





# Computational Geosciences

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## Preface

Welcome to the Computational Geosciences resource at the University of Stavanger, Norway (UiS). Computational Geosciences is not a new subject. A course in Computational Geology was offered for the first time at the University of South Florida in 1996 (Vacher, 2000). Computational Geosciences makes connections between mathematics, computation and geology. It promotes a mathematical problem-solving disposition (Vacher, 2000).

This resource is designed based on the same principles and with emphasis on problem-solving. However, the access to data and the tools used to visualize data have improved tremendously over the last 20 years. Today, a geologist carrying a mobile device in the field has access to a collection of sensors collecting data in real time (magnetometer, accelerometers, gravity, GPS, etc.), and accurate databases of topography, aerial photos, and satellite imagery. Such information not only supports the geologist in the field, but also allows her to test hypotheses and take decisions. Computation is greatly facilitated by high-level programming languages (e.g. Matlab and Python) that focus on visualizing and solving problems, rather than on coding details. The digital era is here, and to analyze the large number of data associated with it, we need math and computing.

To develop this resource, we put together an interesting group of faculty from the Departments of Energy Resources (IER) and Mechanical and Structural Engineering (IMBM) at the University of Stavanger, with expertise in Geographic Information Science (GIS, Lisa Watson, IER), Geophysics (Wiktor Weibull, IER), Structural Geology (Nestor Cardozo, IER), and Fluid Mechanics (Knut Giljarhus, IMBM). Master students from Computational Engineering (Angela Hoch), Offshore Engineering (Adham Amer), and Geosciences (Vania Mansoor and Linda Olsen) were instrumental. They wrote our scattered code into functions and notebooks, solve the exercise problems, and help editing the resource in [Overleaf](#).

Python is the programming language of choice. The resource consists of ten chapters covering an introduction to computation in Geosciences and Python (chapter 1), understanding location (chapter 2), orientation and display of geologic features (chapter 3), coordinate systems and vectors (chapter 4), coordinate transformations (chapter 5), tensors (chapter 6), stress (chapter 7), strain (chapter 8), elasticity (chapter 9), and the inverse problem (chapter 10). Each chapter describes shortly the basic theory before going directly into

applications and problems. Exercises at the end of each chapter are essential to master the material. These exercises are not trivial and may require additional research. They are designed to test knowledge of the material.

Much of the material is based on the book Structural Geology Algorithms: Vectors and Tensors (Allmendinger et al., 2012), and the lab manual: Modern Structural Practice (Allmendinger, 2019). However, we have also included additional GIS and Geophysics topics. The resource is focused on our areas of expertise, but we hope you can use and further develop the material for other areas.

You can download or subscribe to changes in the resource using its [git repository](#). We hope you enjoy this resource and learn from it, as well as use it for teaching. This will be the measure of our success. We also hope to spark enough interest for users to contribute to the resource with additional material and more chapters in the future. Finally, we are grateful to the Faculty of Science and Technology at the University of Stavanger for sponsoring this project.

## Accessing the resource material

The best way to access the resource is by cloning or downloading its [git repository](#). This repository contains a [pdf of the book](#) and a folder called [source](#) with the [notebooks](#), [functions](#) and [data](#) in their corresponding folders. The notebooks follow this directory structure. We recommend you use the same structure when running them.

## References

Allmendinger, R.W., Cardozo, N. and Fisher, D.M. 2012. Structural Geology Algorithms: Vectors and Tensors. Cambridge University Press.

Allmendinger, R.W. 2019. Modern Structural Practice: A structural geology laboratory manual for the 21st century. [Online]. [Accessed January, 2020].

Vacher, H.L. 2000. A Course in Geological-Mathematical Problem Solving. Journal of Geoscience Education 48, 478-481.

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# Chapter 1

## Computation in Geosciences

### 1.1 Solving problems by computation

Geology is an interpretive and historical science (Frodeman, 1995). We observe, collect, analyze, and interpret data (what) to tell a story (why). To collect data, we need to take measurements. All measurements have some uncertainty, and therefore uncertainty and error propagation are very important in geosciences, and they are a recurring topic in this resource.

For the last 50 years or more, the methods geoscientists have used to visualize, analyze and interpret data are mostly graphical. For example, in structural geology, students typically learn two types of graphical constructions: orthographic and spherical projections (stereonets) (Ragan, 2009). Although these methods are great to visualize and solve geometrical problems in three-dimensions, they are not amenable to computation, and therefore applying these methods to large datasets with thousands of entries is impractical. Plane and spherical trigonometry allow deriving formulas (e.g. apparent dip formula) for computation (Ragan, 2009). However, these formulas give little insight about the problems. They are just formulas associated with complex geometric constructions, which bear no relation to each other, and which are difficult to combine to solve more complicated problems.

It turns out that many of the most interesting problems in geosciences can be described and solved using linear algebra, and more specifically vectors and tensors (Allmendinger et al., 2012). Linear algebra also happens to be the language of data and computation. The main purpose of this re-

source is to show how to solve problems in geosciences using computation. There are several advantages of following this approach. It will enhance your mathematical and computational skills, as well as promote your geological-mathematical problem solving disposition. In today's digital age, these skills are very useful.

## 1.2 Why Python?

The choice of programming language is important. While computer languages such as C or C++ are ideal to work with large datasets and computer-intensive operations, they involve a steep learning curve associated with their syntax, compilation, and execution (Jacobs et al., 2016). These coding details have little to do with the problem-solving approach of this resource. Interpretive languages such as Python, R or Matlab are a better choice because of their simpler syntax, and the interpretation and execution of commands as they are called (no need for compilation). In addition, these languages have access to an integrated development environment (IDE) that facilitates writing and debugging programs, and to many standard libraries that perform advanced tasks such as matrix operations and data visualization. Thus, Python, R or Matlab are “scientific packages” rather than just programming languages.

In this resource, the language of choice is Python. Besides the reasons above, Python has the following advantages:

- Python can be learned quickly. It typically involves less code than other languages and its syntax is easier to read.
- Python comes with robust standard libraries for arrays and mathematical functions (NumPy), visualization (PyPlot), and scientific computing (SciPy).
- Python is one of the most popular programming languages, with a large base of developers and users. It is used by every major technology company and it is almost a skill you must have in your CV to land a job as a geoscientist.
- Because of its large developers base, Python has access to a large amount of additional libraries, including several libraries for geosciences. We make use of some of these libraries.

- Python can be installed easily through a single distribution that includes all the standard libraries and provides access to additional libraries (see next section).
- Last but not least, Python is free and open source. This is probably why Python is more popular than its commercial counterpart Matlab.

## 1.3 Installing Python

We recommend installing Python using the free Anaconda distribution. This distribution includes Python as well as many other useful applications, including Jupyter, which is the system we use to write the notebooks in this resource. Anaconda can be easily installed on any major operating system, including Windows, macOS, or Linux.

The installation process is quite straightforward. From the [Anaconda distribution](#) page, go to the Download section. Windows and macOS users just need to download the Graphical installer, run it, and follow the steps to install Anaconda. Linux users need to download the installer and type a set of commands in a terminal window. Further instructions can be found in the [Anaconda installation](#) section.

## 1.4 A first introduction to Python

In this section, we use our first Jupyter notebook to learn the basics of Python. Clone or download the resource [git repository](#). Open Anaconda and then launch Jupyter Notebook. This will open a browser with a list of files and folders in your home directory. Navigate to the folder source/notebooks in the repository and open the notebook [ch1](#). Alternatively, follow the notebook in the sections below. Surprisingly, few lines of code are required to introduce key topics such as conditionals, loops, functions, array mathematics, and plotting. This shows the power of Python.

### 1.4.1 Basics

A notebook is divided into computational units called *cells*. Cells can contain text such as this one or Python code. Below is a cell with some typical Python statements. Try changing the variables and re-run the cell. To run a cell, either click the *Run* button, or type *Ctrl+Enter*.

```

1 a = 2
2 b = 9.0
3 c = a + b
4 print('The sum is: ', c)
5
6 # This is just a comment
7
8 name = 'Donald'
9 print('Hello, my name is', name)
```

Output:

The sum is: 11.0  
Hello, my name is Donald

There are some other useful shortcuts you should know. To run a cell and move to the next cell, type *Shift+Enter*. To run a cell and insert a new cell below, type *Alt+Enter*. You can use the arrow keys to move quickly between cells. To run all the cells of a notebook, choose the *Cell → Run all* menu.

### 1.4.2 Conditionals

A conditional is used to perform different operations depending on a conditional statement. In Python, this is expressed in the following way:

```

1 a = 3
2 b = 5
3 if a > b:
4     print('a is bigger than b')
5 elif a < b:
6     print('a is smaller than b')
7 else:
8     print('a is equal to b')
```

```
Output:  
a is smaller than b
```

Try changing the values of *a* and *b* to see how the output changes. Also, note that Python cares about white spaces, so there must be a tab indent or 4 spaces for each operation in the if statement. You can also use the boolean operators *and*, *or*, and *not* in the conditional statement:

```
1 age = 30  
2 if age > 18 and age < 34:  
3     print('You are a young adult')  
4  
5 if age < 18 or age > 80:  
6     print('You are not allowed to drive a car')
```

```
Output:  
You are a young adult
```

### 1.4.3 Loops

A loop is used to execute a group of statements multiple times. For instance, to print all numbers from 1 to 10 divisible by 3, we can use a *for* loop together with an *if* statement, and the modulus operator %:

```
1 print('Number divisible by three:')
```

```
2 for i in range(1, 11):  
3     if i % 3 == 0:  
4         print(i)
```

```
Output:  
Numbers divisible by three:  
3  
6  
9
```

*range* is a Python function that iterates from the given first number up to the second number (but not including it). If we only give one number, the iteration will go from zero up to (but not including) the given number. There are more examples of *for* loops later in this notebook.

### 1.4.4 Functions and modules

If we have written a useful piece of code, we often want to use it again without copying and pasting the code multiple times. To do this, we use functions and modules. For instance, if we want to convert an angle from degrees to radians, we can use the following formula:

$$\alpha_{\text{radians}} = \alpha_{\text{degrees}} \frac{\pi}{180} \quad (1.1)$$

To put this into a callable function, we use the *def* keyword:

```

1 def deg_to_rad(angle_degrees):
2     pi = 3.141592
3     return angle_degrees*pi/180.0
4
5 angle_degrees = 45.0
6 print('Radians', deg_to_rad(angle_degrees))

```

Output:  
Radians 0.785398

We can also include code from other places. This is useful to make your own library of functions that you can then use in other notebooks. This is the modus operandi of this resource. We will implement and use functions that solve common problems in geosciences. Using a text editor, create a file called *mylib.py* and put it in the same folder the notebook is. In the file, write a function to convert from radians to degrees:

```

1 def rad_to_deg(angle_radians):
2     pi = 3.141592
3     return angle_radians*180/pi

```

We can then import in the notebook the code from the file and use it like this:

```

1 try:
2     import mylib
3     angle_radians = 0.785398

```

```

4     print('Degrees', mylib.rad_to_deg(angle_radians))
5
6 except ModuleNotFoundError:
7     print('Create a file called mylib.py')

```

Output:  
Degrees 45.0

Note: If you make a change in *mylib.py*, the changes will not be immediately available in the notebook and it needs to be restarted. To circumvent this, we can use the following commands to always reload imported modules:

```

1 %load_ext autoreload
2 %autoreload

```

### 1.4.5 Mathematics

To use Python as an environment for numerical mathematics, it is useful to use the NumPy library for arrays and matrices, and the Matplotlib for plotting. See the links in the *Help* menu for more information on these libraries. The following two lines import these libraries:

```

1 import numpy as np
2 import matplotlib.pyplot as plt

```

To define an array, we use the NumPy *array* function:

```

1 a = np.array( [1, 2, 3, 4] )
2 print(a)

```

Output:  
[1 2 3 4]

To access an array element, we use brackets with the index of the element. A very important difference compared to Matlab is that in Python the first element has index zero (like most other programming languages). We can also use negative indices to access values starting from the end of the array.

```

1 print(a[0], a[2])
2 print(a[-1])

```

Output:

```

1 3
4

```

Slicing is a very useful feature to extract subarrays. For instance:

```

1 print(a[2:])
2 print(a[1:3])

```

Output:

```

[ 3 4 ]
[ 2 3 ]

```

Matrices are defined as multi-dimensional arrays:

```

1 a_matrix = np.array( [[1, 2, 3],
2                         [4, 5, 6],
3                         [7, 8, 9]] )
4 b_matrix = np.array( [[2, 4],
5                         [3, 5],
6                         [5, 7]] )
7 print(a_matrix)
8 print(b_matrix)

```

Output:

```

[[1 2 3]
[4 5 6]
[7 8 9]]
[[2 4]
[3 5]
[5 7]]

```

We can get the number of rows and columns of the matrix from the *shape* variable:

```

1 nrow, ncol = b_matrix.shape
2 print('b has {} rows and {} columns'.format(nrow, ncol))

```

Output:  
b has 3 rows and 2 columns.

Let us make a function to multiply two matrices. Consider a  $n \times m$  matrix **A** and a  $m \times p$  matrix **B**. The formula to multiply these matrices can be written as:

$$\mathbf{C} = \mathbf{AB} = \sum_{k=1}^m A_{ik}B_{kj} \quad (1.2)$$

for  $i = 1, \dots, n$  and  $j = 1, \dots, p$ . Here **C** will be a  $n \times p$  matrix. To implement this formula, we need to use a triple-nested loop, as shown in the function below:

```

1 def matrix_multiply(A,B):
2     n, m = A.shape
3     nrow_B, p = B.shape
4
5     # Check that matrices are conformable
6     if not nrow_B == m:
7         print('Error, the number of columns in A must be
8 equal to the number of rows in B!')
8     return -1
9
10    # Initialize C using the numpy zeros function
11    C = np.zeros((n,p))
12    for i in range(n):
13        for j in range (p):
14            for k in range (m):
15                C [i,j] = C[i,j] + A[i,k]*B[k,j]
16
17 print(matrix_multiply(a_matrix, b_matrix))

```

Output:  
[[23. 35.]  
[53. 83.]  
[83. 131.]]

Verify by hand calculation that the above result is correct. Remember, the element in the first row and first column of **C** is equal to the sum of the product of the elements in the first row of **A** times the elements in the first column of **B**, and so on. What happens if you try the multiplication **BA**? Try it.

Although the function above is elegant, it is not very efficient. The NumPy library contains super-optimized code for common operations such as matrix multiplication. The NumPy *dot* function can be used for matrix multiplication. Let's repeat the matrix multiplication above using the *dot* function:

```
1 C = np.dot(a_matrix, b_matrix)
2 print(C)
```

Output:  
[[23 35]  
 [53 83]  
 [83 131]]

When working with large matrices, there is a significant impact on the run-time. To illustrate this, let's generate two  $100 \times 100$  matrices and time how long it takes to multiply them. The `%%timeit` command will run the cell a number of times and output the average time spent per run. The NumPy *random.rand* function generates the arrays and fill them with random numbers.

```
1 %%timeit
2 N = 100
3 A = np.random.rand(N,N)
4 B = np.random.rand(N,N)
5 C = matrix_multiply(A,B)
```

Output:  
625 ms ± 3.11 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)

Change the multiplication function from *matrix\_multiply* to *np.dot* and note the difference in runtime. On a standard computer, our *matrix\_multiply* function uses  $\approx 600$  milliseconds per loop, while NumPy *dot* function uses  $\approx 200$  microseconds. The NumPy *dot* function is a staggering 3000 times faster!

### 1.4.6 Plotting

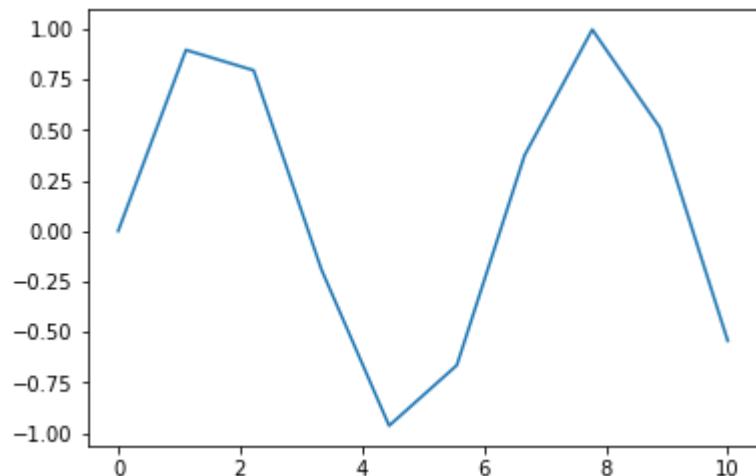
Arrays can be easily plotted using the Matplotlib *plot* command. Below we plot the sinusoidal function. We use the NumPy *linspace* function to generate an array with equally spaced values between the start and end point, and the NumPy *sin* function to take the sine of the array. The *plot* command plots the data and the semicolon after it removes any message output. With a low number of points, the curve is actually jagged. Increase the number of points *n* in the *linspace* command to get a smoother curve. Try values of *n* = 100, 1000, and 10000.

```

1 # The linspace command gives us an equally spaced array
2 # The syntax is:
3 # linspace(start_point, end_point, number_of_points)
4 n = 10
5 x = np.linspace(0, 10, n)
6 y = np.sin(x)
7 plt.plot(x, y);

```

Output:



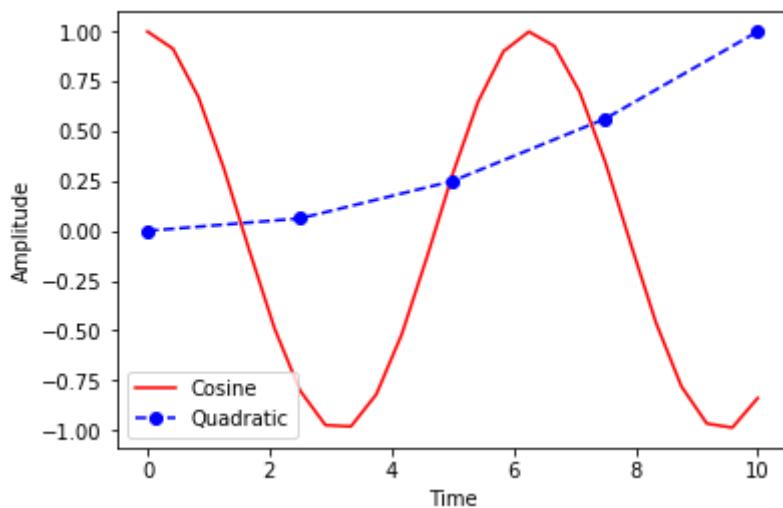
We end with a slightly more advanced plot, showing how to change line style and markers, and add axes labels and a legend. The NumPy *cos* function takes the cosine of the array, and *xlabel*, *ylabel* and *legend* are all Matplotlib commands to add labels to the axes and a legend to the graph.

```

1 n = 25
2 x = np.linspace(0, 10, 25)
3 y = np.cos(x)
4 # plot cosine function as a red line
5 plt.plot(x, y, 'r')
6 x = np.linspace(0, 10, 5)
7 y = 0.01*x**2
8 # plot quadratic function as blue dashed line with dots
9 plt.plot(x, y, 'bo--')
10 # label axes
11 plt.xlabel('Time')
12 plt.ylabel('Amplitude')
13 # Add legend
14 plt.legend(['Cosine', 'Quadratic']);

```

Output:



## 1.5 Exercises

1. Write a program that prints each number from 1 to 20 on a new line. For each multiple of 3, print "Fizz" instead of the number. For each multiple of 5, print "Buzz" instead of the number. For numbers which are multiples of both 3 and 5, print "FizzBuzz" instead of the number. The correct answer is: 1 2 Fizz 4 Buzz Fizz 7 8 Fizz Buzz 11 Fizz 13 14 FizzBuzz 16 17 Fizz 19 Buzz. *Hint:* You will need to use a loop and conditionals to solve this problem.

2. Write a function to convert an angle from degrees to radians or from radians to degrees. The function should accept two inputs: the angle, and a flag to tell the function whether the angle should be converted from degrees to radians (flag = 1) or from radians to degrees (flag = 2).  
*Hint:* In the function, you should use a conditional to either convert the angle from degrees to radians, or from radians to degrees.

3. Given two  $3 \times 3$  matrices  $\mathbf{A} = [ [1, 2, 3], [4, 5, 6], [7, 8, 9] ]$  and  $\mathbf{B} = [ [5, 7, 2], [3, 5, 1], [2, 4, 3] ]$ , compute:

- (a) the sum of the matrices ( $\mathbf{A} + \mathbf{B}$ ),
- (b) The difference of the matrices ( $\mathbf{A} - \mathbf{B}$ ),
- (c) The product of the matrices ( $\mathbf{AB}$ ),
- (d) The square root of matrix  $\mathbf{A}$ ,
- (e) The sum of all elements of matrix  $\mathbf{B}$ ,
- (f) The column sum of matrix  $\mathbf{A}$ ,
- (g) The row sum of matrix  $\mathbf{A}$ ,
- (h) The transpose of matrix  $\mathbf{A}$  ( $\mathbf{A}^T$ ),
- (i) The product  $\mathbf{AA}^T$ . What is this product equal to?

*Hint:* Look at the functions *add*, *subtract*, *dot*, *sqrt*, *sum* and *transpose* in the NumPy library.

4. The apparent dip  $\alpha$  of a plane is given by the following equation:

$$\tan \alpha = \tan \delta \sin \beta \quad (1.3)$$

where  $\delta$  is the true dip of the plane, and  $\beta$  is the structural bearing (Fig. 3.1b). We will talk about this equation in chapter 3.

- (a) Make a function to compute the apparent dip  $\alpha$  from the true dip  $\delta$  and structural bearing  $\beta$ . For the function, these angles should be entered in radians.
- (b) Use this function to make a graph of apparent dip  $\alpha$  (0 to  $90^\circ$ , vertical axis) versus the structural bearing  $\beta$  (0 to  $90^\circ$ , horizontal axis), for values of true dip  $\delta$  of 10, 20, 30, 40, 50, 60, 70, and  $80^\circ$ .

The graph should look like Figure 1.1 below:

*Hint:* You will need to import the NumPy and Matplotlib libraries to solve this problem. The problem is intendedly hard, don't give up.

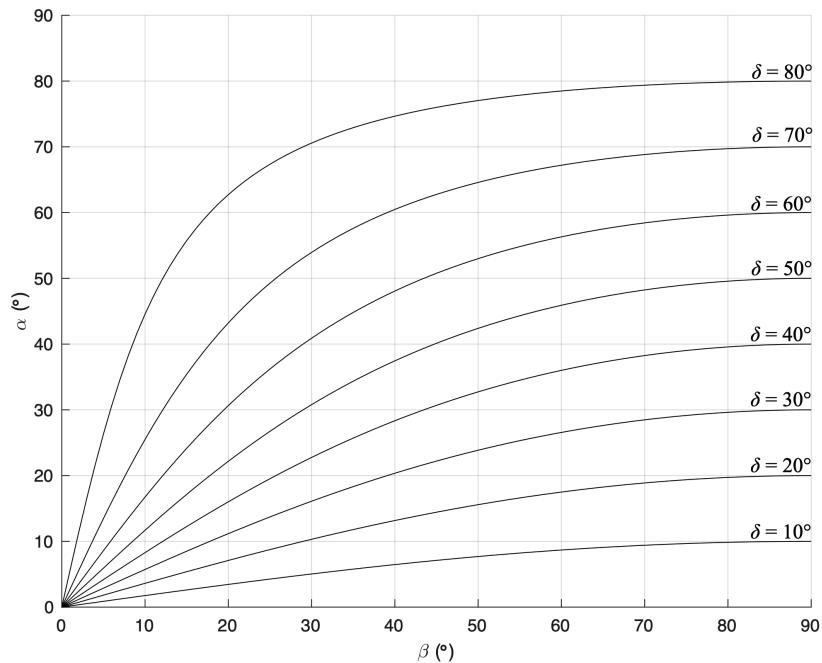


Figure 1.1: Apparent dip  $\alpha$  as function of section bearing  $\beta$  and true dip  $\delta$ .

