidence range of 15.2 to sample\_size when code was executed pole pairs being marked. This plot is Figure 4 of the manuscript



## 1.2 Example developing Fisher distributed data, plotting the data and comparing two data sets using a test for a common mean.

Let's start by generating a set of directions from a Fisher distribution using the `IPmag.ifishrot` function.

```
In [3]: data1 = IPmag.ifishrot(k=42,n=40,Dec=204,Inc=-42)
```

```
In [4]: data1
```

```
Out[4]: [[218.11569556120406, -50.274554383096415, 1.0],
[208.42469985977803, -44.983564159695767, 1.0],
[230.88947292192859, -46.624745623253688, 1.0],
[202.18890087664008, -22.717319275764698, 1.0],
[216.82955908650555, -28.907758493266957, 1.0],
[196.85975068187085, -46.435678919773139, 1.0],
[213.48898715459782, -43.464854834824145, 1.0],
[220.88017633760342, -48.523977578214293, 1.0],
[204.66975050330208, -44.219106889261496, 1.0],
[212.07833966805737, -45.226257597348543, 1.0],
[218.52170309556112, -45.655245287636959, 1.0],
[171.10001720046739, -32.625265305237932, 1.0],
[209.62896427763317, -27.200382379310234, 1.0],
[202.02376663609701, -31.373611015918822, 1.0],
[219.858098969628, -26.181647562457623, 1.0],
```

```
[201.51084707027249, -46.029599137054497, 1.0],
[196.93792773272156, -32.375759325022891, 1.0],
[219.15260167019571, -46.979181620208472, 1.0],
[199.03833390387695, -36.189397551310819, 1.0],
[211.22798485822273, -33.793088122986404, 1.0],
[213.30212668033019, -29.480685522187063, 1.0],
[193.4351277787006, -37.781229447382039, 1.0],
[205.47753870083065, -53.551303539771652, 1.0],
[189.82561803175119, -45.872681086591527, 1.0],
[197.9108349577906, -24.471405779328361, 1.0],
[214.68041398680762, -37.105229923997953, 1.0],
[208.66798870032272, -22.849704879992224, 1.0],
[209.74777009800195, -39.414303337458669, 1.0],
[188.02618595628297, -43.09564330913679, 1.0],
[203.12121565256541, -29.344790964074413, 1.0],
[213.58458948006586, -45.960383273200165, 1.0],
[211.60375134783246, -51.953865045454421, 1.0],
[200.38259909486771, -32.842769713928099, 1.0],
[199.74223825029202, -32.53772194490282, 1.0],
[187.56945652997442, -45.430366188485181, 1.0],
[202.25418233704036, -49.545747549334799, 1.0],
[198.70069062957035, -37.795954796139377, 1.0],
[208.96878897950532, -26.498413076478503, 1.0],
[197.6424438647874, -45.158617064842765, 1.0],
[185.35850695695143, -47.496901204778986, 1.0]]
```