## References

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# Chapter 2

## Understanding location

### 2.1 Locations

Understanding where we are located or where an object of interest is located is extremely important in geosciences. Geographic information science is the study of geographic information; it includes theory and concepts and provides methods to combine and analyze spatial data (Watson, 2017). Geographic information systems is the software and technology that supports the application of geographic information theory (Watson, 2017). GIS is an acronym used for either geographic information systems or geographic information science.

Geosciences are Earth-based and so location-based. The geographic aspect is highly applicable for the geosciences. The basic usage of GIS is cartographic – making maps. In this chapter, you will become familiar with some of the basic concepts in defining locations on the Earth. These concepts are also used for defining locations on other planets as well.

### 2.2 Geodesy basics

Geodesy is “the branch of mathematics dealing with the shape and area of the Earth or large portions of it” (Lexico, 2019); however, the discipline is expanding to include other planets. We need geodesy to model the Earth

and make calculations because the Earth is not a perfect sphere nor flat.

### 2.2.1 Scales

In cartography, we use scales to describe how the real world length has been reduced to fit on a page or screen. Usually, map scales are described as ratios, such as 1:50,000. When we describe the scale, we say it is either small or large. The description of small or large refers to the scale, not the size of the area. Therefore, if we describe a scale as small, it means the fraction described by the scale ratio is small; this in turn means the map covers a large area. The inverse is true for large scales; the fraction described by the scale is large and in turn covers a small area (Kraak and Ormeling, 2003, Lisle et al., 2011). There is not an official categorical differentiation between small and large scales. Generally speaking, small scale maps cover regions, countries, and continents, while large scale maps cover neighborhoods, towns, or counties. The following example illustrates this.

#### Example 1: Understanding Map Scales

A map has a scale of 1:1,000,000. Would you refer to this as a small or large scale?

1. First, rewrite this as a fraction:  $1/1,000,000$
2. Is this a small fraction or a large fraction? This is a relatively small fraction, so it is a small scale.

Figure 2.1 is an example of a map with a scale of 1:1,000,000.

A map has a scale of 1:10,000. Would you refer to this as a small or large scale?

1. First, rewrite this as a fraction:  $1/10,000$
2. Is this a small fraction or a large fraction? This is a relatively large fraction, so it is a large scale.

Figure 2.2 is an example of a map with a scale of 1:10,000.

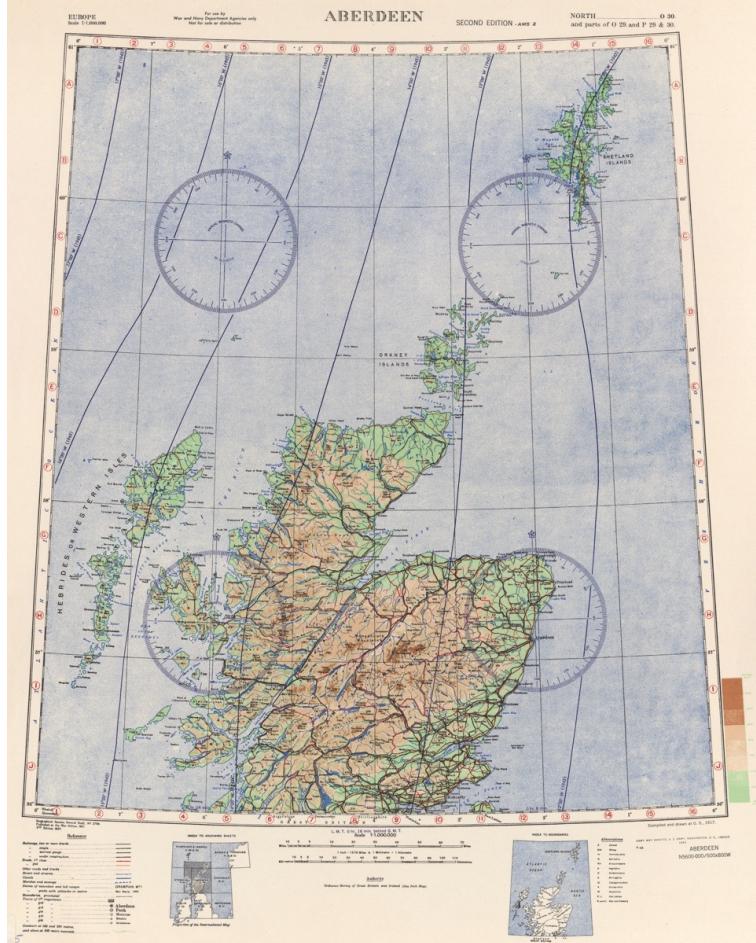


Figure 2.1: A historical map of northern Scotland at the scale of 1:1,000,000 (Geographic Section - General Staff, 1941).

### 2.2.2 Authalic Sphere

The authalic sphere is a sphere used for the basic surface for mapping (Fig. 2.3); its surface area is the same as the ellipsoid (Robinson et al., 1995). Based on the WGS-84 ellipsoid, the Earth has a radius of 6371 km and a circumference of 40,030.2 km. The radius is an often-used constant in geodesy (Robinson et al., 1995). The authalic sphere is used in small scale mapping (small scale covers a large area) because the difference between the authalic sphere and the ellipsoid is minimum over large areas (Robinson et al., 1995).



Figure 2.2: A historical map of Rome, Italy at the scale of 1:10,000 (C.I.U. and War Office, 1944).

### 2.2.3 Ellipsoidal Earth

Due to gravity, the Earth flattens at the poles. In a cross-section, the Earth looks like an oblate ellipsoid (Fig. 2.3) (Robinson et al., 1995). Oblateness refers to flatness. When mapping over small areas (large scale mapping), the oblateness of the ellipsoid must be taken into account. The GPS network uses the WGS-84 ellipsoid (Robinson et al., 1995).

There are varying ellipsoidal measurements on different continents and times. These continental differences are due to gravity. Temporal differences are due to technological accuracy. The WGS-84 ellipsoid is based on satellite observations and is accepted as being highly accurate (Robinson et al., 1995).

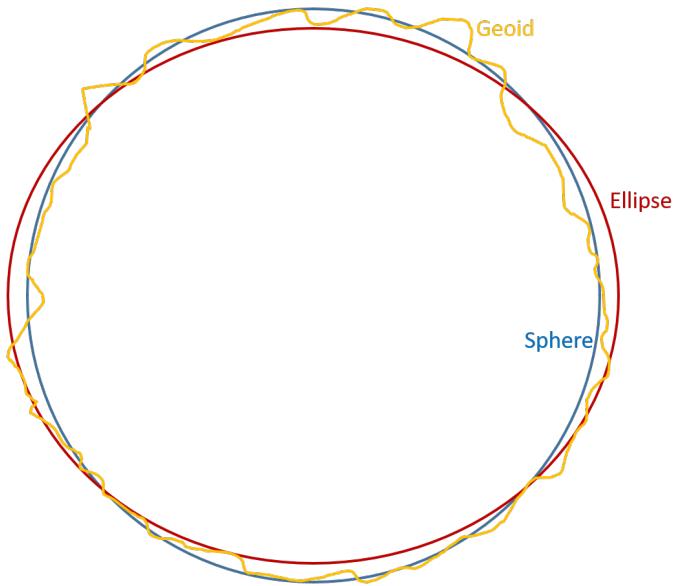


Figure 2.3: Highly stylized comparison of sphere, ellipse, and geoid.

#### 2.2.4 Geoid

Geoid means Earth-like and is in 3D. It is based on the equipotential gravity surface. The geoid follows the mean sea level in oceans and hypothetical sea-level canals on the continents (Robinson et al., 1995). Due to geology (rock density) and topography, the geoid deviates from the ellipsoid (Fig. 2.3). The geoid is a “reference surface for ground surveyed horizontal and vertical positions” (Robinson et al., 1995).

### 2.3 Projections

A projection is a mathematical equation to transfer a region, of whatever size, of the round Earth onto a flat surface. Projections are used because distance and surface area calculations are more difficult on a sphere. A flat map can show greater detail than a sphere and is more transportable. Imagine how large a globe you would need to sufficiently show the streets in your neighborhood! We need projections to transform our 3D ellipsoidal Earth onto a flat map. Projections may be based on the authalic sphere, ellipsoid, or geoid.

Before proceeding, take a moment to look over an informational [pictographic](#) by the U.S. Geological Survey describing different types of projection.

### 2.3.1 Distortions

All projections have distortions that vary by projection type (i.e. transverse Mercator vs. Miller cylindrical – see pictograph mentioned in previous section). Selecting a projection depends on discipline, size of area, orientation of area, regional standards, map purpose, and map scale. There are many resources for determining which projection you should use. Large-scale mapping uses conformal projection because angles measured on the ground are the same as those in the map (Iliffe and Lott, 2008). Four types of distortion are: area, shape, direction, and distance. The Tissot’s Indicatrix is a graphic device to show the distortion at a point (Robinson et al., 1995). We will investigate this phenomenon using the Python library [Cartopy](#). To install this library, follow the steps below:

## Installing Cartopy

We will use the Cartopy library to visualize projection distortions using the Tissot’s Indicatrix. We will make a special Cartopy Environment in Anaconda. This is because Cartopy dependencies are lower than some other libraries we’ll be using. This happens from time to time when we use open-source libraries.

1. Open Anaconda Navigator.
2. In the left panel, click on “Environments”.
3. In the middle panel, click ”Create” to create a new environment
4. Name this environment: ch2cartopy
5. Select Python version 3.7
6. Click ”Create”. This will take a few minutes.
7. We need to install Cartopy. In the right panel in the search field, type: cartopy

8. You will get the message "0 packages available matching cartopy" since Cartopy is not installed.
9. In the right panel, change "Installed" to "Not installed"
10. Cartopy now shows up<sup>1</sup>. Click the check box next to "cartopy".
11. In the screen lower right corner, click "Apply"
12. Please wait while Cartopy is collected and then click "Apply"
13. The Cartopy library and any dependencies will be installed or updated. This may take a few minutes.
14. Click on "Home"
15. Install the console of your choice for the new environment. Click on "Install" under Jupyter Notebook, for example.
16. Click on "Launch"

## Example 2: Tissot's Indicatrix

This example will introduce you to understanding distortions in projections. As you change the projection name, a different mathematical equation will be used to portray the round Earth in a flat presentation. Pay particular attention to the size, shape, and spacing of the ellipses describing the distortion. The Tissot's Indicatrix quickly and easily visualizes the changes in area and spatial relationships between different projections.

The notebook `ch2-1` contains this example. If you just launched Jupyter Notebook as indicated above, open the notebook. If you closed Anaconda, follow these steps:

1. Open Anaconda Navigator
2. Click on "Environments"
3. Choose "ch2cartopy"
4. Click "Home"

---

<sup>1</sup>If cartopy does not show up, you may need to press "Update index" in the right panel.

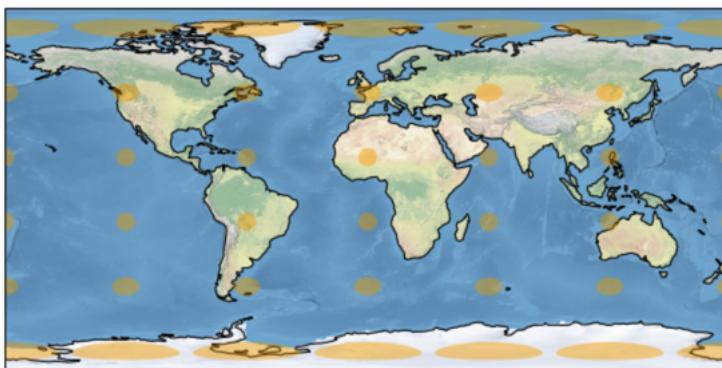
5. Launch Jupyter Notebook

6. Open the notebook ch2-1

This example starts with the Plate Carree projection ([Cartopy, 2018b](#)). Run the code below:

```
1 # Import cartopy and matplotlib
2 import cartopy.crs as ccrs
3 import matplotlib.pyplot as plt
4
5 # Hide warnings
6 import warnings
7 warnings.simplefilter('ignore')
8
9 # Figure
10 plt.figure(figsize=(10, 5))
11
12 # Plate Carree projection
13 ax = plt.axes(projection=ccrs.PlateCarree())
14
15 # Make the map global rather than have it zoom in to
16 # the extents of any plotted data
17 ax.set_global()
18
19 # Earth image
20 ax.stock_img()
21 # Coastlines
22 ax.coastlines()
23
24 # Tissot's indicatrix: Orange ellipses
25 ax.tissot(facecolor='orange', alpha=0.4)
26 plt.show()
```

Output:



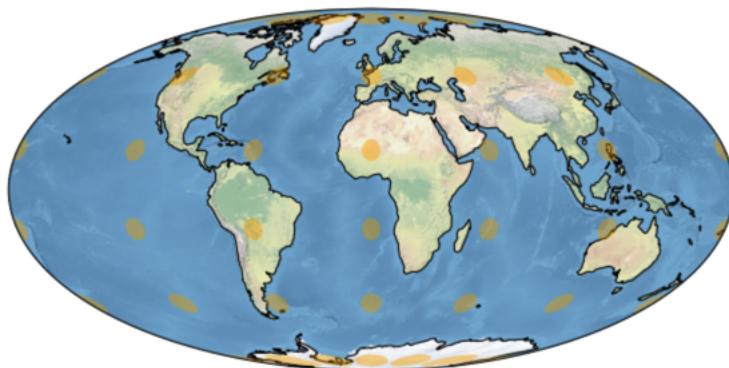
The Tissot's Indicatrix is symbolized by the orange ellipses. Closer to the poles, the ellipses become more oblate; while closer to the Equator, they are more circular. The Plate Carrée projection is a specific form of the Equidistant Cylindrical projection. Plate Carrée has the latitude of origin at the Equator.

Change the code to use the Mollweide projection:

```

1 # Figure
2 plt.figure(figsize=(10, 5))
3
4 # Mollweide projection
5 ax = plt.axes(projection=ccrs.Mollweide())
6
7 # Make the map global rather than have it zoom in to
8 # the extents of any plotted data
9 ax.set_global()
10
11 ax.stock_img()
12 ax.coastlines()
13
14 ax.tissot(facecolor='orange', alpha=0.4)
15 plt.show()
```

Output:



Notice how the sizes of the ellipses are very similar throughout the map. All of the ellipses are more rounded and circular regardless of their position, as compared to the Plate Carrée projection. Mollweide is often used for world maps.

Cartopy has a list of projections that are included in the library ([Cartopy, 2018a](#)). Change the code above to project the map in Azimuthal Equidistant.

## 2.4 Reference systems and datums

A coordinate reference system is a coordinate system that has been referenced to a datum. A datum is the location used for a reference point from which spatial measurements are made. There are geographic and Cartesian coordinate systems. Coordinates are for specific locations on the Earth. They can be expressed as geographic using latitude and longitude. Latitude are parallels that are evenly spaced and longitude are meridians that converge at the poles. These are measured in degrees. Cartesian coordinates are expressed in x and y and may have units that are meters, feet, or kilometers, for example. Coordinates only have meaning when the coordinate system and datum are known (Iliffe and Lott, 2008, Robinson et al., 1995).

### Example 3: Defining the coordinate reference system

In any GIS program, including spatial libraries and code, the user must ensure that the coordinate reference system is defined for the spatial data. The GIS software will make assumptions, sometimes erroneous, if the coordinate reference system is not properly defined. In this example, we will see a demonstration of these assumptions and how to prevent them. This example is from the SciTools tutorials to understand Cartopy ([Cartopy, 2018c](#)).

In Cartopy, there are two keywords that you must understand in order to properly display your data. The “projection” argument is used for display of your data. This only affects the map or plot. It does not define the coordinate reference system of the data itself. The “transform” argument, on the other hand, defines the coordinate reference system. The best practice is to define both of these. We will investigate the error that occurs when the best practice is not followed and compare this to when the best practice is followed. The notebook [ch2-2](#) contains this example.

First we will create some dummy data on a regular latitude/longitude grid:

```

1 import numpy as np
2
3 lon = np.linspace(-80, 80, 25)
4 lat = np.linspace(30, 70, 25)
5 lon2d, lat2d = np.meshgrid(lon, lat)
6

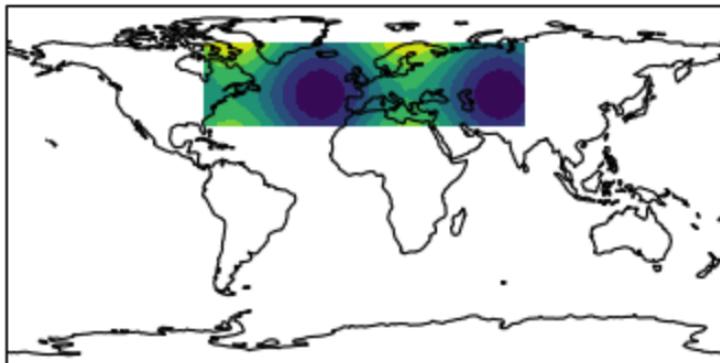
```

```
7 data = np.cos(np.deg2rad(lat2d) * 4) + np.sin(np.deg2rad(
    lon2d) * 4)
```

In order to demonstrate the error before "best practice", we will create a map using the Plate Carree projection but only specify the "projection" argument. Remember that the best practice requires both projection and transform arguments to be defined.

```
1 # Import cartopy and matplotlib
2 import cartopy.crs as ccrs
3 import matplotlib.pyplot as plt
4
5 # The projection keyword determines how the plot will look
6 plt.figure(figsize=(6, 3))
7 ax = plt.axes(projection=ccrs.PlateCarree())
8 ax.set_global()
9 ax.coastlines()
10
11 # didn't use transform, but looks ok...
12 ax.contourf(lon, lat, data)
13 plt.show()
```

Output:



In this case, the data just happen to fall in the correct location. Now, we will define the data coordinate reference system (first line of code below) and add the transform argument to the plot (second last line of code below).

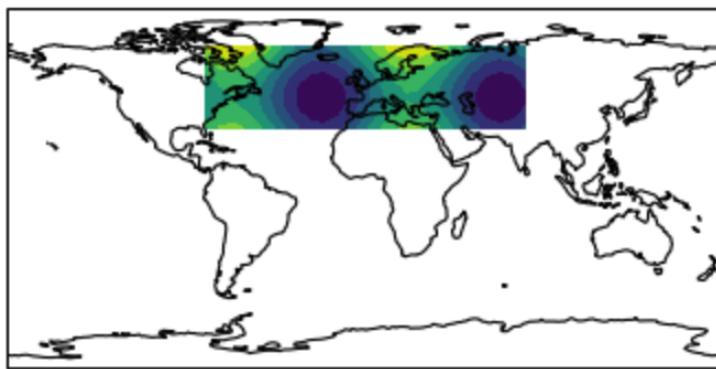
```
1 # The data are defined in lat/lon coordinate system,
2 # so PlateCarree() is the appropriate choice:
```

```

3 data_crs = ccrs.PlateCarree()
4
5 # The projection keyword determines how the plot will look
6 plt.figure(figsize=(6, 3))
7 ax = plt.axes(projection=ccrs.PlateCarree())
8 ax.set_global()
9 ax.coastlines()
10
11 # use transform
12 ax.contourf(lon, lat, data, transform=data_crs)
13 plt.show()

```

Output:



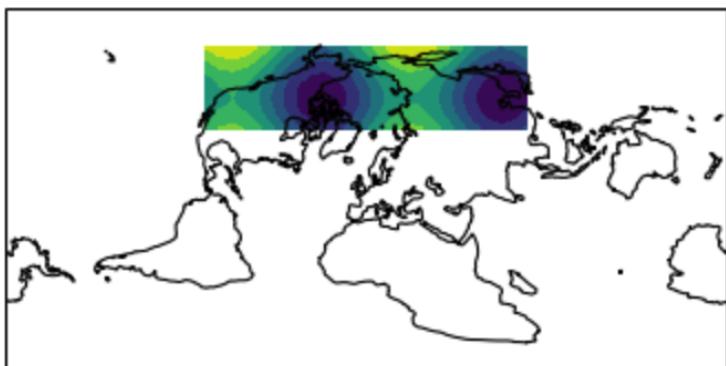
You will notice that our plot remains unchanged. The assumption, as stated previously, is that if the coordinate reference system of the data is undefined, it is the same as the map (or plot) projection. In the example above, this has been the case. Let us now investigate what happens when changing the projection of the map without defining the coordinate reference system of the data. We now define the projection to "RotatedPole" and omit the transform argument to see what happens:

```

1 # Now we plot a rotated pole projection
2 projection = ccrs.RotatedPole(pole_longitude=-177.5,
3                                pole_latitude=37.5)
4 plt.figure(figsize=(6, 3))
5 ax = plt.axes(projection=projection)
6 ax.set_global()
7 ax.coastlines()
8
9 ax.contourf(lon, lat, data) # didn't use transform, uh oh!
10 plt.show()

```

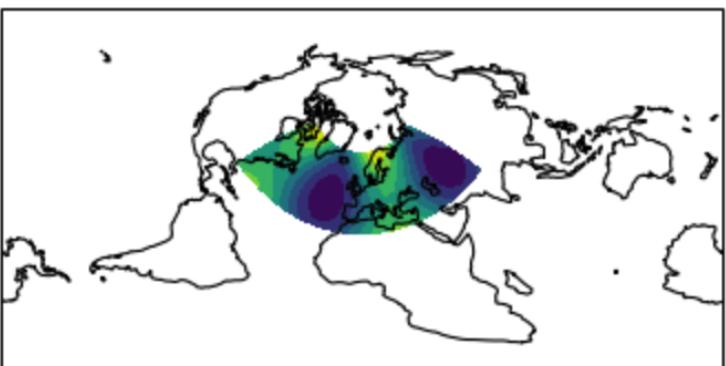
Output:



In this case, we see that the country boundaries have rotated and changed shape, however, the data did not move with the the country boundaries. We made a wrong assumption in the data definition. Therefore we need to define the transform argument:

```
1 # A rotated pole projection again...
2 projection = ccrs.RotatedPole(pole_longitude=-177.5,
3     pole_latitude=37.5)
4 plt.figure(figsize=(6, 3))
5 ax = plt.axes(projection=projection)
6 ax.set_global()
7 ax.coastlines()
8 # ...but now using the transform argument
9 ax.contourf(lon, lat, data, transform=data_crs)
10 plt.show()
```

Output:



Now the data are correctly projected. Get in the habit of always defining the coordinate reference system and the map plot projection. It will save headaches and misunderstandings of the data.

Here is another script using an entirely different projection and additional plotting parameters. Can you figure out what the script will produce before running the cell? Notice the presence of the Matplotlib function *subplot*. What do you think this function does?

```

1 # We can choose any projection we like...
2 projection = ccrs.InterruptedGoodeHomolosine()
3 plt.figure(figsize=(6, 7))
4 ax1 = plt.subplot(211, projection=projection)
5 ax1.set_global()
6 ax1.coastlines()
7 ax2 = plt.subplot(212, projection=ccrs.NorthPolarStereo())
8 ax2.set_extent([-180, 180, 20, 90], crs=ccrs.PlateCarree())
9 ax2.coastlines()
10
11 # ...as long as we provide the correct transform,
12 # the plot will be correct
13 ax1.contourf(lon, lat, data, transform=data_crs)
14 ax2.contourf(lon, lat, data, transform=data_crs)
15 plt.show()
```

Now that you have worked through the exercise, you should have an understanding of why it is important to fully define the coordinate reference system and the projection when creating a map.

## 2.5 Conversion vs. transformation

When working with data collected from several sources or in different coordinate reference systems, the data must be redefined to have the same coordinate reference system and datum. Consistent coordinate reference systems for data in a map is important because there may be spatial differences between the coordinate reference systems creating locational errors. A coordinate conversion is when the coordinate reference systems have the same datum. A coordinate transformation is when the coordinate reference systems have different datums.

When making a map, all of the data in the map should have the same coordinate reference system definition. Software include many definitions and transformations but refer to Snyder (1987) and International Association of Oil and Gas Producers (2018) for projection formulae (Iliffe and Lott, 2008). In Example 2, the Tissot’s Indicatrix ellipses did not change coordinate reference systems. The method used to plot the ellipses changed. In Example 3, we also only changed the projection of the map, not the coordinate reference system. In the following examples, we will make coordinate conversions and transformations. For this purpose, we will use the [pyproj](#) Python library and examples from the pyproj documentation ([Whitaker, 2019](#)).

## Installing pyproj

A version of pyproj was installed with Cartopy, but you need the latest version which has different dependencies than Cartopy. You will create a new environment.

1. Open Anaconda Navigator.
2. In the left panel, click on "Environments"
3. In the middle panel, click "Create" to create a new environment
4. Name this environment: ch2pyproj
5. Select Python version 3.7
6. Click "Create". This will take a few minutes
7. We need to install pyproj. In the right panel in the search field, type: pyproj
8. You will get the message "0 packages available matching pyproj" since pyproj is not installed.
9. In the right panel, change "Installed" to "Not installed"
10. pyproj now shows up. Click the check box next to "pyproj".
11. In the screen lower right corner, click "Apply"
12. Please wait while pyproj is collected and then click "Apply"

13. The pyproj library and any dependencies will be installed or updated. This may take a few minutes.
14. Click on "Home"
15. Install the console of your choice for the new environment. Click on "Install" under Jupyter Notebook, for example.
16. Click on "Launch"

### Example 4: Coordinate conversion

The notebook `ch2-3` contains this example. If you just launched Jupyter Notebook as indicated above, open the notebook. If you closed Anaconda, follow these steps:

1. Open Anaconda Navigator
2. Click on "Environments"
3. Choose "ch2pyproj"
4. Click "Home"
5. Launch Jupyter Notebook
6. Open the notebook ch2-3

We have a coordinate pair defined in decimal degrees of latitude and longitude. The longitude is  $-120.108^{\circ}$  and latitude is  $34.3611666^{\circ}$ . We want to make a coordinate conversion from latitude and longitude to Universal Transverse Mercator, where the point is defined by east and north coordinates in meters. To learn more about Universal Transverse Mercator (UTM), refer to (Snyder, 1987). In the code, we use the pyproj *Proj* function. We can only use *Proj* when making a coordinate conversion (i.e. the same datum):

```

1 # Import pyproj
2 from pyproj import Proj
3
4 # Construct the projection matrix

```

```

5 p = Proj(proj='utm',zone=10,ellps='WGS84', preserve_units=False)
6
7 # Apply the projection to the lat-long point
8 x,y = p(-120.108, 34.36116666)
9
10 print(f'x={x:9.3f}, y={y:11.3f}')

```

Output:

x=765975.641, y=3805993.134

This is the same location but only expressed in east and north coordinates in meters using the UTM coordinate reference system. The datum used is WGS84. We can convert the UTM coordinates back to latitude and longitude by adding two lines of code:

```

1 # Apply the inverse of the projection matrix
2 # to the point in UTM
3 lon,lat = p(x,y,inverse=True)
4 print(f'lon={lon:8.3f}, lat={lat:5.3f}')

```

Output:

lon=-120.108, lat=34.361

In the two cells of code above, we've truncated the output to only three decimal places, but we can confirm that the inverse conversion arrives at the original pair. Let's now try converting several points of different latitude and longitude using a collection of objects in Python, or tuples. Add the following code:

```

1 # three points in lat-long
2 lons = (-119.72,-118.40,-122.38)
3 lats = (36.77, 33.93, 37.62 )
4 # Apply the projection to the points
5 x1,y1 = p(lons, lats)
6 print(x1,y1)

```

Output:

(792763.8631257227, 925321.5373562573, 554714.3009414743)  
(4074377.6167697194, 3763936.9410883673, 4163835.3033114495)

Now, let's do a more advanced exercise: In the cartographic community, an easy way to communicate the coordinate reference system is to use the EPSG Geodetic Parameter Data set. Every coordinate reference system is given a code. This ensures that if someone uses UTM zone 10 North with datum WGS-84 and tells you UTM zone 10, that you do not accidentally use UTM zone 10 North with datum GRS80, for example.

Earlier in this exercise, we defined the UTM zone in the *Proj* function. Here, we will refer to the EPSG code. First, we will take a coordinate pair in longitude and latitude with datum WGS84 and convert it to EPSG:32667. Before proceeding, conduct a quick internet search on what EPSG:32667 means. This is important to understand what we will do next. The first part of the code is:

```

1 # silence warnings
2 import warnings
3 warnings.simplefilter('ignore')
4
5 # initial coordinate conversion
6 p = Proj(init='EPSG:32667', preserve_units=True)
7 # Apply the conversion to the lat-long point
8 x,y = p(-114.057222, 51.045)
9 print(f'x={x:9.3f}, y={y:11.3f} (feet)')

```

Output:  
x=-5851386.754, y=20320914.191 (feet)

Let's dissect this as the pyproj code looks quite a bit different. The first part of the function *Proj* calls EPSG:32667. If you looked up EPSG:32667 online, you found that it is for UTM zone 17 North, but the units are in feet. The default mode for *Proj* is “*preserve\_units=False*”, which forces any unit to meters. However, we want to see the units in US Survey Feet as the projection defines; therefore, we change the argument to *True*.

Now, suppose we want to see the output in meters. How will you amend the code? Here is what you should add:

```

1 # Print the coordinate pair in meters
2 p1 = Proj(init='EPSG:32667', preserve_units=False)
3 x1,y1 = p1(-114.057222, 51.045)
4 print(f'x={x1:9.3f}, y={y1:11.3f} (meters)')

```

Output:  
x=-1783506.250, y=6193827.033 (meters)

As discussed, you should change “`preserve_units=False`” and change the unit to be printed from “feet” to “meters”. Congratulations! You now have a good understanding of coordinate conversion.

## Example 5: Coordinate transformation

We learned earlier that we have a coordinate conversion where a coordinate pair is converted between coordinate reference systems with the same datum. In many instances, the coordinate reference system will also undergo a datum shift – this is a coordinate transformation.

This example is included in the notebook [ch2-4](#). We will use the `pyproj CRS` and `transform` functions. The `CRS` function defines the coordinate reference system while the `transform` function specifies which coordinate reference system is the original and which is the output. `CRS` has the same ability to refer directly to an EPSG code.

The input coordinates are in EPSG:4326, which is a commonly used code. It is the geographic coordinate system with datum WGS84. The output coordinates are EPSG:31984, which is for UTM zone 24 S with datum SIR-GAS2000.

```

1 # Import transform and CRS functions
2 from pyproj import transform
3 from pyproj import CRS
4
5 # input coordinates
6 c1 = CRS('EPSG:4326')
7 # coordinate pair
8 y1=-10.754283
9 x1=-39.866132
10 # output coordinates
11 c2 = CRS('EPSG:31984')
12 # Coordinate transformation
13 x2, y2 = transform(c1, c2, x1, y1)
14 print(f'x={x2:9.3f}, y={y2:11.3f}')

```

Output:  
x=2930179.850, y=5185231.716

## Example 6: Transforming several points at once

We have focused our examples on one coordinate pair at a time. The reality is that you will more often have several coordinates to transform at one time. The notebook [ch2-5](#) explains how to do this.

We have a csv file with two columns: longitude and latitude. Each coordinate pair is the center of a volcano around the world. There are 1,509 volcanoes in our dataset. The original coordinate reference system is geographic coordinates with datum WGS84. We want to make a coordinate transformation of these data points to World Mercator. It will take much too long to manually transform these coordinates as we have done in the notebooks before. Therefore, our new code will read the csv file and create a new csv file.

Check that the pathway of *in\_path* and *out\_path* matches the directory where the csv file is. In this example, the volcanoes file ([volc\\_longlat.csv](#)) is in the directory data/ch2-5. Run the code, you will know the process is finished when the message "process completed" and the time of execution are returned:

```

1 # Import libraries
2 import csv, pyproj
3 from functools import partial
4 from os import listdir, path
5
6 # Time the execution of the code
7 import time
8 start_time = time.time()
9
10 # Remove warnings
11 import warnings
12 warnings.simplefilter('ignore')
13
14 # Define some constants at the top
15
16 lon = 'LONGITUDE' #name of longitude field in original files
17 lat = 'LATITUDE' #name of latitude field in original files
18 f_x = 'x' #name of new x value field in new projected files
19 f_y = 'y' #name of new y value field in new projected files
20 in_path = path.abspath('../data/ch2-5') #input directory
21 out_path = path.abspath('../data/ch2-5') #output directory
22 input_projection = 'EPSG:4326' #WGS84
23 output_projection = 'EPSG:3395' #World Mercator
24
25 # Get CSVs to reproject from input path

```

```

26 files= [f for f in listdir(in_path) if f.endswith('.csv')]
27
28 # Define partial function for use later when reprojecting
29 project = partial(
30     pyproj.transform,
31     pyproj.Proj(init=input_projection),
32     pyproj.Proj(init=output_projection))
33
34 for csvfile in files:
35     # Open a writer, appending '_project' onto the base name
36     with open(path.join(out_path, csvfile.replace('.csv', '_project.csv')), 'w') as w:
37         # Open the reader
38         with open(path.join(in_path, csvfile), 'r') as r:
39             reader = csv.DictReader(r, dialect='excel')
40             # Create new fieldnames list from reader
41             # replacing lon and lat fields with
42             # x and y fields
43             fn = [x for x in reader.fieldnames]
44             fn[fn.index(lon)] = f_x
45             fn[fn.index(lat)] = f_y
46             writer = csv.DictWriter(w, fieldnames=fn)
47             # Write the output
48             writer.writeheader()
49             for row in reader:
50                 x,y = (float(row[lon]), float(row[lat]))
51                 try:
52                     # Add x,y keys and remove lon, lat keys
53                     # project point
54                     row[f_x], row[f_y] = project(x, y)
55                     row.pop(lon, None)
56                     row.pop(lat, None)
57                     writer.writerow(row)
58                 except Exception as e:
59                     # If coordinates are out of bounds,
60                     # skip row and print the error
61                     print (e)
62 print('process completed')
63 end_time = time.time()
64 print("it took {} seconds to run the code".format(end_time-
    start_time))

```

Output:

process completed

it took 55.04537224769592 seconds to run the code

It takes about 55 seconds to run this code in a standard computer. Check the

newly created csv file and notice that you now have a listing of coordinates in meters. The EPSG definition of the output coordinate reference system is listed under *output\_projection*. You can easily change this variable to another EPSG and rerun the script. Notice that the code is written so that every csv file in the directory will undergo a coordinate transformation.

## 2.6 Exercises

1. So far, you have worked with data sets that have been provided to you. It is an important skill to be able to find data sets online and to prepare them for use in your work.

The United States Geological Survey (USGS) Earthquake Hazards Program monitors, records, and maintains a global database of earthquake activity. The public can query the archive and download earthquake epicenter data. Go to the [Search Earthquake Catalog](#) page of the USGS. Using the Basic Options, download all of the 4.5+ earthquakes in the last year in the world. In the Output Options, choose a CSV format.

- (a) Modify the notebook [ch2-5](#) to transform the earthquake epicenters from latitude-longitude to World Mercator (or another map projection of your choice). Use this [pictographic](#) for further information. The datum of the earthquake epicenters is likely WGS84.
- (b) Plot the earthquake epicenters. Make sure to include the outline of the continents. *Hint:* Look at the notebook [ch2-2](#) for a starting point, and check the [Cartopy](#) website for examples of how to plot localities on a map.
- (c) Now modify your plot to color the earthquakes by depth (red are shallow and blue are deep earthquakes), and the size of the points by the earthquake magnitude.
- (d) Add the volcanoes from Example 6 ([volc\\_longlat.csv](#)) to the map (use triangles to indicate volcanoes). Do you see any correlation between the earthquake epicenters and the volcanoes?

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# Chapter 3

## Geologic features

### 3.1 Primitive objects: Lines and planes

The fundamental geometric features of geology are lines (e.g. a lineation or a fold axis) and planes (e.g. bedding or a foliation). A *line* is the element generated by a moving point. It can be straight or curved. We will treat straight lines here. A *plane* is a flat surface; a line joining two points on the plane lies wholly on its surface, and two intersecting lines on the plane define the plane. This is equivalent to say that three non-collinear points on the plane define the plane (this is the principle of the well-known three-point problem). Obviously, linear features can be curved (e.g. the intersection of bedding with irregular topography), and surfaces can be non-planar (e.g. bedding on a fold). However, even these more complex cases can be expressed as a collection of lines and planes.

### 3.2 Lines and planes orientations

Two important properties of lines and planes are location (chapter 2) and orientation (this chapter). Lines and planes orientations are measured with respect to the geographic north and the angle downward or upward from the horizontal. We refer to this coordinate system as the spherical coordinate system, and the measurements defining the lines or planes orientations as the spherical coordinates.

### 3.2.1 Planes: Strike and dip

A plane orientation can be defined by the angle a horizontal line on the plane makes with the geographic north, known as the *strike* and the maximum angle measured downward from the horizontal to the plane, known as the *dip* (Fig 3.1a). The strike is measured as an azimuth, an angle between 0 and  $360^\circ$  ( $0 = \text{north}$ ,  $90 = \text{east}$ ,  $180 = \text{south}$ ,  $270 = \text{west}$ ). The dip is an angle between 0 (horizontal plane) and  $90^\circ$  (vertical plane). The projection of the dip onto the horizontal is known as the *dip direction* and is always  $90^\circ$  from the strike. However, is the dip direction plus or minus  $90^\circ$  the given strike? Which end of the strike line should we use? To avoid ambiguities, we will use a format known as the *right hand rule* (RHR). In the RHR format, one gives the strike such that the dip direction is always the strike plus  $90^\circ$ , i.e. the dip direction is to the right of the strike (Fig. 3.1a).

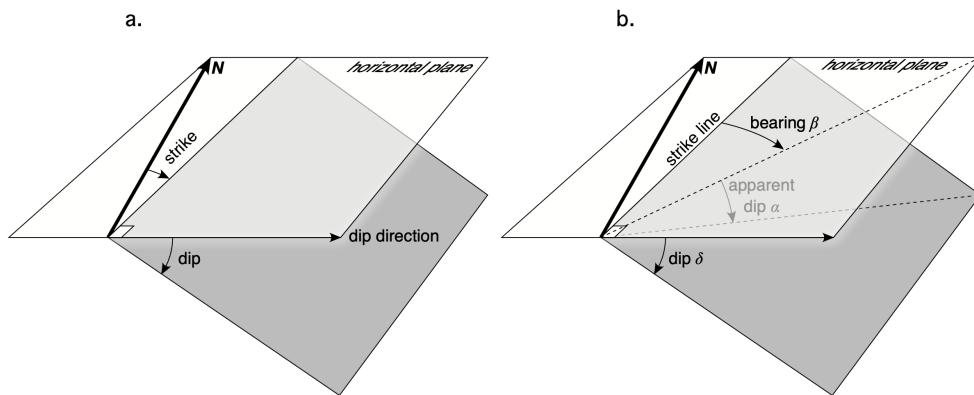


Figure 3.1: **a.** Strike and dip of a plane, **b.** Apparent dip of a plane. Modified from Allmendinger et al. (2012).

It is only along the dip direction that the true dip can be measured, any other direction will give a lower apparent dip (Fig. 3.1b). The relation between the dip ( $\delta$ ) and the apparent dip ( $\alpha$ ) is given by the equation:

$$\tan \alpha = \tan \delta \sin \beta \quad (3.1)$$

where  $\beta$  is the angle between the strike (horizontal) line on the plane and the vertical section on which the apparent dip is measured (Fig. 3.1b). This is also Eq. 1.3, which we plotted in problem 4 of chapter 1 (Fig. 1.1). You can quickly verify that it works by setting  $\beta = 0$  (a cross section parallel to

strike) which gives  $\alpha = 0$  (since  $\sin(0)$  is 0), and  $\beta = 90^\circ$  (a cross section perpendicular to strike) which gives  $\alpha = \delta$  (since  $\sin(90)$  is 1). This leads to a very important observation: *Any plane on a vertical section parallel to strike looks horizontal (even if it's dipping), and the true dip of the plane can only be observed on a vertical section perpendicular to strike.* This is why we should always visualize planes (bedding, faults, etc.) on cross sections perpendicular to strike.

### 3.2.2 Lines: Trend and plunge or rake

The orientation of a line is specified by the azimuth of the horizontal projection of the line, or *trend*, and the vertical angle measured downward from the horizontal to the line, or *plunge* (Fig. 3.2a). The plunge has a range between  $-90$  and  $90^\circ$ . Positive plunge indicates lines pointing downwards, and negative plunge lines pointing upwards. To measure the trend and plunge one must determine the vertical plane containing the line. This is quite difficult and often results in errors (section 3.2.5). For this reason, and if the line is on a plane, it is more convenient (and accurate) to measure the angle on the plane between the strike line and the line. This angle is known as the *rake* or *pitch* (Fig. 3.2b). To avoid any confusion, the rake should be always measured from the given strike and thus it varies between  $0$  and  $180^\circ$ .

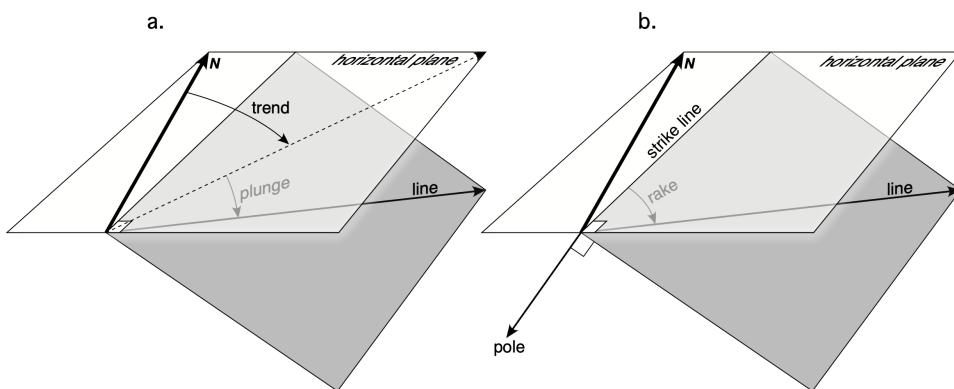


Figure 3.2: **a.** Trend and plunge of a line, **b.** Rake of a line and pole to a plane. Modified from Allmendinger et al. (2012).

### 3.2.3 The pole to the plane

Any plane can be uniquely represented by its downward normal. This line is known as the pole to the plane (Fig. 3.2b). If we use the RHR format, the orientation of the pole is given by:

$$\begin{aligned} \text{trend of pole} &= \text{strike of plane} - 90^\circ \\ \text{plunge of pole} &= 90^\circ - \text{dip of plane} \end{aligned} \quad (3.2)$$

The pole facilitates analyzing planes graphically and by computation. Our first function *Pole* computes the pole to a plane ( $k = 1$ ) or the plane from its pole ( $k = 0$ ). It is followed by the helper function *ZeroTwoPi* which makes sure azimuths are always between 0 and  $360^\circ$ . Notice that angles (*trd* and *plg*) should be entered in radians, and the plane must follow the RHR format.

```

1 import math
2 from ZeroTwoPi import ZeroTwoPi as ZeroTwoPi
3
4 def Pole(trd, plg, k):
5     """
6         Pole returns the pole to a plane or the plane from a pole
7
8         If k = 0, Pole returns the strike (trd1) and dip (plg1)
9         of a plane, given the trend (trd) and plunge (plg)
10        of its pole.
11
12        If k = 1, Pole returns the trend (trd1) and plunge (plg1)
13        of a pole, given the strike (trd) and dip (plg)
14        of its plane.
15
16        NOTE: Input/Output angles are in radians.
17        Input/Output strike and dip follow the RHR format
18
19        Pole uses function ZeroTwoPi
20        """
21
22        # Some constants
23        east = math.pi/2
24
25        # Eq. 3.2
26        # Calculate plane given its pole
27        if k == 0:
28            if plg >= 0:
                    plg1 = east - plg

```

```

29     trd1 = ZeroTwoPi(trd + east)
30     else: # Unusual case of pole pointing upwards
31         plg1 = east + plg
32         trd1 = ZeroTwoPi(trd - east)
33     # Else calculate pole given its plane
34     elif k == 1:
35         plg1 = east - plg;
36         trd1 = ZeroTwoPi (trd - east)
37
38     return trd1, plg1

```

```

1 import math
2
3 def ZeroTwoPi(a):
4     '''
5     This function makes sure input azimuth (a)
6     is within 0 to 2*pi (b)
7
8     NOTE: Azimuths a and b are input/output in radians
9
10    Python function translated from the Matlab function
11    ZeroTwoPi in Allmendinger et al. (2012)
12    '''
13
14    b=a
15    twopi = 2*math.pi
16    if b < 0:
17        b += twopi
18    elif b >= twopi:
19        b -= twopi
20
21    return b

```

### 3.2.4 Instruments used in the field

Traditionally, geologists use a geological compass/clinometer to measure the orientation of planes and lines in the field. Figure 3.3 shows four of the most common compasses used in geology: the Silva compass (Fig. 3.3a), the Brunton compass (Fig. 3.3b), the Krantz compass (Fig. 3.3c, a less expensive variant of the Freiberg compass), and the Brunton Geo compass (Fig. 3.3d). All these compasses have a magnetic needle that points to the magnetic north (N or white end of the needle), a horizontal level, and a clinometer (an instrument to measure vertical angles). The Silva compass has an azimuth scale that can be rotated to follow the magnetic needle, while

in the other three compasses the azimuth scale is fixed. This is why east-west (E-W) are in the right place in the Silva compass, while they are flipped in the other three compasses (Fig. 3.3a-d).

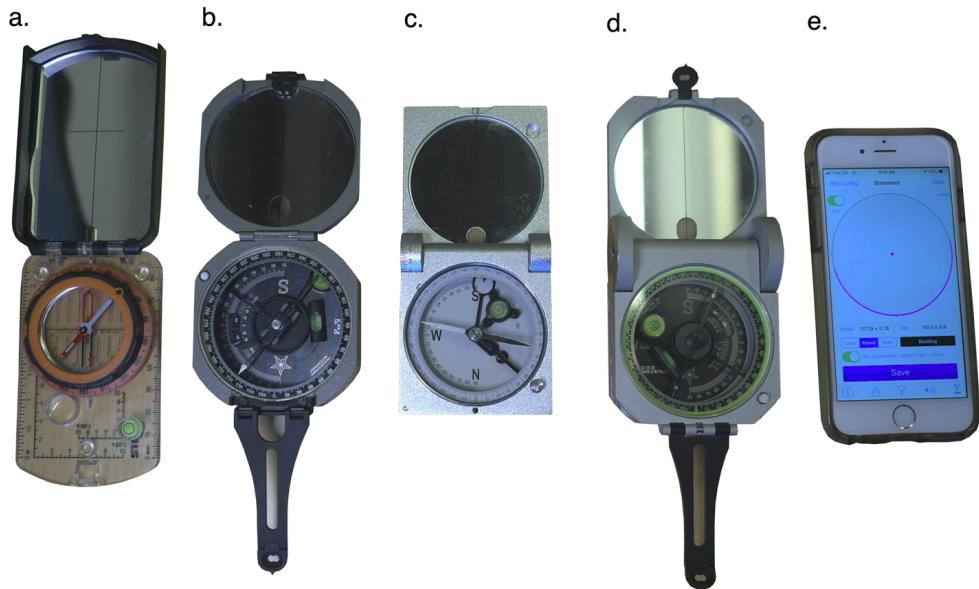


Figure 3.3: **a.** Silva, **b.** Brunton, **c.** Krantz, **d.** Brunton Geo, and **e.** Smartphone with Stereonet Mobile.

The Silva and Brunton compasses are designed to measure strike and dip through two measurements, while the Krantz compass measures dip direction and dip at once. The Brunton Geo compass can work either as a Brunton or Krantz compass, and it has higher precision than the other three compasses (it is also the most expensive). The use of these compasses is well explained in field geology books such as Compton (1985) and Coe (2010). For illustration, Figure 3.4 shows how strike and dip are measured with the Brunton compass (the same principles apply to the Silva compass). Notice that in this measurement, it is crucial to determine when the compass is horizontal (Fig. 3.4a). We will see that this can be a source of error (section 3.2.5).