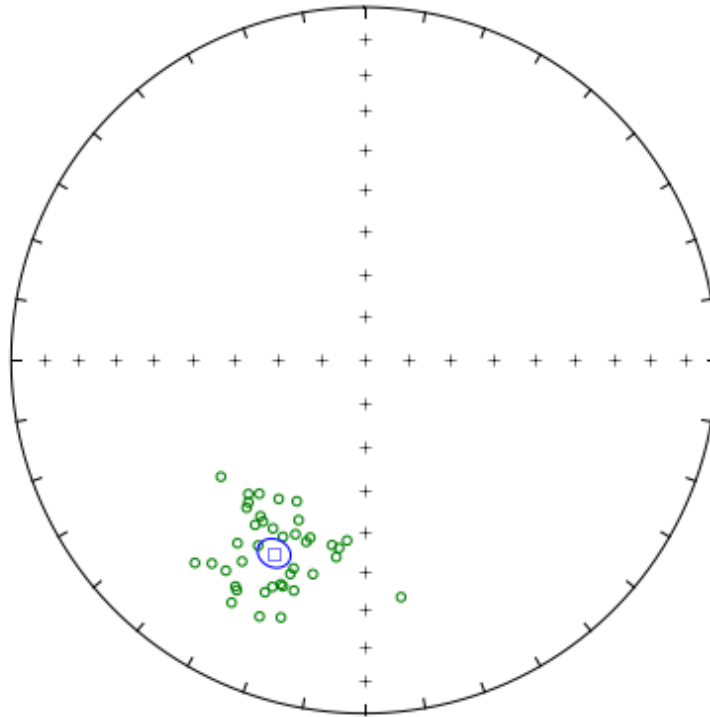
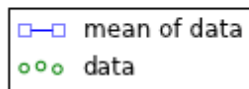
Let's use the `pmag.fisher_mean` function to calculate the Fisher statistical parameters for the data.

```
In [5]: data1_mean = pmag.fisher_mean(data1)
        data1_mean
```

```
Out[5]: {'alpha95': 3.5406501384077265,
         'csd': 12.534764892280513,
         'dec': 204.99558465507852,
         'inc': -39.509178691305621,
         'k': 41.757804112425852,
         'n': 40,
         'r': 39.066042843273102}
```

```
In [6]: pmag.fisher_mean[?]
```

```
In [7]: fignum = 1
        plt.figure(num=fignum,figsize=(8,8),dpi=160)
        IPmag.ipplotNET(fignum)
        IPmag.ipplotDI(data1,color='g',label='data',legend='yes')
        IPmag.ipplotDImean(data1_mean['dec'],data1_mean['inc'],data1_mean['alpha95'],
                             color='b',marker='s',label='mean of data',legend='yes')
```



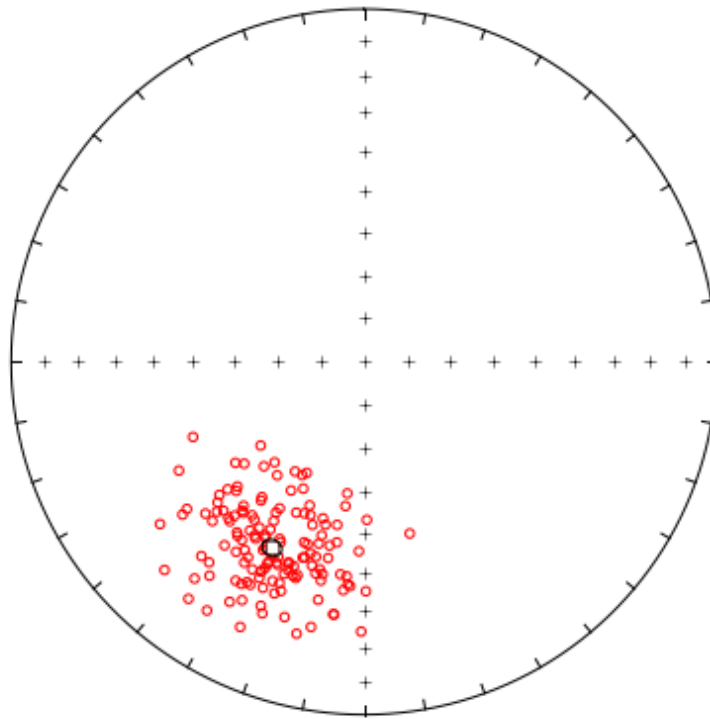
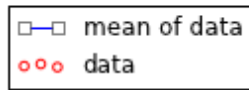
```
In [8]: data2 = IPmag.ifishrot(k=36,n=140,Dec=206,Inc=-41)
```

```
In [9]: data2_mean = pmag.fisher_mean(data2)
        data2_mean
```