These days, digital devices in the form of smartphone programs or apps (Fig. 3.3e) are slowly replacing the analog compasses. Smartphones contain instruments such as accelerometers, gyroscopes, and magnetometers, which enable apps such as [Stereonet Mobile](#) (Richard Allmendinger) or [Fieldmove Clino](#) (Petroleum Experts) to determine the exact orientation of the device in space. Measuring a plane or a line just requires placing the phone on the plane or along the line. Thus, one can capture a large number of measure-

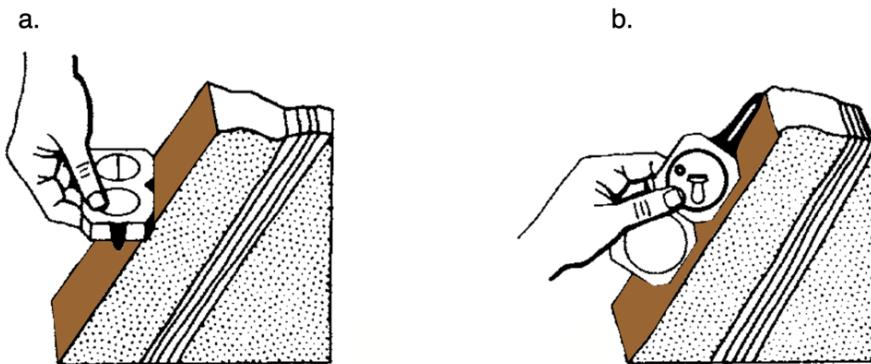


Figure 3.4: Measuring the **a.** strike and **b.** dip of a plane. Modified from Compton (1985).

ments quickly. However, smartphones are very sensitive to nearby magnetic fields and one can easily get spurious results (Novakova and Plavlis, 2017). Smartphones also have access to accurate geographic location (GPS, cell and wireless networks) as well as satellite imagery and raster data such as elevation. They can greatly facilitate mapping in the field.

### 3.2.5 Uncertainties in orientations

Geological planes and lines are irregular and therefore it is difficult to take exact measurements of them. Every plane or line measurement has an uncertainty (an error). There are different ways to try to reduce this error, either by placing a smooth planar object (e.g. a field notebook) on the plane or along the line, or by sighting the plane or line from the distance (Compton, 1985). Figure 3.5 illustrates the error associated to the strike and dip measurement of a plane. If the compass is not exactly horizontal then a direction other than the strike will be measured. The departure of the compass from the horizontal or operator error ( $\varepsilon_o$ ) will give a strike error ( $\varepsilon_s$ ).

From the three right-triangles and their corresponding equations in Figure 3.5, and by substituting the first two equations for  $w$  and  $l$  into the third equation for  $\varepsilon_s$ , one gets the following relation (Woodcock, 1976):

$$\sin \varepsilon_s = \frac{\tan \varepsilon_o}{\tan \delta} \quad (3.3)$$

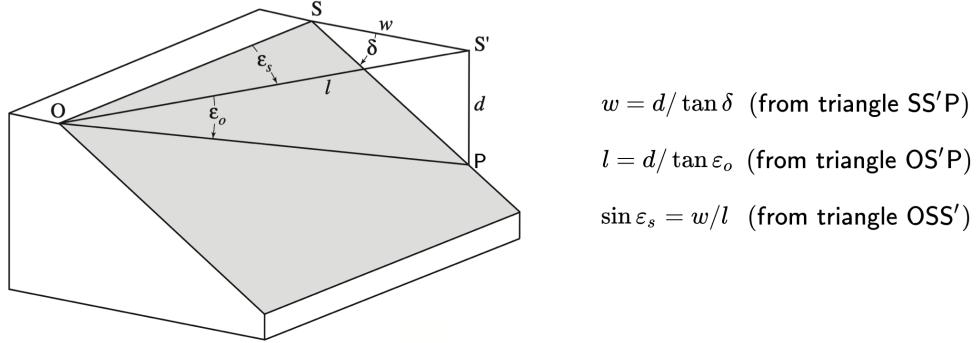


Figure 3.5: Geometrical relations for estimating the strike error  $\varepsilon_s$  from the operator error (or departure of the compass from the horizontal)  $\varepsilon_o$ . Modified from Ragan (2009).

where  $\delta$  is the dip angle of the plane. This equation is plotted in Figure 3.6 for dip angles  $\delta$  of 0 to 40° and operator errors  $\varepsilon_o$  of 1 to 5°. It is clear that the strike error  $\varepsilon_s$  increases with decreasing dip. For a gentle 5°dipping plane, an operator error  $\varepsilon_o$  of 2°(a compass just 2°off the horizontal) results in a strike error  $\varepsilon_s$  of about 24°! Thus, one should always be suspicious about the accuracy of strike and dip measurements, particularly if they are from gently dipping planes.

For line measurements, the situation is not better. When measuring the orientation of a line, it is common practice to align the compass in the direction of the horizontal projection of the line, which as anyone who has tried this in the field knows, is quite difficult. There will be an operator error and the measured trend  $\beta'$  will differ from the true trend  $\beta$  (Fig. 3.7a). The trend error  $\varepsilon_t$  ( $|\beta' - \beta|$ )in terms of the angle on the plane  $\varepsilon_o$  which the measured line makes with the true line, is given by the following equations (Woodcock, 1976):

$$\begin{aligned} \tan \varepsilon_t &= \frac{[\tan(r + \varepsilon_o) - \tan(r)] \cos \delta}{1 + [\tan(r + \varepsilon_o) \tan(r)] \cos^2 \delta} \quad \text{if } \beta' > \beta \\ & \qquad \qquad \qquad (3.4) \\ \tan \varepsilon_t &= \frac{[\tan(r) - \tan(r - \varepsilon_o)] \cos \delta}{1 + [\tan(r) \tan(r - \varepsilon_o)] \cos^2 \delta} \quad \text{if } \beta' < \beta \end{aligned}$$

where  $r$  is the rake of the line, and  $\delta$  is the dip of the plane (Fig. 3.7a).

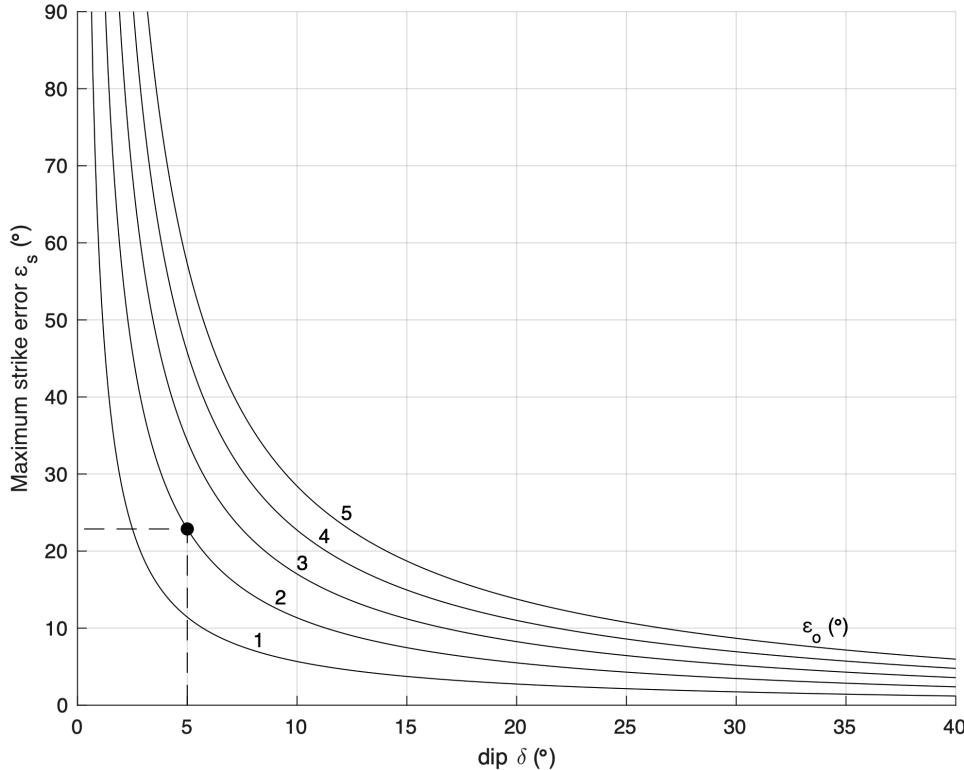


Figure 3.6: Strike error  $\varepsilon_s$  as a function of dip  $\delta$  for values of operator error  $\varepsilon_o$  of 1-5°. The [notebook](#) that produced this graph is available from the resource git repository.

These equations are plotted in Figure 3.7b-c for an  $\varepsilon_o$  of 3°. The trend error is greater for a measured line on the down-dip ( $\beta' > \beta$ ) side of the line (Fig. 3.7b), than for a measured line on the up-dip ( $\beta' < \beta$ ) side of the line (Fig. 3.7c). This means that repeated measurements will not be symmetrically distributed around the true trend  $\beta$ . Also for a given  $\varepsilon_o$ , the trend error  $\varepsilon_t$  increases with the dip  $\delta$  of the plane and the rake  $r$  of the line, i.e. a combination of a steep plane and a large rake may result in a large trend error.

Equations 3.3 and 3.4 allow determining the uncertainties associated to the measurement of planes and lines. As we will see in section 4.5, these errors propagate in any computation making use of these orientations.

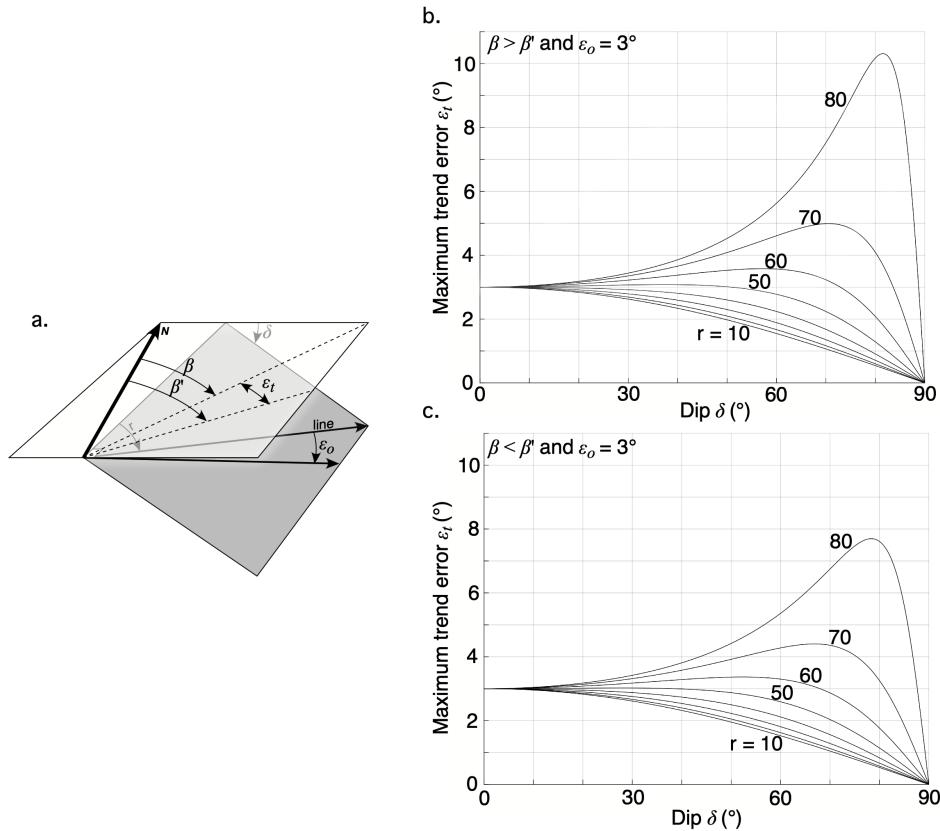


Figure 3.7: **a.** Geometrical relations for estimating the trend error  $\varepsilon_t$  from the rake  $r$  of the line, the dip  $\delta$  of the plane, and the angle on the plane  $\varepsilon_o$  between the measured and the true lines. Trend error as function of dip for **b.** a measured line on the down-dip side of the line, and **c.** a measured line on the up-dip side of the line. In b and c,  $\varepsilon_o$  is  $3^\circ$ . The notebooks that produced graphs **b** and **c** are available from the resource git repository.

### 3.3 Displaying geologic features

There are two fundamental ways geologists display geologic features: maps and stereonets. In maps, we are concerned about the location and orientation of the features, and the spatial relation of one feature to another. In stereonets, we are just concerned with the orientation of the features.

### 3.3.1 Maps

All maps are a projection of surface or subsurface geologic features onto a horizontal plane. In section 2.3, we looked at the different methods used to project data from the approximately spherical Earth to a flat surface, and the distortions associated to these methods. Geologic features (bedding, faults, the ground surface) are rarely flat, and therefore to display the spatial variation of their elevation (or depth) on maps, we use contours. A contour line is a line joining the points in the map area of equal value for a specific parameter. On a topographic map, for example, contour lines join points of equal elevation on the ground surface. Contour lines should not cross (unless very unusual circumstances) or disappear in the middle of the map (unless the contoured feature is intersected by another). If the difference in value between adjacent contours or contour interval is held constant throughout the map, the gradient (rate of change) of the parameter in a given direction is proportional to the spacing of the contour lines: high gradient is represented by closely spaced contours, and low gradient by widely spaced contours. This is expressed by the following relation:

$$\text{gradient} = \arctan \frac{\text{parameter change between contours}}{\text{map distance between contours}} \quad (3.5a)$$

For a topographic map, this relation becomes:

$$\text{slope angle} = \arctan \frac{\text{elevation change between contours}}{\text{map distance between contours}} \quad (3.5b)$$

which is why when choosing the walking path to a high ground area, you should look for the widely spaced contours (unless you are a climber or a goat).

Geologic features are rarely isolated, and they usually have different orientations, so we should expect them to intersect. The intersection of two non-parallel planes (e.g. bedding contacts) is a straight line. In chapter 4, we will see how to determine this type of intersection using vector operations. If one of the surfaces is not planar but is irregular, the intersection is a curved line which is more difficult to determine. One of the most fundamental mapping problem geology students are early confronted with is the intersection of a planar feature (e.g. bedding or a fault) with the irregular land surface.

This is elegantly summarized by the *Rule of V's* (Fig. 3.8).

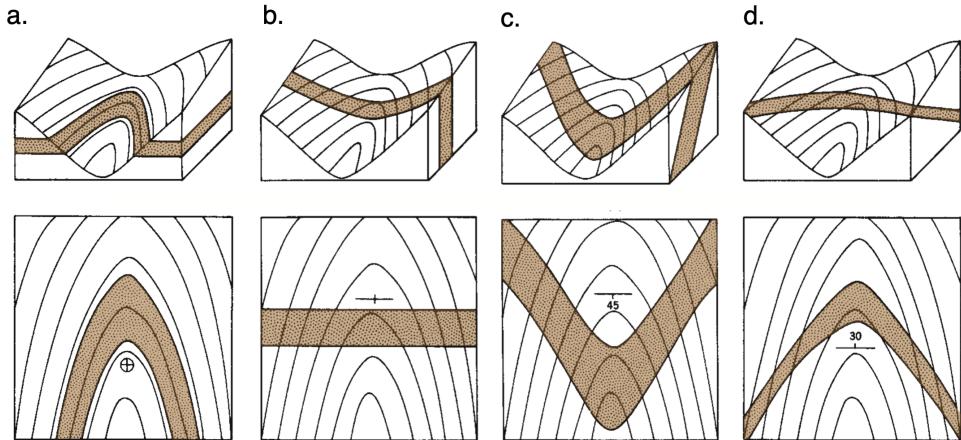


Figure 3.8: Outcrop pattern across a valley of **a.** Horizontal bed, **b.** Vertical bed, **c.** Bed dipping downstream, and **d.** Bed dipping upstream. Modified from Ragan (2009).

The Rule of V's says that when a planar contact crosses a valley, its outcrop pattern will V or curve in the direction that the contact is dipping, but only if the contact is steeper than the slope of the valley, which is normally the case (Fig. 3.8c-d). There are two exceptions: 1. If the contact is horizontal, its outcrop pattern will follow the topographic contours, which makes sense since the contours are the intersection of horizontal planes of different elevation with the ground (Fig. 3.8a), and 2. If the contact is vertical, its outcrop pattern across the valley is a straight line. Vertical planes *ignore* topography.

Determining the outcrop trace of a planar contact on irregular topography is not straightforward. Graphically, this problem involves making elevation contours on the planar contact. These are called structure contours. Then one should look at the locations where the structure contours of the contact have the same elevation than the topographic contours of the land surface. On these locations, the contact outcrops. Finally, one should join these locations with a line, to make the outcrop trace of the contact. Figure 3.9 illustrates this procedure for a plane dipping north and intersecting irregular topography. Notice how in the stream valleys, the outcrop trace of the plane curves to the north, clearly following the Rule of V's.

This graphical approach requires a great deal of patience and drawing skills. Later in section 5.2.2, we will see that if we know the plane's orientation and one outcrop location, it is possible to project the plane throughout the

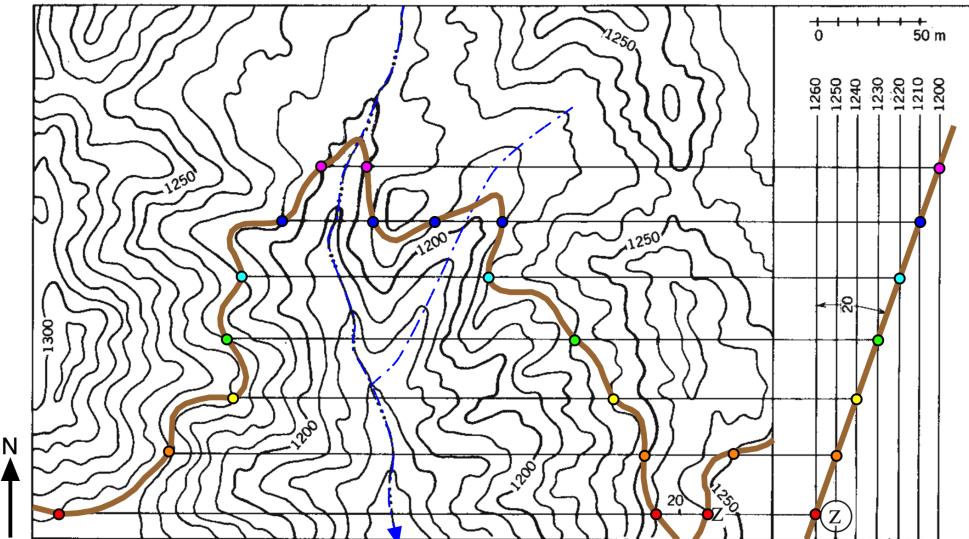


Figure 3.9: Outcrop trace of a plane dipping  $20^{\circ}\text{N}$ . The left figure is the map, and the right figure is a N-S cross section. Color points are the locations where the plane’s structure contours have the same elevation than the topographic contours. The line joining these points is the outcrop trace of the plane. Modified from Ragan (2009).

terrain using computation, provided we have a digital elevation model (DEM) of the terrain. This saves a lot of time and it’s a great way to quality control mapping, test different hypotheses, and take better decisions in the field.

### 3.3.2 Stereonets

Spherical projections can be used to represent the orientation of a plane or a line if the plane or line is positioned so that it passes through the center of the sphere. A plane will intersect the sphere along a great circle, and a line will pierce the sphere at a point (Fig. 3.10a). Obviously, it would be inconvenient to carry a sphere everywhere. Fortunately, it is possible to project the sphere onto a plane using, for example, an azimuthal projection (section 2.3).

A *stereonet* or stereographic projection is a special kind of azimuthal projection, where the point source or viewpoint lies on the surface of the sphere, and the projection plane passes through the center of the sphere. In a stere-

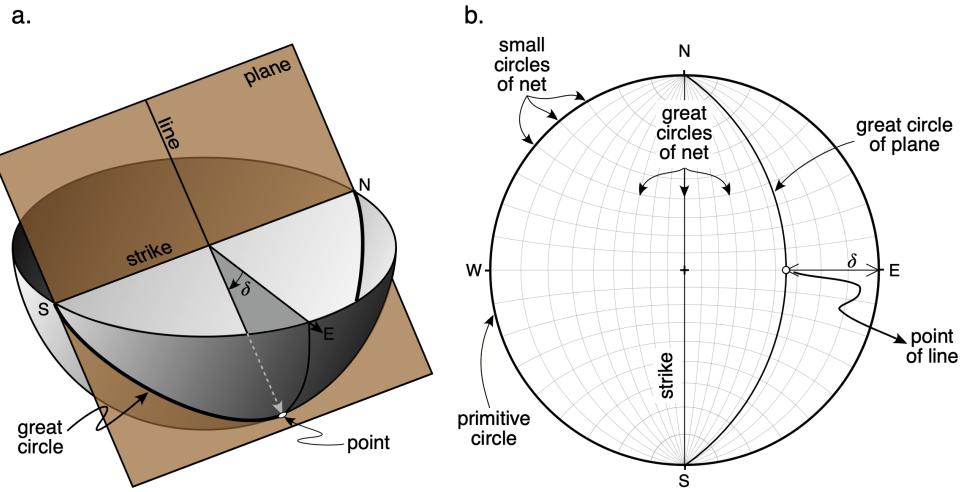


Figure 3.10: **a.** Plane and line intersecting the lower half of a sphere. The rake of the line is  $90^\circ$  and therefore its plunge is equal to the plane's dip  $\delta$ . **b.** Lower hemisphere stereographic projection of plane and line. Modified from Allmendiger et al. (2012) and Allmendiger (2019).

onet, the viewpoint is at the top of the sphere or zenith, the view direction is downwards, the projection plane is the equatorial plane dividing the sphere into lower and upper hemispheres, and the lower hemisphere (bowl in Fig. 3.10a) is projected. In the stereonet, the rim of the bowl is called the primitive circle and it represents a horizontal plane (Fig. 3.10b). A net consisting of great circles representing N-S striking,  $0-90^\circ$ E and W dipping planes, and small circles representing cones of N-S horizontal axis and  $0-90^\circ$ apical radius opening to the S and N, helps drawing any plane or line (Fig. 3.10b). Several books explain how to do this and solve orientation problems (including rotations) using the stereonet (e.g. Marshak and Mitra, 1988).

For our purpose, it is more important to know how this projection actually works. Figure 3.11a illustrates this on a vertical section passing through the center of the sphere. Any line from the zenith (the top of the sphere) pinches the equatorial plane at one point, and this is the location where the point plots in the stereonet. This is defined by the following equation:

$$x = R \tan \left( 45^\circ - \frac{\phi}{2} \right) \quad (3.6)$$

where  $x$  is the distance of the point from the center of the net,  $R$  is

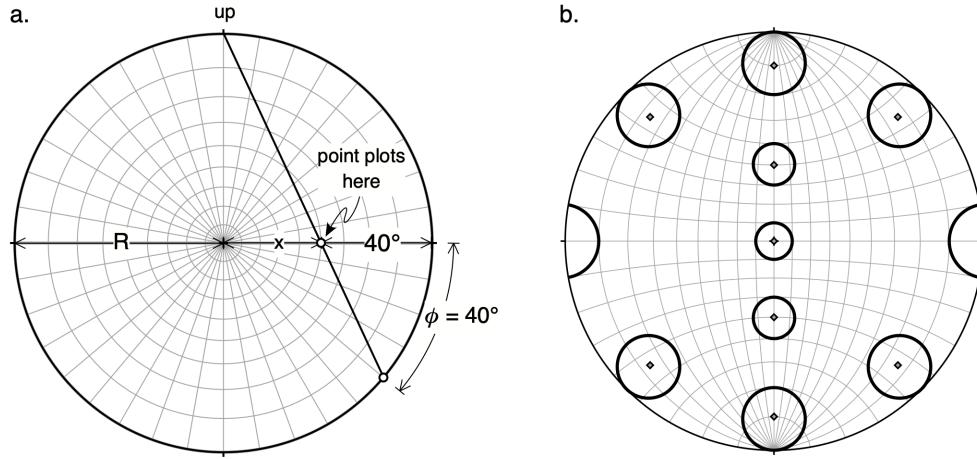


Figure 3.11: **a.** The equal angle stereonet illustrated on a vertical plane passing through the center of the sphere. **b.** Lower hemisphere equal angle projection of small circles of 10°radius but different axis orientations. Modified from Allmendinger et al. (2012).

the radius of the net, and  $\phi$  is the plunge of the line. This method preserves angles perfectly and thus, on the primitive circle, degrees are equally spaced, and a small circle will be a circle anywhere on the net (Fig. 3.11b). This is why this projection is called the equal angle or Wulff stereonet. However, the preservation of angles has a disadvantage: areas are distorted. Thus, for example, a 10°radius small circle will look smaller near the center of the net but larger near the edges (Fig. 3.11b). This poses a problem when trying to assess visually or graphically the density of points plotted on the net.

The equal area or Schmidt net (Fig. 3.12) overcomes this problem. Strictly speaking, this projection is not a stereographic projection because the projection plane is at the bottom of the sphere. The point of intersection of the line and the surface of the lower hemisphere, is projected to the horizontal plane at the lowest point of the sphere, along a circular arc centered at the bottom of the sphere. The  $x$  distance of the point is then scaled by a factor of  $\sqrt{2}$  to fit the radius  $R$  of the net (Fig. 3.12a). This is expressed by the following equation:

$$x = R\sqrt{2} \sin \left( 45^\circ - \frac{\phi}{2} \right) \quad (3.7)$$

The tradeoff is that angles are no longer preserved, and small circles are no

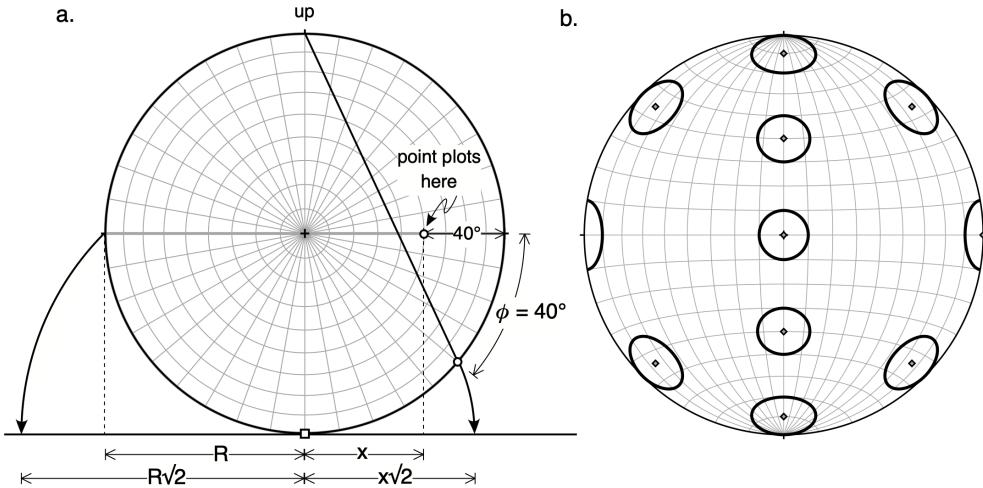


Figure 3.12: **a.** The equal area stereonet illustrated on a vertical plane passing through the center of the sphere. **b.** Lower hemisphere equal area projection of small circles of  $10^\circ$  radius but different axis orientations. Modified from Allmendinger et al. (2012).

longer true circles (Fig. 3.12b). The equal angle or Wulff net is used in problems where visualizing correctly angles on the net is important such as in crystallography and geography, while the equal area or Schmidt net is used in cases where analyzing the concentration of points on the net is important such as in structural analysis.

The function `StCoordLine` computes the coordinates of a line in an equal angle or an equal area net (equations 3.7 and 3.8). Notice that angles (`trd` and `plg`) should be entered in radians.

```

1 import math
2 from ZeroTwoPi import ZeroTwoPi as ZeroTwoPi
3
4 def StCoordLine(trd,plg,sttype):
5     ''
6     StCoordLine computes the coordinates of a line
7     in an equal angle or equal area stereonet of unit radius
8
9     trd = trend of line
10    plg = plunge of line
11    sttype = Stereonet type: 0 = equal angle, 1 = equal area
12    xp and yp = Coordinates of the line in the stereonet
13
14    NOTE: trend and plunge should be entered in radians

```

```

15     StCoordLine uses function ZeroTwoPi
16
17     Python function translated from the Matlab function
18     StCoordLine in Allmendinger et al. (2012)
19     ''
20
21     # Take care of negative plunges
22     if plg < 0:
23         trd = ZeroTwoPi(trd+math.pi)
24         plg = -plg
25
26     # Some constants
27     piS4 = math.pi/4
28     s2 = math.sqrt(2)
29     plgS2 = plg/2
30
31     # Equal angle stereonet, Eq. 3.6
32     if sttype == 0:
33         xp = math.tan(piS4 - plgS2)*math.sin(trd)
34         yp = math.tan(piS4 - plgS2)*math.cos(trd)
35     # Equal area stereonet, Eq. 3.7
36     elif sttype == 1:
37         xp = s2*math.sin(piS4 - plgS2)*math.sin(trd)
38         yp = s2*math.sin(piS4 - plgS2)*math.cos(trd)
39
40     return xp, yp

```

### 3.3.3 Plotting lines and poles in a stereonet

The notebook [ch3](#) illustrates the use of the *StCoordLine* and *Pole* functions to plot lines and poles to planes on an equal angle or an equal area stereonet. You will get the chance to practice more with these functions in section [3.4](#).

```

1 # Import libraries
2 import numpy as np
3 import matplotlib.pyplot as plt
4
5 # Import functions Pole and StCoordLine
6 import sys, os
7 sys.path.append(os.path.abspath('../functions'))
8 from Pole import Pole as Pole
9 from StCoordLine import StCoordLine as StCoordLine
10
11 # Plot the following four lines (trend and plunge)
12 # on an equal angle or equal area stereonet

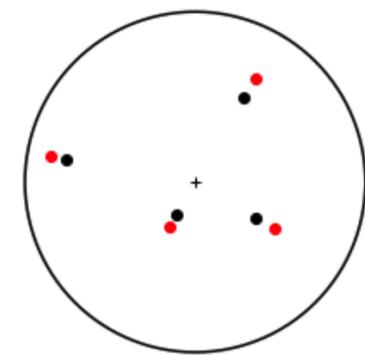
```

```

13 lines = np.array([[30, 30],[120, 45],[210, 65],[280, 15]])
14 pi = np.pi
15 linesr = lines * pi/180 # lines in radians
16
17 # Plot the primitive of the stereonet
18 r = 1; # unit radius
19 TH = np.arange(0,360,1)*pi/180
20 x = r * np.cos(TH)
21 y = r * np.sin(TH)
22 plt.plot(x,y,'k')
23 # Plot center of circle
24 plt.plot(0,0,'k+')
25 # Make axes equal and remove them
26 plt.axis('equal')
27 plt.axis('off')
28
29 # Find the coordinates of the lines in the
30 # equal angle or equal area stereonet
31 nrow, ncol = lines.shape
32 eqAngle = np.zeros((nrow, ncol))
33 eqArea = np.zeros((nrow, ncol))
34
35 for i in range(nrow):
36     # Equal angle coordinates
37     eqAngle[i,0], eqAngle[i,1] = StCoordLine(linesr[i,0],
38         linesr[i,1],0)
39     # Equal area coordinates
40     eqArea[i,0], eqArea[i,1] = StCoordLine(linesr[i,0],linesr
41         [i,1],1)
42
43 # Plot the lines
44 # Equal angle as black dots
45 plt.plot(eqAngle[:,0],eqAngle[:,1], 'ko')
46 # Equal area as red dots
47 plt.plot(eqArea[:,0],eqArea[:,1], 'ro');

```

Output:

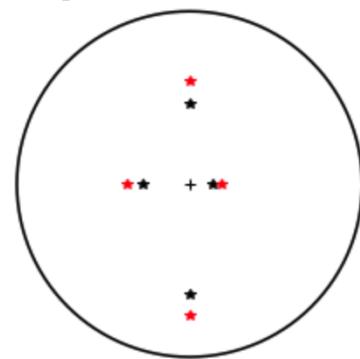


```

1 # Plot the following four planes (strike and dip, RHR)
2 # as poles on an equal angle or equal area stereonet
3 planes = np.array([[0, 30], [90, 50], [180, 15], [270, 65]])
4 planesr = planes * pi/180 # planes in radians
5
6 # Plot the primitive of the stereonet
7 plt.plot(x,y,'k')
8 # Plot center of circle
9 plt.plot(0,0,'k+')
10 # Make axes equal and remove them
11 plt.axis('equal')
12 plt.axis('off')
13
14 # Find the coordinates of the poles to the planes in the
15 # equal angle or equal area stereonet
16 for i in range(nrow):
17     # Compute pole of plane
18     trend, plunge = Pole(planestr[i,0], planestr[i,1],1)
19     # Equal angle coordinates
20     eqAngle[i,0], eqAngle[i,1] = StCoordLine(trend,plunge,0)
21     # Equal area coordinates
22     eqArea[i,0], eqArea[i,1] = StCoordLine(trend,plunge,1)
23
24 # Plot the poles
25 # Equal angle as black asterisks
26 plt.plot(eqAngle[:,0],eqAngle[:,1], 'k*')
27 # Equal area as red asterisks
28 plt.plot(eqArea[:,0],eqArea[:,1], 'r*');

```

Output:



### 3.4 Exercises

1. Modify the notebook that makes Fig. 3.6 to extend the range of dip  $\delta$  angles from 0 to 90° and the operator error  $\varepsilon_o$  from 1 to 10°.

2. Modify the notebooks that make Fig. 3.7 b and c for an  $\varepsilon_o$  of 5°.

3. You can draw a great circle on a stereonet by plotting closely spaced points along the great circle. These are lines on the plane. The following arrays contain the trend and plunge of lines on a plane of orientation 030/40 (strike and dip, RHR format):

trend = [30, 34, 38, 42, 46, 50, 54, 58, 63, 67, 72, 78, 83, 89, 95, 101, 107, 113, 120, 127, 133, 139, 145, 151, 157, 162, 168, 173, 177, 182, 186, 190, 194, 198, 202, 206, 210]

plunge = [0, 3, 6, 10, 13, 16, 19, 22, 24, 27, 29, 32, 34, 36, 37, 38, 39, 40, 40, 40, 39, 38, 37, 36, 34, 32, 29, 27, 24, 22, 19, 16, 13, 10, 6, 3, 0]

Plot these lines on an equal angle and an equal area stereonet. From the resulting great circle, can you guess how a plane of orientation 050/60 (RHR) would look like on the stereonet?

4. You can also draw a small circle on a stereonet by plotting closely spaced points along the small circle. These are lines on the conical surface. The following arrays contain the trend and plunge of lines on a small circle of axis 050/30 (trend and plunge) and radius 20°:

trend = [50, 53, 57, 60, 63, 66, 68, 70, 72, 73, 73, 73, 72, 70, 68, 64, 60, 55, 50, 45, 40, 36, 32, 30, 28, 27, 27, 27, 28, 30, 32, 34, 37, 40, 43, 47, 50]

plunge = [10, 10, 11, 12, 14, 16, 19, 22, 25, 28, 31, 35, 38, 41, 44, 47, 48, 50, 50, 50, 48, 47, 44, 41, 38, 35, 31, 28, 25, 22, 19, 16, 14, 12, 11, 10, 10]

Plot these lines on an equal angle and an equal area stereonet. What are the differences between the small circle in the equal angle and equal area stereonets?

5. The strike and dip arrays below contain the strike and dip (RHR format) of 50 bedding surfaces in a fold:

strike = [8, 22, 19, 33, 27, 37, 41, 47, 55, 40, 32, 55, 65, 68, 89, 79, 102, 105, 108, 122, 132, 136, 145, 159, 156, 164, 176, 169, 179, 173, 167, 160, 145, 148, 141, 125, 108, 92, 75, 57, 50, 39, 22, 10, 1, 9, 15, 16, 114, 78]

dip = [75, 79, 68, 72, 61, 46, 50, 67, 51, 66, 55, 42, 49, 58, 54, 45, 35, 49, 63, 45, 52, 66, 52, 59, 76, 64, 72, 83, 78, 88, 72, 81, 73, 62, 50, 63, 42, 48, 56, 62, 50, 65, 76, 87, 81, 68, 74, 83, 56, 37]

Plot the poles to these planes in an equal area stereonet. The resultant diagram is called a *point-, scatter-* or  $\pi-$  diagram. You can approximate a great circle through the poles. What is the approximate orientation of this great circle? What does the pole to this great circle represent?

## References

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# Chapter 4

## Coordinate systems and vectors

Strike and dip, and trend and plunge, are a convenient way to represent the orientation of planes and lines. However, it is difficult to handle these angles using computation. In this chapter, we will see how to convert linear features (lines and poles to planes) from spherical (trend and plunge) to Cartesian (direction cosines) coordinates, thus representing these features as vectors. This facilitates the analysis of planes and lines using linear algebra and computation, and it will allow us to solve a range of interesting problems using vector operations.

### 4.1 Coordinate systems

Any point or location in space can be represented by the coordinates of the point with respect to the three orthogonal axes of a Cartesian coordinate system. We will call the three axes of this coordinate system  $\mathbf{X}_1$ ,  $\mathbf{X}_2$  and  $\mathbf{X}_3$  (Fig. 4.1). In addition, we will follow a right-handed naming convention: If you hold your right hand so that your thumb points in the positive direction of the first axis  $\mathbf{X}_1$ , your other fingers should curl from the positive direction of the second axis  $\mathbf{X}_2$  toward the positive direction of the third axis  $\mathbf{X}_3$  (Fig. 4.1). Such a coordinate system is called a right-handed coordinate system.

In geosciences, we use mainly two types of right-handed coordinate systems: An east (**E**), north (**N**), up (**U**) coordinate system (Fig. 4.1a), and a north (**N**), east (**E**), down (**D**) coordinate system (Fig. 4.1b). The **ENU** coor-

dinate system is used in GIS and Geophysics when dealing with elevations (e.g. topography), while the **NED** coordinate system is used in Structural Geology where, by convention, angles measured downwards from the horizontal (e.g. plunge of a downward pointing line) are considered positive. In this chapter, we will use the **NED** coordinate system, but when dealing with topography and elevations, we will use the **ENU** coordinate system.

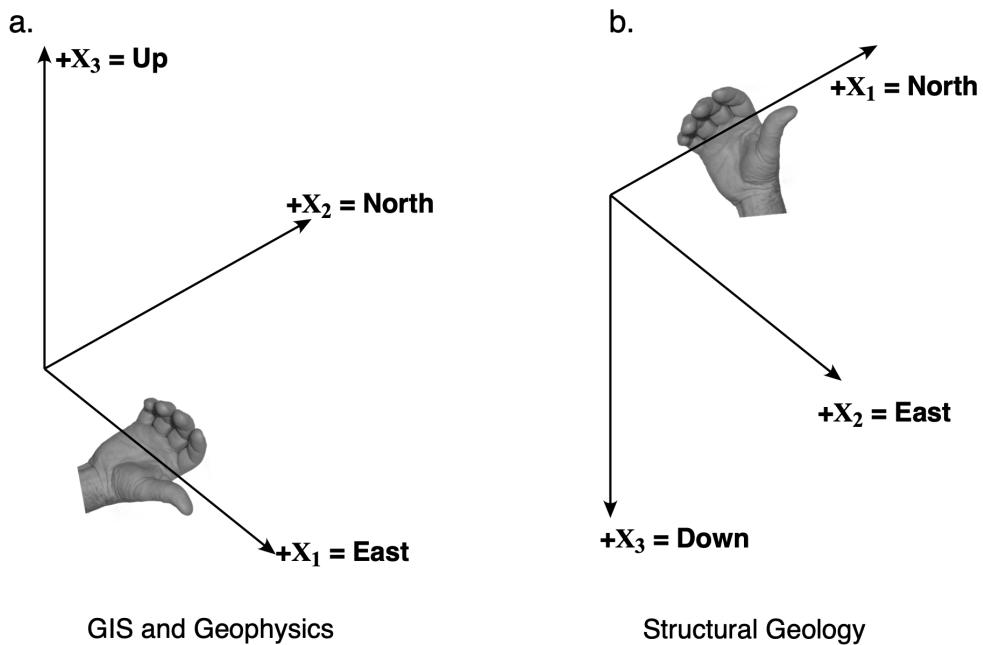


Figure 4.1: Right-handed Cartesian coordinate systems. **a.** The **ENU** coordinate system used when dealing with topography, and **b.** The **NED** coordinate system used in Structural Geology. Modified from Allmendinger et al. (2012).

## 4.2 Vectors

### 4.2.1 Vector components, magnitude, and unit vectors

A line from the origin of the Cartesian coordinate system to a point in space is the position *vector* of the point. A *vector* is an object that has both a magnitude and a direction. Displacement, velocity, force, acceleration, and poles to planes, are all vectors. A vector is defined by its three components

with respect to the axes of the Cartesian coordinate system; these are the projections of the vector onto the axes  $\mathbf{X}_1$ ,  $\mathbf{X}_2$  and  $\mathbf{X}_3$  (Fig. 4.2a).

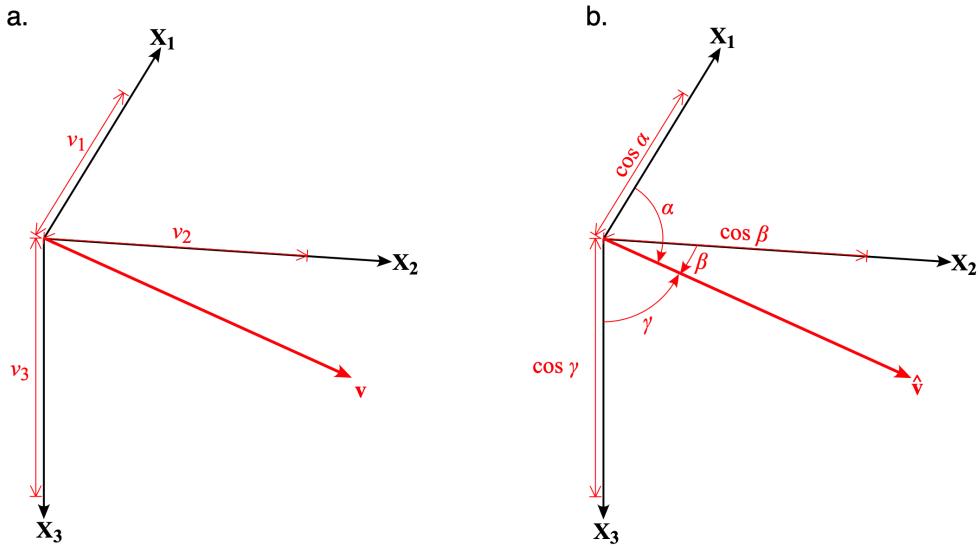


Figure 4.2: **a.** Components of a vector. **b.** Direction cosines of a unit vector.  
Modified from Allmendinger et al. (2012)

This is expressed by the following equation:

$$\mathbf{v} = [v_1, v_2, v_3] \quad (4.1)$$

We use lower capital letters to denote vectors. The magnitude (length) of a vector can be computed using Pythagoras' theorem:

$$v = (v_1^2 + v_2^2 + v_3^2)^{1/2} \quad (4.2)$$

The result is just a number, a scalar. We use regular, non-capital letters to denote scalars. If we divide each of the components of a vector by its magnitude, the result is a unit vector, a vector with the same orientation but with a magnitude (length) of one (Fig. 4.2b):

$$\hat{\mathbf{v}} = [v_1/v, v_2/v, v_3/v] \quad (4.3)$$

We use a hat to indicate unit vectors. There is a very interesting property of unit vectors; the components of a unit vector are the cosines of the angles the vector makes with the axes of the coordinate system (Fig. 4.2b):

$$\hat{\mathbf{v}} = [\cos \alpha, \cos \beta, \cos \gamma] \quad (4.4)$$

these are called the *direction cosines* of the vector. By convention,  $\cos \alpha$  is the direction cosine of the vector with respect to  $\mathbf{X}_1$ ,  $\cos \beta$  is the direction cosine of the vector with respect to  $\mathbf{X}_2$ , and  $\cos \gamma$  is the direction cosine of the vector with respect to  $\mathbf{X}_3$  (Fig. 4.2b).

In Python, we can use the NumPy *linalg.norm* function to compute the magnitude of a vector and convert it to a unit vector as illustrated in the following notebook [ch4-1](#):

```

1 # Import numpy
2 import numpy as np
3 # Import linear algebra functions
4 from numpy import linalg as la
5 # Make vector
6 v = np.array([1,2,3])
7 print('Vector: ', v)
8 # Magnitude of the vector
9 length = la.norm(v)
10 print('Magnitude of the vector: ', length)
11 # Unit vector
12 v_hat = v / length
13 print('Unit Vector: ', v_hat)
14 # Magnitude of unit vector
15 length = la.norm(v_hat)
16 print('Magnitude of the unit vector: ', length)

```

Output:

Vector: [1 2 3]

Magnitude of the vector: 3.7416573867739413

Unit Vector: [0.26726124 0.53452248 0.80178373]

Magnitude of the unit vector: 1.0

### 4.2.2 Vector operations

To multiply a scalar times a vector, just multiply each component of the vector by the scalar:

$$x\mathbf{v} = [xv_1, xv_2, xv_3] \quad (4.5)$$

This operation is useful, for example, to reverse the direction of the vector; just multiply the vector by -1. To add two vectors, just sum their components:

$$\mathbf{u} + \mathbf{v} = \mathbf{v} + \mathbf{u} = [u_1 + v_1, u_2 + v_2, u_3 + v_3] \quad (4.6)$$

Vector addition is commutative but vector subtraction is not. Vector addition and subtraction obey the parallelogram rule, whereby the resulting vector bisects the two vectors to be added or subtracted (Fig. 4.3a).

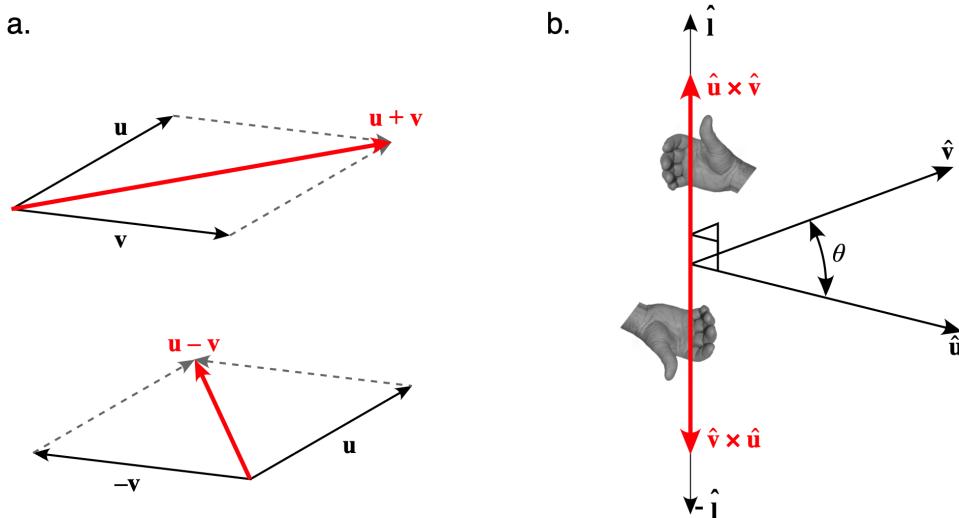


Figure 4.3: a. Vector addition and subtraction. b. Cross product of two unit vectors. Modified from Allmendinger et al. (2012).