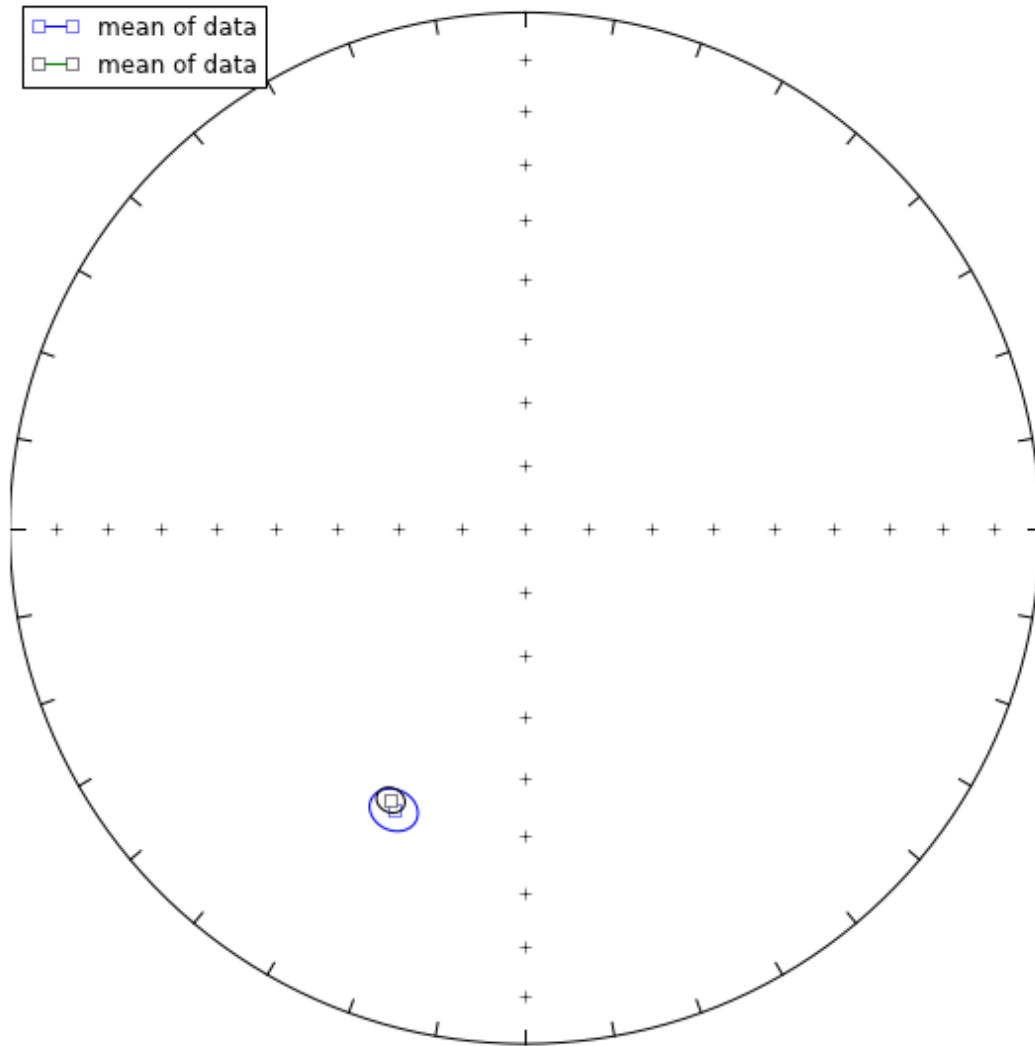
```
Out[9]: {'alpha95': 2.1017754545938985,
         'csd': 14.069339483629621,
         'dec': 206.29443911646595,
         'inc': -40.835567769695842,
         'k': 33.145350796410476,
         'n': 140,
         'r': 135.80635001108351}
```

```
In [10]: fignum = 1
         plt.figure(num=fignum,figsize=(8,8),dpi=160)
         IPmag.iplotNET(fignum)
```

```
IPmag.iplotDI(data2,color='r',label='data',legend='yes')
IPmag.iplotDImean(data2_mean['dec'],data2_mean['inc'],data2_mean['alpha95'],
                  color='k',marker='s',label='mean of data',legend='yes')
```



```
In [11]: fignum = 1
plt.figure(num=fignum,figsize=(8,8),dpi=160)
IPmag.iplotNET(fignum)
IPmag.iplotDImean(data1_mean['dec'],data1_mean['inc'],data1_mean['alpha95'],
                  color='b',marker='s',label='mean of data',legend='yes')
IPmag.iplotDImean(data2_mean['dec'],data2_mean['inc'],data2_mean['alpha95'],
                  color='k',marker='s',label='mean of data',legend='yes')
```



```
In [12]: IPmag.iWatsonV(data1,data2,NumSims=500,plot='yes')
```

Results of Watson V test:

Watson's V: 1.0

Critical value of V: 5.6

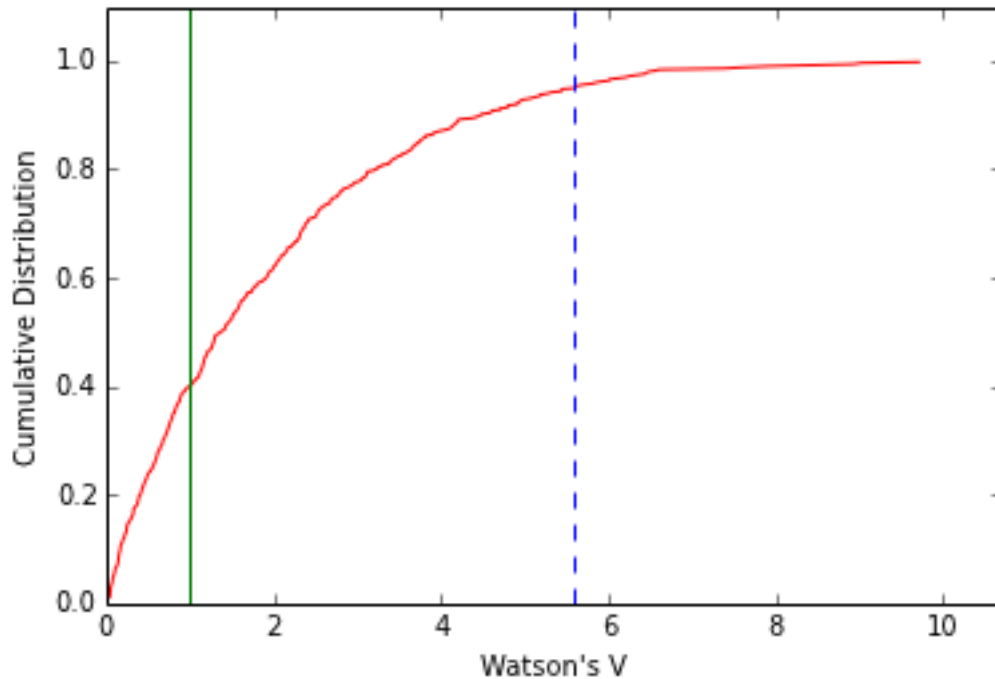
"Pass": Since V is less than Vcrit, the null hypothesis that the two populations are drawn from distributions that share a common mean direction can not be rejected.

M&M1990 classification:

Angle between data set means: 1.7

Critical angle for M&M1990: 3.9

The McFadden and McElhinny (1990) classification for this test is: 'A'



In [13]: `IPmag.iWatsonV?`

### 1.3 Reading data from MagIC format results files (`pmag.magic_read`)

PmagPy has built in functions to deal with data in MagIC database format files. One such function is the `pmag.magic_read` function. In the code block below, this function is used to read in data from a `pmag_results.txt` file. The `pmag.magic_read` function creates two outputs:

1. the data from the Magic template file in a list of dictionaries
2. the type of data in the file (e.g. 'pmag\_results')

Let's look at data from:

Tauxe, L., Lusk, C., Selkin, P., Gans, P. and Calvert, A. (2004). Paleomagnetic results from the Snake River Plain: Contribution to the time[0-2010] averaged field global database. *Geochemistry Geophysics Geosystems* 5: doi: 10.1029/2003GC000661. <http://onlinelibrary.wiley.com/doi/10.1029/2003GC000661/>

Downloaded from the MagIC database:

<http://earthref.org/MAGIC/9207/>

```
In [14]: data,file_type=pmag.magic_read('Example_Data/pmag_results.txt')
         results = pd.DataFrame(data)
         results.average_dec = results.average_dec.astype(float)
         results.average_inc = results.average_inc.astype(float)
         results.average_alpha95 = results.average_alpha95.astype(float)
         results
```

```
Out[14]:  antipodal average_age average_age.sigma average_age.unit  average_alpha95 \
0          0          3.4          0.03          Ma          2.3
1          1          1          1          Ma          3.0
2          2          2          0.05          Ma          4.3
```