There are two operations that are unique to vectors: the *dot product* and the *cross product*. The result of the dot product is a scalar and is equal to the magnitude of the first vector times the magnitude of the second vector times the cosine of the angle between the vectors:

$$\mathbf{u} \cdot \mathbf{v} = \mathbf{v} \cdot \mathbf{u} = uv \cos \theta = u_1 v_1 + u_2 v_2 + u_3 v_3 = u_i v_i \quad (4.7)$$

The dot product is commutative. If the two vectors are unit vectors, you can easily see that the dot product is:

$$\hat{\mathbf{u}} \cdot \hat{\mathbf{v}} = \cos \theta = u_1 v_1 + u_2 v_2 + u_3 v_3 \quad (4.8)$$

or in terms of the direction cosines of the vectors:

$$\hat{\mathbf{u}} \cdot \hat{\mathbf{v}} = \cos \theta = \cos \alpha_1 \cos \alpha_2 + \cos \beta_1 \cos \beta_2 + \cos \gamma_1 \cos \gamma_2 \quad (4.9)$$

which as we will see later, it is a great way to find the angle between two unit vectors.

The result of the cross product is another vector. This vector is perpendicular to the other two vectors, and has a magnitude that is equal to the product of the magnitude of each vector times the sine of the angle between the vectors:

$$\mathbf{u} \times \mathbf{v} = uv \sin \theta \hat{\mathbf{l}} = [u_2 v_3 - u_3 v_2, u_3 v_1 - u_1 v_3, u_1 v_2 - u_2 v_1] \quad (4.10)$$

The cross product is not commutative. If the vectors are unit vectors, the length of the resulting vector is equal to the sine of the angle between the vectors (Fig. 4.3b). The new vector obeys a right-hand rule; for  $\mathbf{u} \times \mathbf{v}$ , the fingers curl from  $\mathbf{u}$  towards  $\mathbf{v}$  and the thumb points in the direction of the resulting vector, and vice versa (Fig. 4.3b).

In Python, these operations are easy to perform using the NumPy library as shown in the following notebook [ch4-2](#):

```

1 # Import numpy
2 import numpy as np
3 # Make vectors
4 u = np.array([1,2,3])
5 v = np.array([3,2,1])
6 print('u = ', u)
7 print('v = ', v)
8 # Scalar multiplication of vector
9 sv = 3 * u
10 print('3 * u = ', sv)
11 # Sum of vectors
12 vsum = u + v
13 print('u + v = ', vsum)
14 # Dot product of vectors
15 dotp = np.dot(u,v)
16 print('u . v = ', dotp)
17 # Cross product of vectors
18 crossp = np.cross(u,v)
19 print('u x v = ', crossp)

```

Output:

$$\mathbf{u} = [1 \ 2 \ 3]$$

$$\mathbf{v} = [3 \ 2 \ 1]$$

$$3 * \mathbf{u} = [3 \ 6 \ 9]$$

$$\mathbf{u} + \mathbf{v} = [4 \ 4 \ 4]$$

$$\mathbf{u} \cdot \mathbf{v} = 10$$

$$\mathbf{u} \times \mathbf{v} = [-4 \ 8 \ -4]$$

## 4.3 Geologic features as vectors

We have now all the mathematical tools to represent geologic features as vectors. Since we are only interested in the orientation of these features, we will treat lines and poles to planes as unit vectors. We will also use the Structural Geology **NED** coordinate system.

### 4.3.1 From spherical to Cartesian coordinates

Figure 4.4 shows a line as a unit vector  $\hat{\mathbf{v}}$  in the **NED** coordinate system. Clearly, the angle that the line makes with the **D** axis is  $90^\circ$ - *plunge*, therefore:

$$\cos \gamma = \cos(90^\circ - \text{plunge}) = \sin(\text{plunge}) \quad (4.11a)$$

The horizontal projection of the line is  $\cos(\text{plunge})$  (Fig. 4.4).  $\cos \alpha$  and  $\cos \beta$  are just the **N** and **E** components of this horizontal line (Fig. 4.4):

$$\cos \alpha = \cos(\text{trend}) \cos(\text{plunge}) \quad (4.11b)$$

$$\cos \beta = \cos(90^\circ - \text{trend}) \cos(\text{plunge}) = \sin(\text{trend}) \cos(\text{plunge}) \quad (4.11c)$$

The magnitude and sign of the direction cosines tell us a lot about the orientation of the line (Fig. 4.5). A horizontal line ( $\text{plunge} = 0$ ) has  $\cos \gamma = 0$ , a downward pointing line ( $\text{plunge} > 0$ ) has  $+\cos \gamma$ , and if the line is vertical

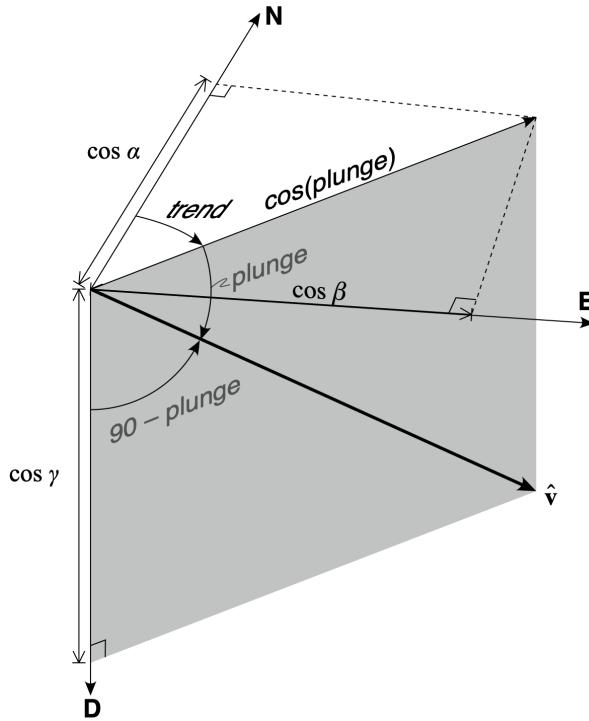


Figure 4.4: Diagram showing the relations between the trend and plunge and the direction cosines in the **NED** coordinate system. Gray plane is the vertical plane in which the plunge is measured. Modified from Allmendinger et al. (2012).

(plunge = 90°)  $\cos \gamma = 1$  and the other two direction cosines are 0. A horizontal or downward pointing line (plunge  $\geq 0$ ) has  $+\cos \alpha$  if it trends NE or NW (first or fourth quadrants), and  $+\cos \beta$  if it trends NE or SE (first or second quadrants). If the line trends N or S,  $\cos \beta = 0$ ; and if the line trends E or W,  $\cos \alpha = 0$ .

To determine the direction cosines of a pole to a plane, we just need to express the trend and plunge of the pole in terms of the strike and dip of the plane assuming a RHR format (Eq. 3.2), and use these in Eq. 4.11. The direction cosines of the pole to the plane are then:

$$\cos \alpha = \cos(\text{strike} - 90^\circ) \cos(90^\circ - \text{dip}) = \sin(\text{strike}) \sin(\text{dip}) \quad (4.12a)$$

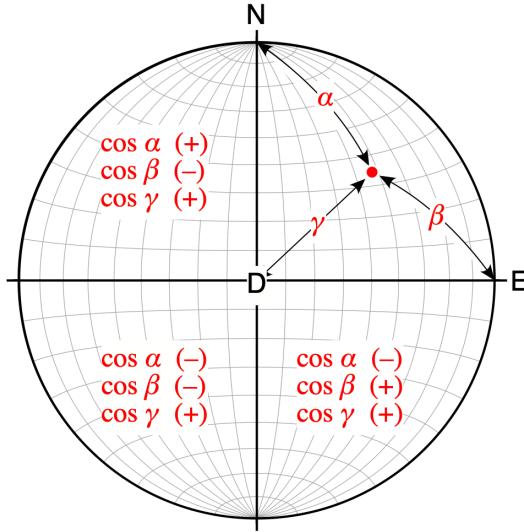


Figure 4.5: Lower hemisphere stereonet showing the sign of the direction cosines in each quadrant. In the NE quadrant, all three direction cosines are positive. Modified from Allmendinger et al. (2012).

$$\cos \beta = \sin(strike - 90^\circ) \cos(90^\circ - dip) = -\cos(strike) \sin(dip) \quad (4.12b)$$

$$\cos \gamma = \sin(90^\circ - dip) = \cos(dip) \quad (4.12c)$$

These equations are summarized in Table 4.1.

Axis	Direction cosines	Lines	Poles to planes (RHR format)
N	$\cos \alpha$	$\cos(trend) \cos(plunge)$	$\sin(strike) \sin(dip)$
E	$\cos \beta$	$\sin(trend) \cos(plunge)$	$-\cos(strike) \sin(dip)$
D	$\cos \gamma$	$\sin(plunge)$	$\cos(dip)$

Table 4.1: Conversion from spherical to Cartesian coordinates

The following function `SphToCart` converts a line ( $k = 0$ ) or a plane ( $k = 1$ ) from spherical to Cartesian coordinates. Notice that the angles ( $trd$  and  $plg$ ) should be entered in radians:

```

1 import math
2
3 def SphToCart(trd,plg,k):
4     '''
5         SphToCart converts from spherical to Cartesian coordinates
6
7         SphToCart(trd,plg,k) returns the north (cn),
8         east (ce), and down (cd) direction cosines of a line.
9
10        k: integer to tell whether the trend and plunge of a line
11            (k = 0) or strike and dip of a plane in right hand rule
12            (k = 1) are being sent in the trd and plg slots. In this
13            last case, the direction cosines of the pole to the plane
14            are returned
15
16        NOTE: Angles should be entered in radians
17
18        Python function translated from the Matlab function
19        SphToCart in Allmendinger et al. (2012)
20        '''
21
22        # If line (see Table 4.1)
23        if k == 0:
24            cn = math.cos(trd) * math.cos(plg)
25            ce = math.sin(trd) * math.cos(plg)
26            cd = math.sin(plg)
27        # Else pole to plane (see Table 4.1)
28        elif k == 1:
29            cn = math.sin(trd) * math.sin(plg)
30            ce = -math.cos(trd) * math.sin(plg)
31            cd = math.cos(plg)
32
33        return cn, ce, cd

```

### 4.3.2 From Cartesian to spherical coordinates

Converting from direction cosines (Cartesian coordinates) to trend and plunge (spherical coordinates) is a little less straightforward. The plunge is easy:

$$\text{plunge} = \sin^{-1}(\cos \gamma) \quad (4.13a)$$

The trend can be determined as follows:

$$\frac{\cos \beta}{\cos \alpha} = \frac{\sin(\text{trend}) \cos(\text{plunge})}{\cos(\text{trend}) \cos(\text{plunge})} = \tan(\text{trend})$$

or:

$$\text{trend} = \tan^{-1} \left( \frac{\cos \beta}{\cos \alpha} \right) \quad (4.13b)$$

The problem is that the trend varies from 0 and  $360^\circ$ . For the  $\tan^{-1}$  function, there are two possible angles between 0 and  $360^\circ$ . Which one should we use? The answer is to use the signs of the direction cosines to determine in which quadrant the trend lies within. By inspection of Figure 4.5, one can see that:

$$\text{trend} = \tan^{-1} \left( \frac{\cos \beta}{\cos \alpha} \right) \text{ if } \cos \alpha > 0 \quad (4.14a)$$

$$\text{trend} = 180^\circ + \tan^{-1} \left( \frac{\cos \beta}{\cos \alpha} \right) \text{ if } \cos \alpha < 0 \quad (4.14b)$$

One should also check for the special case of  $\cos \alpha = 0$ :

$$\text{trend} = 90^\circ \text{ if } (\cos \alpha = 0 \text{ and } \cos(\beta) \geq 0) \quad (4.14c)$$

$$\text{trend} = 270^\circ \text{ if } (\cos \alpha = 0 \text{ and } \cos(\beta) < 0) \quad (4.14d)$$

The following function *CartToSph* converts a line from Cartesian to spherical coordinates. Notice that the trend and plunge are returned in radians:

```

1 import math
2 from ZeroTwoPi import ZeroTwoPi as ZeroTwoPi
3
4 def CartToSph(cn, ce, cd):
5     """
6         CartToSph converts from Cartesian to spherical coordinates
7
8     CartToSph(cn,ce,cd) returns the trend (trd)
9     and plunge (plg) of a line for input north (cn),

```

```

10    east (ce), and down (cd) direction cosines
11
12    NOTE: Trend and plunge are returned in radians
13
14    CartToSph uses function ZeroTwoPi
15
16    Python function translated from the Matlab function
17    CartToSph in Allmendinger et al. (2012)
18    ...
19
20    pi = math.pi
21    # Plunge
22    plg = math.asin(cd) # Eq. 4.13a
23
24    # Trend: If north direction cosine is zero, trend
25    # is east or west. Choose which one by the sign of
26    # the east direction cosine
27    if cn == 0.0:
28        if ce < 0.0:
29            trd = 3.0/2.0*pi # Eq. 4.14d, trend is west
30        else:
31            trd = pi/2.0 # Eq. 4.14c, trend is east
32    # Else
33    else:
34        trd = math.atan(ce/cn) # Eq. 4.14a
35        if cn < 0.0:
36            # Add pi
37            trd = trd+pi # Eq. 4.14b
38        # Make sure trend is between 0 and 2*pi
39        trd = ZeroTwoPi(trd)
40
41    return trd, plg

```

## 4.4 Applications

### 4.4.1 Mean vector

An important problem in geosciences is to determine the average or mean vector that represents a group of lines. These lines can be for example poles to bedding, paleocurrent directions, paleomagnetic poles, or slip vectors on a fault surface. This problem can be solved using vector addition. The resultant vector  $\mathbf{r}$  of the sum of the  $N$  unit vectors representing the lines has components:

$$r_1 = \sum_{i=1}^N \alpha_i \quad r_2 = \sum_{i=1}^N \beta_i \quad r_3 = \sum_{i=1}^N \gamma_i \quad (4.15a)$$

where  $\alpha$ ,  $\beta$  and  $\gamma$  are the direction cosines of the unit vectors. The length of the resultant vector  $\mathbf{r}$  is:

$$r = \sqrt{r_1^2 + r_2^2 + r_3^2} \quad (4.15b)$$

and the direction cosines of the unit vector that is parallel to the mean of the individual vectors are:

$$\bar{\alpha} = \frac{r_1}{r} \quad \bar{\beta} = \frac{r_2}{r} \quad \bar{\gamma} = \frac{r_3}{r} \quad (4.15c)$$

These direction cosines define the orientation of the mean vector. A measure of how concentrated the individual vectors are or how representative the mean vector is, is given by the *mean resultant length*:

$$\bar{r} = \frac{r}{N} \quad \text{where} \quad 0 \leq \bar{r} \leq 1 \quad (4.15d)$$

The closer this value is to 1, the better the concentration. The function *CalcMV* calculates the mean vector for a series of lines. It also calculates the Fisher statistics for the mean vector (Fisher et al., 1987), which is the standard way to represent uncertainties in this analysis. Notice that *CalcMV* uses our two previous functions *SphToCart* and *CartToSph* to convert from spherical to Cartesian coordinates, and vice versa.

```

1 import math
2 from SphToCart import SphToCart as SphToCart
3 from CartToSph import CartToSph as CartToSph
4
5 def CalcMV(T,P):
6     """
7         CalcMV calculates the mean vector for a group of lines
8
9     CalcMV(T,P) calculates the trend (trd) and plunge (plg)
10    of the mean vector, its mean resultant length (Rave), and
11    Fisher statistics (concentration factor (conc), 99 (d99)

```

```

12 and 95 (d95) % uncertainty cones); for a series of lines
13 whose trends and plunges are stored in the arrays T and P
14
15 NOTE: Input/Output trends and plunges, as well as
16 uncertainty cones are in radians
17
18 CalcMV uses functions SphToCart and CartToSph
19
20 Python function translated from the Matlab function
21 CalcMV in Allmendinger et al. (2012)
22 '''
23 # Number of lines
24 nlines = len(T)
25
26 # Initialize the 3 direction cosines which contain the
27 # sums of the individual vectors
28 CNsum = 0.0
29 CEsum = 0.0
30 CDsum = 0.0
31
32 #Now add up all the individual vectors. Eq. 4.15a
33 for i in range(nlines):
34     cn,ce,cd = SphToCart(T[i],P[i],0)
35     CNsum += cn
36     CEsum += ce
37     CDsum += cd
38
39 # R is the length of the resultant vector and
40 # Rave is the mean resultant length. Eqs. 4.15b and d
41 R = math.sqrt(CNsum*CNsum + CEsum*CEsum + CDsum*CDsum)
42 Rave = R/nlines
43 # If Rave is lower than 0.1, the mean vector is
44 # insignificant, return error
45 if Rave < 0.1:
46     raise ValueError('Mean vector is insignificant')
47 #Else
48 else:
49     # Divide the resultant vector by its length to get
50     # the direction cosines of the unit vector
51     CNsum = CNsum/R
52     CEsum = CEsum/R
53     CDsum = CDsum/R
54     # Convert the mean vector to the lower hemisphere
55     if CDsum < 0.0:
56         CNsum = -CNsum
57         CEsum = -CEsum
58         CDsum = -CDsum
59     # Convert the mean vector to trend and plunge
60     trd, plg = CartToSph(CNsum,CEsum,CDsum)

```

```

61 # If there are enough measurements calculate the
62 # Fisher statistics (Fisher et al., 1987)
63 if R < nlines:
64     if nlines < 16:
65         afact = 1.0-(1.0/nlines)
66         conc = (nlines/(nlines-R))*afact**2
67     else:
68         conc = (nlines-1.0)/(nlines-R)
69     if Rave >= 0.65 and Rave < 1.0:
70         afact = 1.0/0.01
71         bfact = 1.0/(nlines-1.0)
72         d99 = math.acos(1.0-((nlines-R)/R)*(afact**bfact-1.0))
73         afact = 1.0/0.05
74         d95 = math.acos(1.0-((nlines-R)/R)*(afact**bfact-1.0))
75
76     return trd, plg, Rave, conc, d99, d95

```

The notebook [ch4-3](#) shows the solution to the mean vector problem in Ragan (2009, pp. 147-148), which involves finding the mean orientation of 10 poles to bedding:

```

1 # Import libraries
2 import numpy as np
3 import matplotlib.pyplot as plt
4
5 # Import functions StCoordLine and CalcMV
6 import sys, os
7 sys.path.append(os.path.abspath('../functions'))
8 from StCoordLine import StCoordLine as StCoordLine
9 from CalcMV import CalcMV as CalcMV
10
11 # Arrays T and P contain the trend (T)
12 # and plunge (P) of the 10 poles
13 T = np.array([206, 220, 204, 198, 200, 188, 192, 228, 236,
14             218])
15 P = np.array([32, 30, 46, 40, 20, 32, 54, 56, 36, 44])
16
17 # Convert T and P from degrees to radians
18 pi = np.pi
19 TR = T * pi/180
20 PR = P * pi/180
21
22 # Compute the mean vector and print orientation
23 # and mean resultant length
24 trd, plg, Rave, conc, d99, d95 = CalcMV(TR,PR)
25 print('Mean vector trend = {:.1f}, plunge {:.1f}'.format(trd
26             *180/pi,plg*180/pi))

```

```

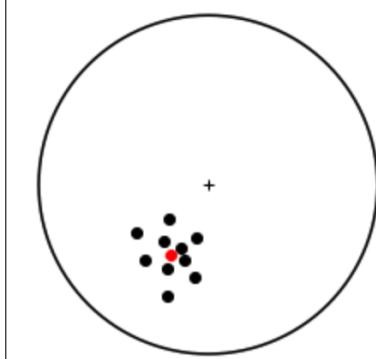
25 print('Mean resultant length = {:.3f}'.format(Rave))
26
27 # Plot the primitive of the stereonet
28 r = 1; # unit radius
29 TH = np.arange(0,360,1)*pi/180
30 x = r * np.cos(TH)
31 y = r * np.sin(TH)
32 plt.plot(x,y,'k')
33 # Plot center of circle
34 plt.plot(0,0,'k+')
35 # Make axes equal and remove them
36 plt.axis('equal')
37 plt.axis('off')
38
39 # Plot the poles as black points
40 # on an equal angle stereonet
41 npoles = len(T)
42 eqAngle = np.zeros((npoles, 2))
43 for i in range(npoles):
44     # Equal angle coordinates
45     eqAngle[i,0], eqAngle[i,1] = StCoordLine(TR[i],PR[i],0)
46 plt.plot(eqAngle[:,0],eqAngle[:,1], 'ko')
47
48 # Plot the mean vector as a red point
49 mvx, mvy = StCoordLine(trd,plg,0)
50 plt.plot(mvx,mvy, 'ro');

```

Output:

Mean vector trend = 208.6, plunge 40.0

Mean resultant length = 0.963



Notice that the mean resultant length is close to 1.0, so that the mean vector (red dot) is a representative orientation of the individual vectors (black dots).

### 4.4.2 Angles, intersections, and poles

Many interesting problems can be solved using the dot and cross product operations. The dot product can be used to find the angle between two lines or planes, while the cross product can be used to find a plane from two lines or the intersection of two planes. Table 4.2 lists some problems that can be solved using these operations.

Problem	Solution
Angle between two lines	arccos of dot product between lines
Angle between two planes	supplement of arccos of dot product between poles to planes
Intersection of two planes	Cross product of poles to planes
Plane containing two lines	Pole to plane is cross product of lines
Apparent dip of plane	Intersection of plane and vertical section of a given orientation
Plane from two apparent dips	Plane containing the two apparent dips (lines)

Table 4.2: Some problems that can be solved using the dot and cross product operations.

The function `Angles` computes the angle between two lines (`ans0 = 'l'`), the angle between two planes (`ans0 = 'p'`), the plane from two lines (`ans0 = 'a'`), or the intersection of two planes (`ans0 = 'i'`).

```

1 import math
2 from SphToCart import SphToCart as SphToCart
3 from CartToSph import CartToSph as CartToSph
4 from Pole import Pole as Pole
5
6 def Angles(trd1, plg1, trd2, plg2, ans0):
7     """
8         Angles calculates the angles between two lines,
9         between two planes, the line which is the intersection
10        of two planes, or the plane containing two apparent dips
11
12        Angles(trd1,plg1,trd2,plg2,ans0) operates on
13        two lines or planes with trend/plunge or
14        strike/dip equal to trd1/plg1 and trd2/plg2
15
16        ans0 is a character that tells the function what
17        to calculate:

```

```

18
19     ans0 = 'a' -> plane from two apparent dips
20     ans0 = 'l' -> the angle between two lines
21
22     In the above two cases, the user sends the trend
23     and plunge of two lines
24
25     ans0 = 'i' -> the intersection of two planes
26     ans0 = 'p' -> the angle between two planes
27
28     In the above two cases the user sends the strike
29     and dip of two planes in RHR format
30
31 NOTE: Input/Output angles are in radians
32
33 Angles uses functions SphToCart, CartToSph and Pole
34
35 Python function translated from the Matlab function
36 Angles in Allmendinger et al. (2012)
37 '''
38 # If planes have been entered
39 if ans0 == 'i' or ans0 == 'p':
40     k = 1
41 # Else if lines have been entered
42 elif ans0 == 'a' or ans0 == 'l':
43     k = 0
44
45 # Calculate the direction cosines of the lines
46 # or poles to planes
47 cn1, ce1, cd1 = SphToCart(trd1, plg1, k)
48 cn2, ce2, cd2 = SphToCart(trd2, plg2, k)
49
50 # If angle between 2 lines or between
51 # the poles to 2 planes
52 if ans0 == 'l' or ans0 == 'p':
53     # Use dot product
54     ans1 = math.acos(cn1*cn2 + ce1*ce2 + cd1*cd2)
55     ans2 = math.pi - ans1
56
57 # If intersection of two planes or pole to
58 # a plane containing two apparent dips
59 if ans0 == 'a' or ans0 == 'i':
60     # If the 2 planes or lines are parallel
61     # return an error
62     if trd1 == trd2 and plg1 == plg2:
63         raise ValueError('Error: lines or planes are parallel')
64     # Else use cross product
65     else:
66         cn = ce1*cd2 - cd1*ce2

```

```

67     ce = cd1*cn2 - cn1*cd2
68     cd = cn1*ce2 - ce1*cn2
69     #Make sure the vector points downe
70     if cd < 0.0:
71         cn = -cn
72         ce = -ce
73         cd = -cd
74     # Convert vector to unit vector
75     r = math.sqrt(cn*cn+ce*ce+cd*cd)
76     # Calculate line of intersection or pole to plane
77     trd, plg = CartToSph(cn/r,ce/r,cd/r)
78     # If intersection of two planes
79     if ans0 == 'i':
80         ans1 = trd
81         ans2 = plg
82     # Else if plane containing two dips,
83     # calculate plane from its pole
84     elif ans0 == 'a':
85         ans1, ans2 = Pole(trd,plg,0)
86
87     return ans1, ans2

```

The notebook [ch4\\_4](#) illustrates the use of the function *Angles* to solve several problems. Let's start with the following problem from Leyshon and Lisle (1996): Two limbs of a chevron fold (A and B) have orientations (RHR) as follows: Limb A = 120/40, Limb B = 250/60. Determine: (a) the trend and plunge of the hinge line of the fold, (b) the rake of the hinge line in limb A, (c) the rake of the hinge line in limb B.

```

1 import math
2 pi = math.pi
3
4 # Import function Angles
5 import sys, os
6 sys.path.append(os.path.abspath('../functions'))
7 from Angles import Angles as Angles
8
9 # Strike and dip of the limbs in radians
10 str1 = 120 * pi/180 # SW dipping limb
11 dip1 = 40 * pi/180
12 str2 = 250 * pi/180 # NE dipping limb
13 dip2 = 60 * pi/180
14
15 # (a) Chevron folds have planar limbs. The hinge
16 # of the fold is the intersection of the limbs
17 htrd, hplg = Angles(str1,dip1,str2,dip2,'i')

```

```

18 print('Hinge trend = {:.1f}, plunge {:.1f}'.format(htrd*180/
19   pi,hplg*180/pi))
20
21 # The rake of the hinge on either limb is the angle
22 # between the hinge and the strike line on the limb.
23 # This line is horizontal and has plunge = 0
24 plg = 0
25
26 # (b) For the SW dipping limb
27 ang1, ang2 = Angles(str1,plg,htrd,hplg,'l')
28 print('Rake of hinge in SW dipping limb = {:.1f}'.format(ang1
29   *180/pi))
30
31 # (c) And for the NE dipping limb
32 ang1, ang2 = Angles(str2,plg,htrd,hplg,'l')
33 print('Rake of hinge in NE dipping limb = {:.1f}'.format(ang1
34   *180/pi))

```

Output:

Hinge trend = 265.8, plunge 25.3  
 Rake of hinge in SW dipping limb = 138.4  
 Rake of hinge in NE dipping limb = 29.5

Let's do another problem from the same book: A quarry has two walls, one trending  $002^{\circ}$  and the other  $135^{\circ}$ . The apparent dip of bedding on the faces are  $40^{\circ}\text{N}$  and  $30^{\circ}\text{SE}$  respectively. Calculate the strike and dip of bedding.

```

1 # The apparent dips are just two lines on bedding
2 # These lines have orientations:
3 trd1 = 2 * pi/180
4 plg1 = 40 * pi/180
5 trd2 = 135 * pi/180
6 plg2 = 30 * pi/180
7
8 # Calculate bedding from these two apparent dips
9 strike, dip = Angles(trd1,plg1,trd2,plg2,'a')
10 print('Bedding strike = {:.1f}, dip {:.1f}'.format(strike
11   *180/pi,dip*180/pi))

```

Output:

Bedding strike = 333.9, dip 60.7

And the final problem also from the same book: Slickenside lineations trending  $074^\circ$  occur on a fault with orientation  $300/50$  (RHR). Determine the plunge of these lineations and their rake in the plane of the fault.

```

1 # The lineation on the fault is just the intersection
2 # of a vertical plane with a strike equal to
3 # the trend of the lineation, and the fault
4 str1 = 74 * pi/180
5 dip1 = 90 * pi/180
6 str2 = 300 * pi/180
7 dip2 = 50 * pi/180
8
9 # Find the intersection of these two planes which is
10 # the lineation on the fault
11 ltrd, lplg = Angles(str1,dip1,str2,dip2,'i')
12 print('Slickensides trend = {:.1f}, plunge {:.1f}'.format(
    ltrd*pi/180/pi,lplg*pi/180/pi))
13
14 # And the rake of this lineation is the angle
15 # between the lineation and the strike line on the fault
16 plg = 0
17 ang1, ang2 = Angles(str2,plg,ltrd,lplg,'l')
18 print('Rake of slickensides = {:.1f}'.format(ang1*pi/180/pi))

```

Output:

Slickensides trend = 74.0, plunge 40.6

Rake of slickensides = 121.8

There are many interesting problems you can solve using the function *Angles*. You will find more problems in section 4.6.

### 4.4.3 Three point problem

The three point problem is a fundamental problem in geology. It is based on the fact that three non-collinear points on a plane define the orientation of the plane. The graphical solution to this problem is introduced early in the Geosciences Bachelor. It involves finding the strike line (a line connecting two points of equal elevation) on the plane, and the dip from two strike lines (two structure contours) on the plane.

However, there is an easier and more accurate solution to this problem using linear algebra: The three points on the plane define two lines, and the cross product between these lines is parallel to the pole to the plane, from which the orientation of the plane can be estimated. The function *ThreePoint* computes the strike and dip of plane from the east (**E**), north (**N**), and up (**U**) coordinates of three points on the plane:

```

1 import numpy as np
2 from numpy import linalg as la
3 from CartToSph import CartToSph as CartToSph
4 from Pole import Pole as Pole
5
6 def ThreePoint(p1,p2,p3):
7     """
8         ThreePoint calculates the strike (strike) and dip (dip)
9         of a plane given the east (E), north (N), and up (U)
10        coordinates of three non-collinear points on the plane
11
12    p1, p2 and p3 are 1 x 3 arrays defining the location
13    of the points in an ENU coordinate system. For each one
14    of these arrays the first entry is the E coordinate,
15    the second entry the N coordinate, and the third entry
16    the U coordinate
17
18    NOTE: strike and dip are returned in radians and they
19    follow the right-hand rule format
20
21    ThreePoint uses functions CartToSph and Pole
22    """
23
24    # make vectors v (p1 - p3) and u (p2 - p3)
25    v = p1 - p3
26    u = p2 - p3
27
28    # take the cross product of v and u
29    vcu = np.cross(v,u)
30
31    # make this vector a unit vector
32    mvcu = la.norm(vcu) # magnitude of the vector
33    uvcu = vcu/mvcu # unit vector
34
35    # make the pole vector in NED coordinates
36    p = [uvcu[1], uvcu[0], -uvcu[2]]
37
38    # Make pole point downwards
39    if p[2] < 0:
40        p = [-elem for elem in p]
41
42    # find the trend and plunge of the pole

```

```

42     trd, plg = CartToSph(p[0], p[1], p[2])
43
44     # find strike and dip of plane
45     strike, dip = Pole(trd, plg, 0)
46
47     return strike, dip

```

Let's use this function in the following example. The geologic map in Fig. 4.6 shows a sequence of sedimentary units dipping south (you can see this by the outcrop V in the valley). Points 1, 2 and 3 are located on the base of unit S and their **ENU** coordinates are:

point1 = [509, 2041, 400]

point2 = [1323, 2362, 500]

point3 = [2003, 2913, 700]

Calculate the strike and dip of the plane. The notebook [ch4-5](#) shows the solution to this problem:

```

1 import numpy as np
2 pi = np.pi
3
4 # Import function ThreePoint
5 import sys, os
6 sys.path.append(os.path.abspath('../functions'))
7 from ThreePoint import ThreePoint as ThreePoint
8
9 # ENU coordinates of the three points
10 p1 = np.array([509, 2041, 400])
11 p2 = np.array([1323, 2362, 500])
12 p3 = np.array([2003, 2913, 700])
13
14 # Compute the orientation of the plane
15 strike, dip = ThreePoint(p1,p2,p3)
16 print('Plane strike = {:.1f}, dip = {:.1f}'.format(strike
    *180/pi,dip*180/pi))

```

Output:

Plane strike = 84.5, dip = 22.5

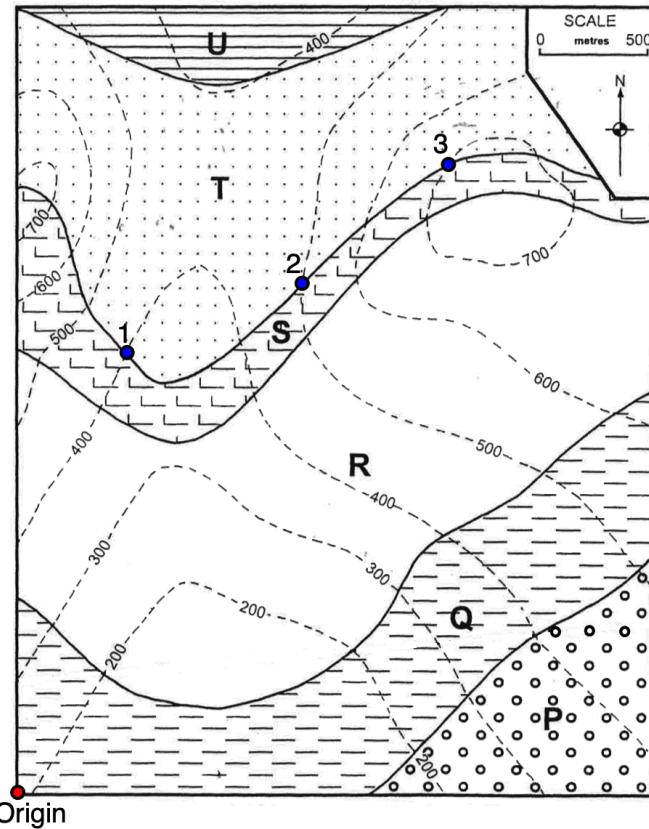


Figure 4.6: Geologic map of sedimentary units dipping south (Bennison et al., 2011). Points 1 to 3 on the base of unit S are used to estimate the orientation of bedding. Notice that the origin is at the map lower left corner.

## 4.5 Uncertainties

As we saw in section 3.2.5, strike and dip or trend and plunge measurements have errors (Figs. 3.6 and 3.7), and these errors propagate in any computation making use of these angles. Also, as accurate as GPS and elevation measurements are today, they also have errors. Thus, functions *Angles* and *ThreePoint* lack this important element of uncertainty.

Suppose that  $x, \dots, z$  are measured with uncertainties (or errors)  $\delta x, \dots, \delta z$  and the measured values are used to compute the function  $q(x, \dots, z)$ . If the uncertainties in  $x, \dots, z$  are independent and random, then the uncertainty (or error) in  $q$  is (Taylor, 1997):

$$\delta q = \sqrt{\left(\frac{\partial q}{\partial x}\delta x\right)^2 + \dots + \left(\frac{\partial q}{\partial z}\delta z\right)^2} \quad (4.16)$$

This formula is easy to calculate for a few operations, but it can become quite complex for a long chain of operations. Fortunately, there is a Python package that handles calculations with numbers with uncertainties. This package is called *uncertainties* and it was developed by Eric Lebigot. You can find details about the package as well as instructions for installing it in the [uncertainties](#) website. If you have the Python *pip* package-management system, you can install the uncertainties package by entering in a terminal:

```
1 pip install --upgrade uncertainties
```

After this, you can use the uncertainties package in your functions. The functions *AnglesU* and *ThreePointU* in the resource git repository, are the corresponding *Angles* and *ThreePoint* functions with uncertainties. We don't list these functions here, but rather illustrate their use in the following notebook [ch4-6](#).

In the first problem on page 64, the uncertainty in strike is  $4^\circ$  and in dip is  $2^\circ$ . What is the uncertainty in the hinge orientation and its rake on the limbs? This problem can be solved as follows:

```
1 # Import libraries
2 import numpy as np
3 pi = np.pi
4 import uncertainties as unc
5
6 # Import function AnglesU
7 import sys, os
8 sys.path.append(os.path.abspath('../functions'))
9 from AnglesU import AnglesU as AnglesU
10
11 # Strike and dip of the limbs in radians
12 str1 = 120 * pi/180 # SW dipping limb
13 dip1 = 40 * pi/180
14 str2 = 250 * pi/180 # NE dipping limb
15 dip2 = 60 * pi/180
16
17 # Errors in radians
18 ustr = 4 * pi/180 # Error in strike
```

```

19 udip = 2 * pi/180 # Error in dip
20
21 # Create the input values with uncertainties
22 str1 = unc.ufloat(str1, ustr) # str1 = str1 +/-ustr
23 dip1 = unc.ufloat(dip1, udip) # dip1 = dip1 +/-udip
24 str2 = unc.ufloat(str2, ustr) # str2 = str2 +/-ustr
25 dip2 = unc.ufloat(dip2, udip) # dip2 = dip2 +/-udip
26
27 # (a) Chevron folds have planar limbs. The hinge
28 # of the fold is the intersection of the limbs
29 htrd, hplg = AnglesU(str1,dip1,str2,dip2,'i')
30 print('Hinge trend = {:.1f}, plunge {:.1f}'.format(htrd*180/
    pi,hplg*180/pi))
31
32 # The rake of the hinge on either limb is the angle
33 # between the hinge and the strike line on the limb.
34 # This line is horizontal and has plunge = 0
35 plg = unc.ufloat(0, udip) # plg = 0 +/-udip
36
37 # (b) For the SW dipping limb
38 ang1, ang2 = AnglesU(str1,plg,htrd,hplg,'l')
39 print('Rake of hinge in SW dipping limb = {:.1f}'.format(ang1
    *180/pi))
40
41 # (c) And for the NE dipping limb
42 ang1, ang2 = AnglesU(str2,plg,htrd,hplg,'l')
43 print('Rake of hinge in NE dipping limb = {:.1f}'.format(ang1
    *180/pi))

```

Output:

Hinge trend = 265.8+/-3.3, plunge 25.3+/-2.6  
 Rake of hinge in SW dipping limb = 138.4+/-4.6  
 Rake of hinge in NE dipping limb = 29.5+/-3.5

In the map of Fig. 4.6, the error in east and north coordinates is 10 m, and in elevation is 5 m. What is uncertainty in the strike and dip of the T-S contact?

```

1 # Import function ThreePointU
2 from ThreePointU import ThreePointU as ThreePointU
3
4 # ENU coordinates of the three points
5 # with uncertainties in E-N = 10, and U = 5
6 p1 = np.array([unc.ufloat(509, 10), unc.ufloat(2041, 10), unc
    .ufloat(400, 5)])

```

```

7 p2 = np.array([unc.ufloat(1323, 10), unc.ufloat(2362, 10),
8   unc.ufloat(500, 5)])
9 p3 = np.array([unc.ufloat(2003, 10), unc.ufloat(2913, 10),
10  unc.ufloat(700, 5)])
11 # Compute the orientation of the plane
12 strike, dip = ThreePointU(p1,p2,p3)
13 print('Plane strike = {:.1f}, dip = {:.1f}'.format(strike
14   *180/pi,dip*180/pi))

```

Output:

Plane strike = 84.5+/-3.5, dip = 22.5+/-2.7

## 4.6 Exercises

Problems 1-3 are from Marshak and Mitra (1988). Solve these problems using the function *Angles*.

1. A fault surface has an orientation (RHR) 190/80. Slickenlines on the fault trend 300°.
  - (a) What is the plunge of the lineation?
  - (b) What is the rake of the lineation on the fault?
2. A shale bed has an orientation (RHR) 115/42. What is the apparent dip of the bed in the direction 265°?
3. A sandstone bed strikes 140°across a stream. The stream flows down a narrow gorge with vertical walls. The apparent dip of the bed on the walls of the gorge is 095/25. What is the true dip of the bed?
4. In the geologic map of Fig. 4.7, points 1 to 9 have the following ENU coordinates:

```

point1 = [1580, 379, 400]
point2 = [1234, 992, 300]
point3 = [2054, 1753, 400]
point4 = [448, 1424, 600]
point5 = [1921, 2195, 500]

```

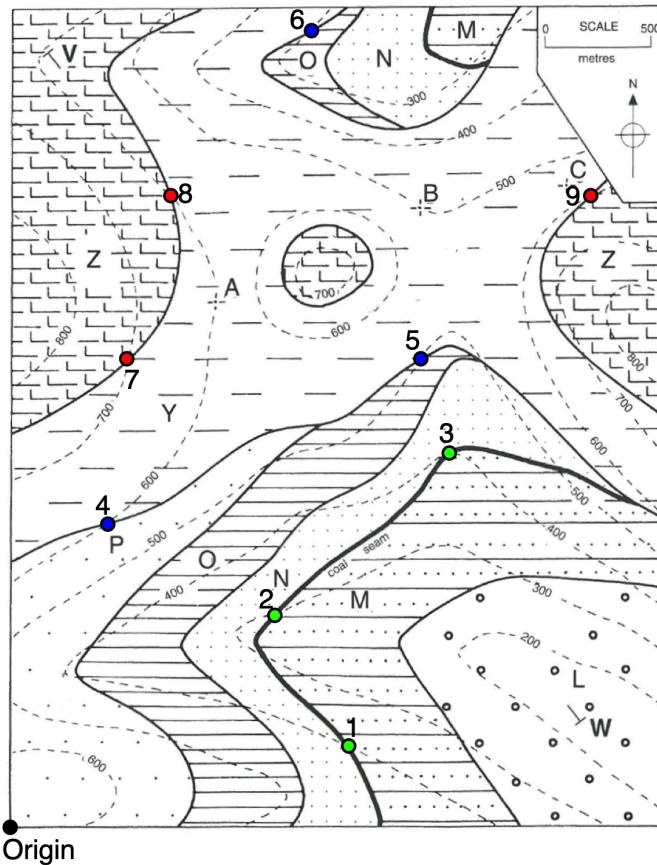


Figure 4.7: Map for exercise 4. This is map 10 of Bennison et al. (2011).

point6 = [1408, 3737, 300]

point7 = [536, 2196, 700]

point8 = [743, 2963, 600]

point9 = [2720, 2963, 600]

- Compute the strike and dip of the coal seam (points 1-3).
- Compute the strike and dip of the contact where the blue points 4-6 are located. What kind of contact is this? Is the coal seam below or above this contact?
- Compute the strike and dip of the contact between units Y and Z (points 7-9). Is this contact below or above the contact in b?
- The line of section V-W has a trend of  $142^\circ$ . What is the apparent dip of the three contacts above along the section?

(e) Draw a schematic cross section along line V-W

*Hint:* Use function *ThreePoint* to solve a, b and c. Use function *Angles* to solve d.

5. The map of Fig. 4.8 shows an area of a reconnaissance survey in the Appalachian Valley and Ridge Province of western Maryland, USA. On the western half of the map, the contact between a shale horizon (B) and a sandstone unit (C) has been located in two areas. Three points on this contact have the following ENU coordinates:

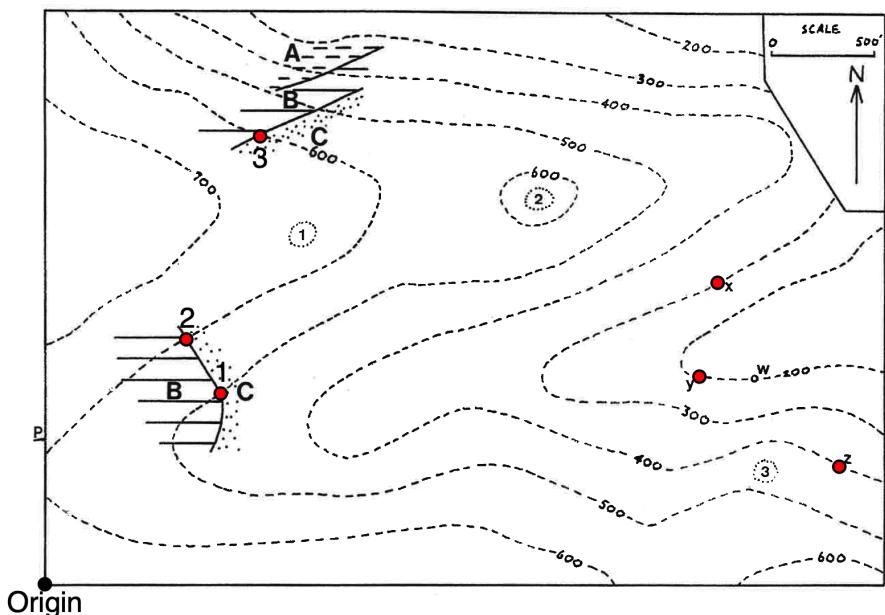


Figure 4.8: Map for exercise 5

point1 = [862, 943, 500]

point2 = [692, 1212, 600]

point3 = [1050, 2205, 600]

On the eastern half of the map, the contact between B and C was found exposed at three locations labelled x, y, and z. The ENU coordinates of these points are:

pointx = [3298, 1487, 300]

pointy = [3203, 1031, 200]

pointz = [3894, 590, 400]

- (a) Compute the strike and dip of the contact on the western half of the map.
- (b) Compute the strike and dip of the contact on the eastern half of the map.
- (c) What kind of structure is present on the map?
- (d) Compute the intersection of the western and eastern contacts. What does this line represent?

*Hint:* Use function *ThreePoint* to solve a and b. Use function *Angles* to solve d.

6. In problem 3, the error in azimuth is  $5^\circ$  and in apparent dip is  $3^\circ$ . What is the uncertainty in the true dip of the bed? *Hint:* Use function *AnglesU*.
7. In the map of Fig. 4.7, the east and north coordinates of the points have 15 m error, and the elevations have 5 m error.
  - (a) What is the uncertainty in the strike and dip of the coal seam?
  - (b) What is the uncertainty in the strike and dip of the unconformity?
  - (c) What is the angle between the unconformity and the coal seam and what is the uncertainty in this angle?

*Hint:* Use functions *ThreePointU* and *AnglesU*.

## References

- Allmendinger, R.W., Cardozo, N. and Fisher, D.W. 2012. Structural Geology Algorithms: Vectors and Tensors. Cambridge University Press.
- Bennison, G.M., Olver, P.A. and Moseley, K.A. 2011. An Introduction to Geological Structures and Maps, 8th edition. Hodder Education.
- Fisher, N.I., Lewis, T. and Embleton, B.J.J. 1987. Statistical analysis of spherical data. Cambridge University Press.
- Leyshon, P.R. and Lisle, R.J. 1996. Stereographic Projection Techniques in Structural Geology. Butterworth Heinemann.

Marshak, S. and Mitra, G. 1988. Basic Methods of Structural Geology. Prentice Hall.

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Taylor, J.R. 1997. An Introduction to Error Analysis, 2nd edition. University Science Books.



# Chapter 5

## Transformations

Many problems in geology become simpler when viewed from another perspective. For example, when studying the movement of continents through time because of plate tectonics (Fig. 5.1a), two coordinate systems are required, one in a present-day geographic frame, and another one attached to the continent. Or to analyze a fault (Fig. 5.1b), we need one coordinate system attached to the fault (with one axis parallel to the pole and another to the slickensides), which we want to relate to the more familiar **NED** system. A change in coordinate system is called a coordinate transformation and this is an operation that happens everytime and everywhere. Computer games, flight simulators, and 3D interpretation programs rely heavily on coordinate transformations.