3		0.095	0.05	Ma	3.0
4		0.395	0.01	Ma	3.0
5		0.373	0.06	Ma	5.1
6		0.404	0.07	Ma	4.0
7		1.76	0.016	Ma	2.6
8		2.26	0.05	Ma	3.3
9		1.69	0.02	Ma	2.5
10		0.591	0.015	Ma	4.2
11		0.291	0.016	Ma	2.6
12		1.73	0.01	Ma	4.9
13		2.94	0.025	Ma	3.2
14		1	1	Ma	1.6
15		5.75	0.125	Ma	2.7
16		0.184	0.014	Ma	1.3
17		0.191	0.008	Ma	2.4
18		0.124	0.039	Ma	5.7
19		1	1	Ma	5.2
20		1	1	Ma	4.2
21		1.5055	1.6253	Ma	7.7
22		1.0757	0.91686	Ma	8.7
23	177.2	1.3418	1.3874	Ma	5.4

	average_dec	average_inc	average_int	average_int_n	average_int_sigma \
0	330.1	64.9	3.61e-05	5	1.32e-05
1	151.8	-57.5			
2	16.5	54.6			
3	14.6	77.9			
4	346.3	73.8			
5	15.3	44.8			
6	347.4	65.6			
7	172.5	-66.9			
8	6.3	29.7			
9	14.5	45.5			
10	163.3	-62.2			
11	2.9	61.9			
12	358.6	62.5			
13	197.4	-51.2			
14	9.5	62.8			
15	7.5	66.7	4.88e-05	2	1.7e-06
16	23.2	54.0			
17	205.8	-49.4	7.85e-05	3	4.7e-06
18	197.6	-65.5			
19	188.1	-47.2	5.02e-05	2	2.7e-06
20	192.9	-60.7			
21	6.1	59.6			
22	185.1	-58.8			
23	5.7	59.3			

	average_k	average_lat	average_lat_sigma	average_lon	average_lon_sigma \
0	572.7	42.6026		245.602	
1	408.8	42.6035		245.599	
2	313.1	42.601		245.596	
3	407.3	42.7366		245.165	
4	428.4	42.8418		245.112	



5	227.8	42.8657		245.127	
6	228.8	42.9203		244.923	
7	892.1	42.4996		245.851	
8	333.8	42.5		245.85	
9	970.1	42.5287		245.979	
10	325.7	42.4556		245.636	
11	872.4	42.4892		245.6	
12	153.9	42.4619		245.615	
13	296.1	42.6529		246.988	
14	1253.3	43.305		247.732	
15	488.7	43.3682		247.345	
16	1820.7	43.4213		247.256	
17	642.1	43.8859		247.199	
18	138.9	43.8427		247.376	
19	168.2	43.5749		248.266	
20	335	44.1566		248.574	
21	30.2	42.8154	0.346	245.9077	0.9269
22	41.9	43.225	0.7166	246.95	1.1686
23	35.4	42.9714	0.5414	246.3048	1.1236

	average_n	average_nn	average_r	conglomerate_test	contact_test
0	8	8	7.9878	ND	ND ...
1	7	7	6.9853	ND	ND ...
2	5	5	4.9872	ND	ND ...
3	7	7	6.9865	ND	ND ...
4	7	7	6.9883	ND	ND ...
5	5	5	4.9824	ND	ND ...
6	7	7	6.9738	ND	ND ...
7	5	5	4.9955	ND	ND ...
8	7	7	6.9835	ND	ND ...
9	5	5	4.9964	ND	ND ...
10	5	5	4.9877	ND	ND ...
11	5	5	4.9954	ND	ND ...
12	7	7	6.9643	ND	ND ...
13	8	8	7.9764	ND	ND ...
14	8	8	7.9944	ND	ND ...
15	7	7	6.9877	ND	ND ...
16	8	8	7.9962	ND	ND ...
17	7	7	6.9914	ND	ND ...
18	6	6	5.964	ND	ND ...
19	6	6	5.9703	ND	ND ...
20	5	5	4.9881	ND	ND ...
21	13		12.602	ND	ND ...
22	8		7.833	ND	ND ...
23	21		20.4344	ND	ND ...

[24 rows x 42 columns]

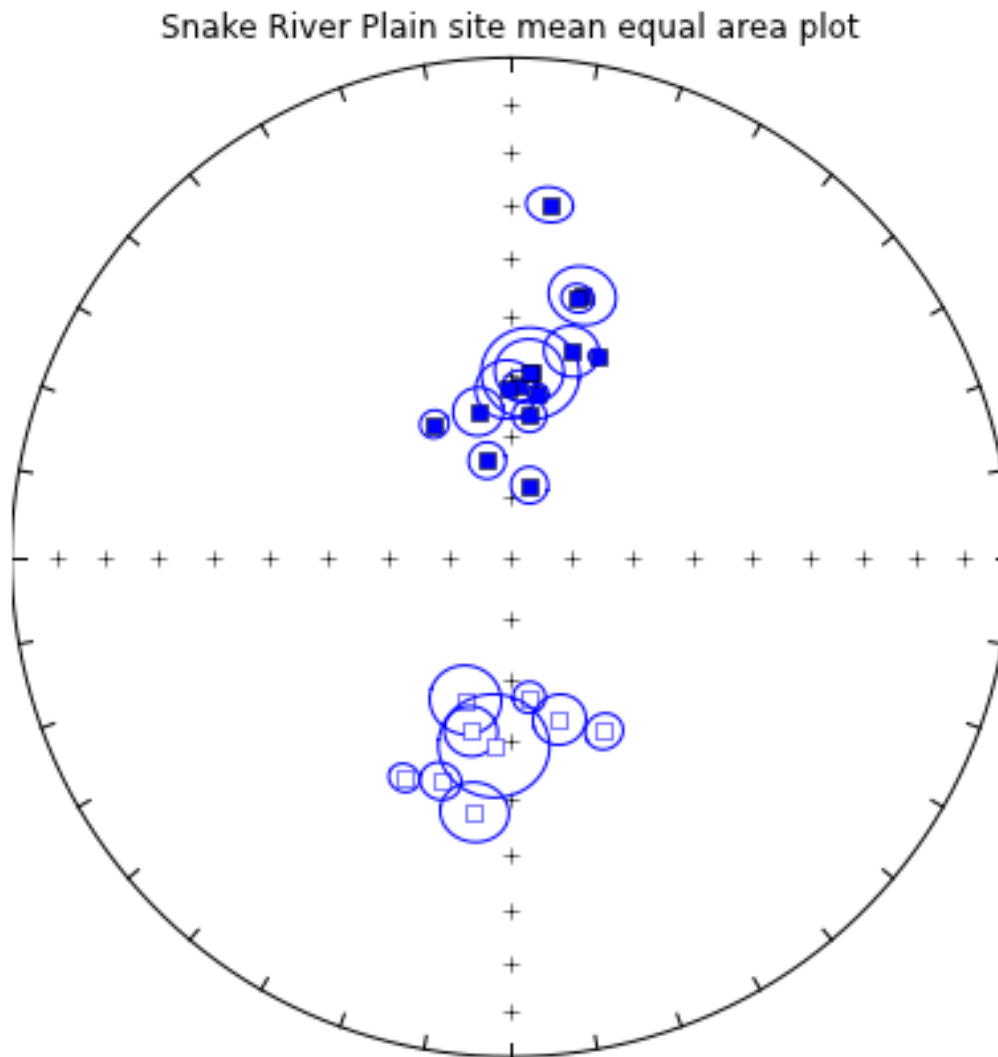
Now that we have imported the data, we can do other things with it such as plot it using IPmag.iplotDImean.

```
In [15]: fignum = 1
plt.figure(num=fignum,figsize=(6,6),dpi=160)
IPmag.iplotNET(fignum)
plt.title('Snake River Plain site mean equal area plot')
```

```

for n in range(0,len(results)):
    IPmag.iplotDImean(results['average_dec'][n],results['average_inc'][n],results['average_alp
        color='b',marker='s',label='mean of data',legend='no')

```



This notebook is available in this Github repository: [https://github.com/Swanson-Hysell/PmagPy\\_IPython](https://github.com/Swanson-Hysell/PmagPy_IPython)

The notebook can be viewed as raw html here: [http://nbviewer.ipython.org/github/Swanson-Hysell/PmagPy\\_IPython/blob/master/IPmag\\_examples.ipynb](http://nbviewer.ipython.org/github/Swanson-Hysell/PmagPy_IPython/blob/master/IPmag_examples.ipynb)

This command can be used to convert this notebook into a PDF document:

```
nbconvert --to latex MagIC_workshop_example.ipynb --post PDF
```

In  :