### 5.1 Transforming coordinates and vectors

#### 5.1.1 Coordinate transformations

A transformation involves a change in the origin and orientation of the coordinate system. We will refer to the new axes as the primed coordinate system,  $\mathbf{X}'$ , and the old coordinate system as the unprimed system,  $\mathbf{X}$  (Fig. 5.2a). Let's assume the origin of the old and new coordinate systems is the same. The change in orientation of the new coordinate system is defined by the angles between the new coordinate axes and the old axes. These angles are marked systematically, the first subscript refers to the new coordinate

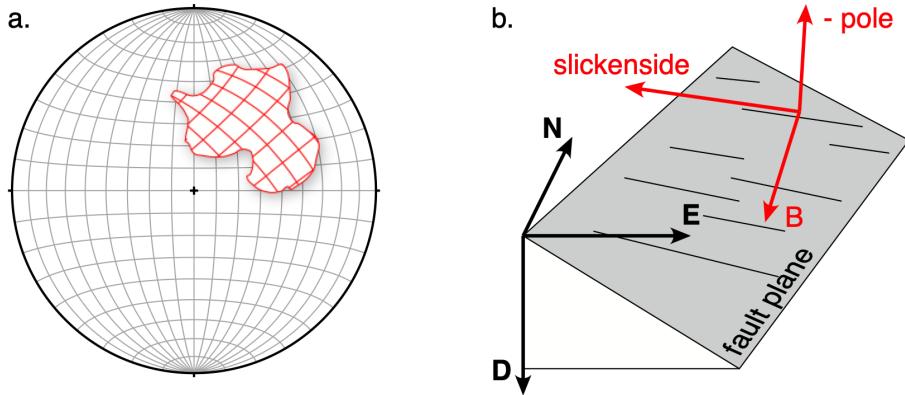


Figure 5.1: Examples of coordinate transformations in geology. **a.** Continental drift, **b.** A fault plane. Red is the coordinate system for analysis, and gray is the geographic coordinate system. Modified from Allmendinger et al. (2012).

axis and the second subscript to the old coordinate axis. For example,  $\theta_{23}$  is the angle between the  $\mathbf{X}_2'$  axis and the  $\mathbf{X}_3$  axis (Fig. 5.2a).

To define the transformation, we use the cosines of these angles rather than the angles themselves (Fig. 5.2b). These are the direction cosines of the new axes with respect to the old axes. The subscript convention is exactly the same. For example,  $a_{23}$  is the direction cosine of the  $\mathbf{X}_2'$  axis with respect to the  $\mathbf{X}_3$  axis. There are nine direction cosines that form a  $3 \times 3$  array, where each row refers to a new axis and each column to an old axis (Fig. 5.2b). This matrix  $\mathbf{a}$  of direction cosines is known as the *transformation matrix*, and it is the key element that defines the transformation.

Fortunately, not all the nine direction cosines in the transformation matrix are independent. Since the base vectors of the new coordinate system are unit vectors, their magnitude is 1:

$$\begin{aligned} a_{11}^2 + a_{12}^2 + a_{13}^2 &= 1 \\ a_{21}^2 + a_{22}^2 + a_{23}^2 &= 1 \\ a_{31}^2 + a_{32}^2 + a_{33}^2 &= 1 \end{aligned} \tag{5.1}$$

and because the base vectors of the new coordinate system are perpendicular to each other, the dot product of two of these axes is zero:

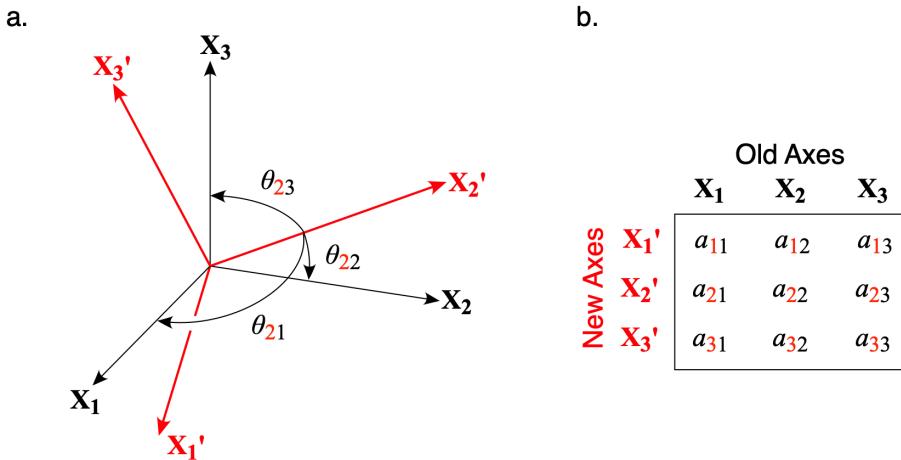


Figure 5.2: **a.** Rotation of a Cartesian coordinate system. The old axes are black, the new axes are primed and red. Only three of the nine possible angles are shown. **b.** Graphic device for remembering how the subscript of the direction cosines relate to the new and the old axes. Modified from Allmendinger et al. (2012).

$$\begin{aligned} a_{21}a_{31} + a_{22}a_{32} + a_{23}a_{33} &= 0 \\ a_{31}a_{11} + a_{32}a_{12} + a_{33}a_{13} &= 0 \\ a_{11}a_{21} + a_{12}a_{22} + a_{13}a_{23} &= 0 \end{aligned} \tag{5.2}$$

Equations 5.1 and 5.2 are known as the *orthogonality relations*. Since we have nine unknowns (i.e. the nine direction cosines) and six equations, there are only three independent direction cosines in the transformation matrix. If we know three of the direction cosines defining the transformation, we can calculate the other six.

### 5.1.2 Transformation of vectors

Once we know the transformation matrix  $\mathbf{a}$  and the components of a vector in the old coordinate system, we can calculate the components of the vector in the new coordinate system. The equations are fairly simple:

$$\begin{aligned} v_1' &= a_{11}v_1 + a_{12}v_2 + a_{13}v_3 \\ v_2' &= a_{21}v_1 + a_{22}v_2 + a_{23}v_3 \\ v_3' &= a_{31}v_1 + a_{32}v_2 + a_{33}v_3 \end{aligned} \tag{5.3}$$

or using the Einstein summation notation:

$$v_i' = a_{ij}v_j \tag{5.4}$$

where  $i$  is the free suffix, and  $j$  is the dummy suffix. Assuming that ( $i, j = 1, 2, 3$ ), Equation 5.4 represents three separate equations (the three indices of  $i$ ), each one with three terms (the three indices of  $j$ ). These equations are easy to implement in Python code:

```

1 for i in range(0,3,1):
2     v_new[i] = 0
3     for j in range(0,3,1):
4         v_new[i] = a[i,j]*v_old[j] + v_new[i]
```

You will see this code snippet repeatedly in the functions of this chapter. Linear algebra is elegant. To convert the vector from the new coordinate system back to the old coordinate system, you just need to do:

$$v_i = a_{ji}v_j' \tag{5.5}$$

or in Python code:

```

1 for i in range(0,3,1):
2     v_old[i] = 0
3     for j in range(0,3,1):
4         v_old[i] = a[j,i]*v_new[j] + v_old[i]
```

### 5.1.3 A simple transformation: From ENU to NED

There is a simple coordinate transformation that nicely illustrates the theory above: the transformation from an **ENU** to a **NED** coordinate system (Fig.

4.1). It is simple because the angles involved are either 0, 90, or 180°. The direction cosines of the new axes (**NED**) with respect to the old axes (**ENU**), and the transformation matrix **a** is:

$$\mathbf{a} = \begin{pmatrix} \cos 90 & \cos 0 & \cos 90 \\ \cos 0 & \cos 90 & \cos 90 \\ \cos 90 & \cos 90 & \cos 180 \end{pmatrix} \quad (5.6)$$

which simplifies to:

$$\mathbf{a} = \begin{pmatrix} 0 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & -1 \end{pmatrix} \quad (5.7)$$

When we use this matrix in Eq. 5.4, we get:

$$v_1' = v_2; \quad v_2' = v_1; \quad v_3' = -v_3; \quad (5.8)$$

Notice that in this special case **a** is symmetric ( $a_{ij} = a_{ji}$ ), so the elements of **a** are also the direction cosines of **ENU** with respect to **NED**. In the following sections, we will look at more complicated coordinate transformations, but the principles mentioned here will still apply.

## 5.2 Applications

### 5.2.1 Stratigraphic thickness

The thickness of a stratigraphic unit is the perpendicular distance between the parallel planes bounding the unit. This is also called the true or stratigraphic thickness (Ragan, 2009). A general problem though is that points on the planes bounding the unit, are commonly given in a geographic (e.g. **ENU**) coordinate system. One therefore must use orthographic projections and trigonometry to determine the stratigraphic thickness of the unit from the points (Ragan, 2009).

An easier approach is to use a transformation. Figure 5.3 illustrates the situation. Points on the top and base of the unit are given in an **ENU** coordinate system. We can transform these points into a coordinate system attached to the bounding planes, where the strike (RHR) of the planes is the first axis, the dip the second axis, and the pole to the planes the third axis. We will call this coordinate system the **SDP** system. The thickness of the unit is just the difference between the **P** coordinate of any point on the top of the unit and the **P** coordinate of any point on the base.

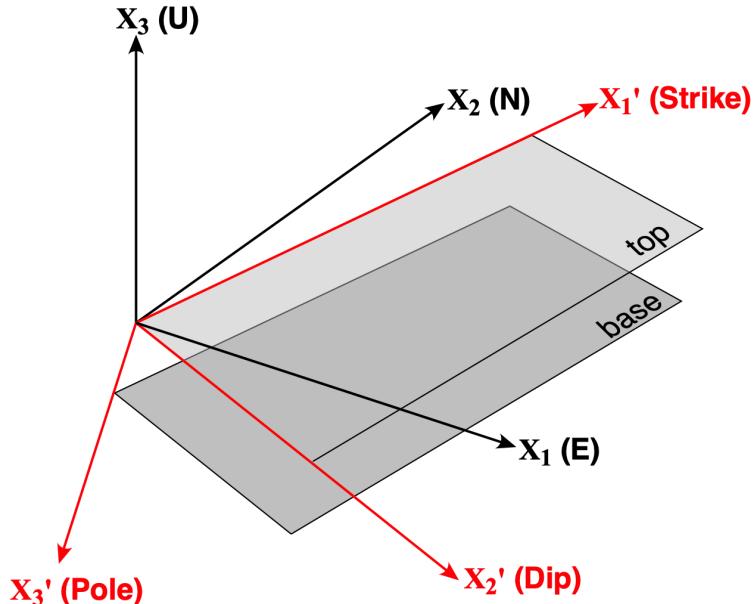


Figure 5.3: Coordinate transformation from an **ENU** to a Strike-Dip-Pole (**SDP**) coordinate system. The thickness of the unit can be calculated by subtracting the **P** coordinates of any point on the top and any point on the base. Modified from Allmendinger (2019).

We can find the elements of the matrix  $\mathbf{a}$  for this transformation using trigonometry. However, we will follow a more didactic approach. We will reference the two **ENU** and **SDP** coordinate systems with respect to the **NED** coordinate system, and use the dot product to determine the direction cosines of **SDP** into **ENU**.

The direction cosines of the **ENU** coordinate system with respect to the **NED** coordinate system are given by Eq. 5.7. The direction cosines of the **SDP** coordinate system with respect to the **NED** coordinate system are given by Table 4.1:

$$\begin{aligned}\mathbf{S} &= [\cos(strike), \sin(strike), 0] \\ \mathbf{D} &= [\cos(strike + 90) \cos(dip), \sin(strike + 90) \cos(dip), \sin(dip)] \\ \mathbf{P} &= [\cos(strike - 90) \cos(90 - dip), \sin(strike - 90) \cos(90 - dip), \sin(90 - dip)]\end{aligned}$$

which simplifies to:

$$\begin{aligned}\mathbf{S} &= [\cos(strike), \sin(strike), 0] \\ \mathbf{D} &= [-\sin(strike) \cos(dip), \cos(strike) \cos(dip), \sin(dip)] \quad (5.9) \\ \mathbf{P} &= [\sin(strike) \sin(dip), -\cos(strike) \sin(dip), \cos(dip)]\end{aligned}$$

The transformation matrix  $\mathbf{a}$  from the **ENU** to the **SDP** coordinate system has as components the direction cosines of the new **SDP** axes into the old **ENU** axes. From Eq. 4.9, one can see that these are just the dot product between the new and old axes:

$$\mathbf{a} = \begin{pmatrix} \mathbf{S} \cdot \mathbf{E} & \mathbf{S} \cdot \mathbf{N} & \mathbf{S} \cdot \mathbf{U} \\ \mathbf{D} \cdot \mathbf{E} & \mathbf{D} \cdot \mathbf{N} & \mathbf{D} \cdot \mathbf{U} \\ \mathbf{P} \cdot \mathbf{E} & \mathbf{P} \cdot \mathbf{N} & \mathbf{P} \cdot \mathbf{U} \end{pmatrix}$$

which is equal to:

$$\mathbf{a} = \begin{pmatrix} \sin(strike) & \cos(strike) & 0 \\ \cos(strike) \cos(dip) & -\sin(strike) \cos(dip) & -\sin(dip) \\ -\cos(strike) \sin(dip) & \sin(strike) \sin(dip) & -\cos(dip) \end{pmatrix} \quad (5.10)$$

So if point 1 is at the top of the unit and has coordinates  $[E_1, N_1, U_1]$ , and point 2 is at the base of the unit and has coordinates  $[E_2, N_2, U_2]$ , the **P** coordinates of these points are:

$$\begin{aligned}P_1 &= -\cos(strike) \sin(dip) E_1 + \sin(strike) \sin(dip) N_1 - \cos(dip) U_1 \\ P_2 &= -\cos(strike) \sin(dip) E_2 + \sin(strike) \sin(dip) N_2 - \cos(dip) U_2 \quad (5.11)\end{aligned}$$

and the thickness of the unit is:

$$t = P_2 - P_1 \quad (5.12)$$

The function `TrueThickness` calculates the thickness of a unit given the strike and dip of the unit, and the ENU coordinates of two top and base points:

```

1 import numpy as np
2
3 def TrueThickness(strike,dip,top,base):
4     """
5         TrueThickness calculates the thickness (t) of a unit
6         given the strike (strike) and dip (dip) of the unit,
7         and points at its top (top) and base (base)
8
9     top and base are 1 x 3 arrays defining the location
10    of top and base points in an ENU coordinate system.
11    For each one of these arrays, the first, second
12    and third entries are the E, N and U coordinates
13
14    NOTE: strike and dip should be input in radians
15    """
16
17    # make the transformation matrix from ENU coordinates
18    # to SDP coordinates. Eq. 5.10
19    sinStr = np.sin(strike)
20    cosStr = np.cos(strike)
21    sinDip = np.sin(dip)
22    cosDip = np.cos(dip)
23    a = np.array([[sinStr, cosStr, 0],
24                  [cosStr*cosDip, -sinStr*cosDip, -sinDip],
25                  [-cosStr*sinDip, sinStr*sinDip, -cosDip]])
26
27    # transform the top and base points
28    # from ENU to SDP coordinates. Eq. 5.4
29    topn = np.zeros(3)
30    basen = np.zeros(3)
31    for i in range(0,3,1):
32        for j in range(0,3,1):
33            topn[i] = a[i,j]*top[j] + topn[i]
34            basen[i] = a[i,j]*base[j] + basen[i]
35
36    # compute the thickness of the unit. Eq. 5.12
37    t = np.abs(basen[2] - topn[2])
38
39    return t

```

Let's use this function to determine the thickness of the sedimentary units T to Q in the geologic map of Fig. 5.4. This time we have points at the top and base of these units, and their ENU coordinates are:

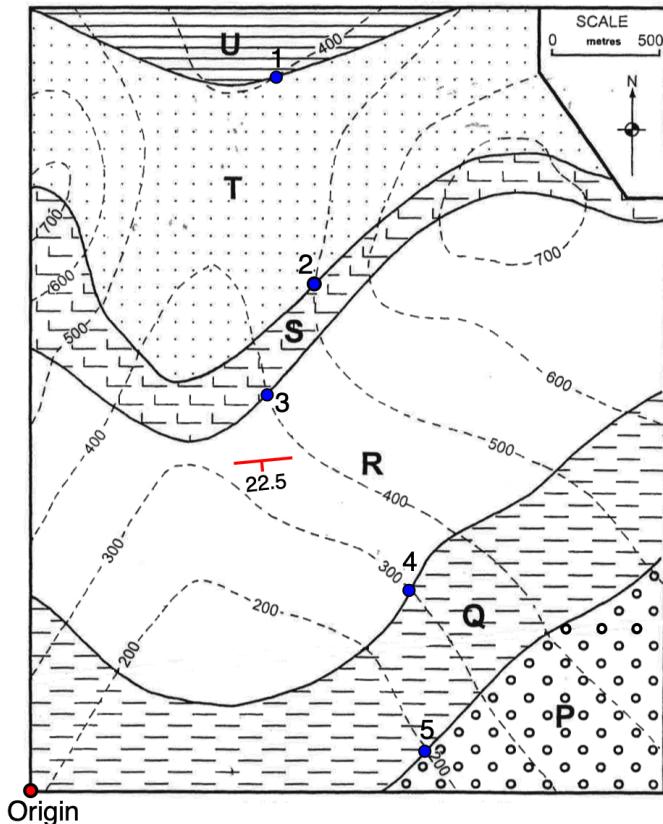


Figure 5.4: Geologic map of sedimentary units with an orientation 84.5/22.5 (RHR) (Bennison et al., 2011). Points at the top and base of units T to Q are used to determine the thickness of the units.

point1 = [1147, 3329, 400]

point2 = [1323, 2362, 500]

point3 = [1105, 1850, 400]

point4 = [1768, 940, 300]

point5 = [1842, 191, 200]

The notebook [ch5-1](#) shows the solution to this problem:

```

1 import numpy as np
2 pi = np.pi
3
4 # Import function TrueThickness
5 import sys, os
6 sys.path.append(os.path.abspath('../functions'))
7 from TrueThickness import TrueThickness as TrueThickness
8
9 # Strike and dip of the unit in radians
10 strike = 84.5 * pi/180
11 dip = 22.5 * pi/180
12
13 # ENU coordinates of the points
14 p1 = np.array([1147, 3329, 400])
15 p2 = np.array([1323, 2362, 500])
16 p3 = np.array([1105, 1850, 400])
17 p4 = np.array([1768, 940, 300])
18 p5 = np.array([1842, 191, 200])
19
20 # Compute the thickness of the units
21 thickT = TrueThickness(strike,dip,p2,p1)
22 thickS = TrueThickness(strike,dip,p3,p2)
23 thickR = TrueThickness(strike,dip,p4,p3)
24 thickQ = TrueThickness(strike,dip,p5,p4)
25 print('Thickness of unit T = {:.1f} m'.format(thickT))
26 print('Thickness of unit S = {:.1f} m'.format(thickS))
27 print('Thickness of unit R = {:.1f} m'.format(thickR))
28 print('Thickness of unit Q = {:.1f} m'.format(thickQ))

```

Output:

Thickness of unit T = 467.2 m

Thickness of unit S = 94.6 m

Thickness of unit R = 278.6 m

Thickness of unit Q = 195.6 m

What about if there are uncertainties in the strike and dip of the unit, and in the top and base points? The function *TrueThicknessU* in the resource git repository handles this case. Suppose that in the problem above, the uncertainties in strike and dip are  $4^\circ$  and  $2^\circ$  respectively, the uncertainty in east and north coordinates is 10 m, and in elevation is 5 m. The notebook [ch5-2](#) shows the solution to this problem:

```
1 # Import libraries
2 import numpy as np
3 pi = np.pi
4 import uncertainties as unc
5
6 # Import function TrueThicknessU
7 import sys, os
8 sys.path.append(os.path.abspath('../functions'))
9 from TrueThicknessU import TrueThicknessU as TrueThicknessU
10
11 # Strike and dip of the unit in radians
12 strike = 84.5 * pi/180
13 dip = 22.5 * pi/180
14
15 # Strike and dip errors in radians
16 ustrike = 4 * pi/180
17 udip = 2 * pi/180
18
19 # Create the strike and dip with uncertainties
20 strike = unc.ufloat(strike, ustrike) # strike +/- ustrike
21 dip = unc.ufloat(dip, udip) # dip +/- udip
22
23 # ENU coordinates of the points
24 # with uncertainties in E-N = 10, and U = 5
25 p1 = np.array([unc.ufloat(1147, 10), unc.ufloat(3329, 10),
   unc.ufloat(400, 5)])
26 p2 = np.array([unc.ufloat(1323, 10), unc.ufloat(2362, 10),
   unc.ufloat(500, 5)])
27 p3 = np.array([unc.ufloat(1105, 10), unc.ufloat(1850, 10), unc
   .ufloat(400, 5)])
28 p4 = np.array([unc.ufloat(1768, 10), unc.ufloat(940, 10), unc
   .ufloat(300, 5)])
29 p5 = np.array([unc.ufloat(1842, 10), unc.ufloat(191, 10), unc
   .ufloat(200, 5)])
30
31 # Compute the thickness of the units
32 thickT = TrueThicknessU(strike, dip, p2, p1)
33 thickS = TrueThicknessU(strike, dip, p3, p2)
34 thickR = TrueThicknessU(strike, dip, p4, p3)
35 thickQ = TrueThicknessU(strike, dip, p5, p4)
36 print('Thickness of unit T = {:.1f} m'.format(thickT))
37 print('Thickness of unit S = {:.1f} m'.format(thickS))
38 print('Thickness of unit R = {:.1f} m'.format(thickR))
39 print('Thickness of unit Q = {:.1f} m'.format(thickQ))
```

Output:

Thickness of unit T = 467.2+/-31.5 m

Thickness of unit S = 94.6+/-20.4 m

Thickness of unit R = 278.6+/-37.0 m

Thickness of unit Q = 195.6+/-27.0 m

For the thinnest unit S, the uncertainty in thickness is as much as 20% the thickness of this unit!

### 5.2.2 Outcrop trace of a plane

The **ENU** to **SDP** transformation is useful to solve another important problem, namely the outcrop trace of a plane on irregular terrain (Fig. 3.9; Allmendinger in press.). If we know the orientation of the plane (strike and dip), the **ENU** coordinates of the location where the plane outcrops, and the topography of the terrain as a digital elevation model (DEM<sup>1</sup>), we can determine the outcrop trace of the plane using computation. The solution is surprisingly simple, the plane outcrops wherever the **P** coordinate of the terrain is equal to the **P** coordinate of the plane's outcrop location.

Let's call the **P** coordinate of the plane's outcrop location  $P_1$ , and the **P** coordinate of a point in the DEM grid  $P_{gp}$ . The difference between these two is:

$$D = P_1 - P_{gp} \quad (5.13)$$

At each point in the DEM grid, we can calculate and store this difference. The plane will outcrop wherever  $D$  is zero. Therefore, to draw the outcrop trace, we just need to contour the  $D$  value of zero on the grid. The function *Outcrop Trace* computes the value of  $D$  on a DEM grid of regularly spaced points defined by **E** (**XG**), **N** (**YG**) and **U** (**ZG**) coordinates. Notice that these arrays must follow the format given by the NumPy *meshgrid* function:

---

<sup>1</sup>A grid of regularly spaced points in east and north and with elevation information.

```

1 import numpy as np
2
3 def OutcropTrace(strike,dip,p1,XG,YG,ZG):
4     '''
5         OutcropTrace estimates the outcrop trace of a plane,
6         given the strike (strike) and dip (dip) of the plane,
7         the ENU coordinates of a point (p1) where the plane
8         outcrops, and a DEM of the terrain as a regular grid
9         of points with E (XG), N (YG) and U (ZG) coordinates.
10
11    After using this function, to draw the outcrop trace
12    of the plane, you just need to draw the contour 0 on
13    the grid XG,YG,DG
14
15    NOTE: strike and dip should be input in radians
16    p1 must be an array
17    XG and YG arrays should be constructed using
18    the Numpy function meshgrid
19    '''
20
21    # make the transformation matrix from ENU coordinates to
22    # SDP coordinates. We just need the third row of this
23    # matrix
24    a = np.zeros((3,3))
25    a[2,0] = -np.cos(strike)*np.sin(dip)
26    a[2,1] = np.sin(strike)*np.sin(dip)
27    a[2,2] = -np.cos(dip);
28
29    # Initialize DG
30    n, m = XG.shape
31    DG = np.zeros((n,m))
32
33    # Estimate the P coordinate of the outcrop point p1
34    P1 = a[2,0]*p1[0] + a[2,1]*p1[1] + a[2,2]*p1[2]
35
36    # Estimate the P coordinate at each point of the DEM
37    # grid and subtract P1. Eq. 5.13
38    for i in range(n):
39        for j in range(m):
40            DG[i,j] = P1 - (a[2,0]*XG[i,j] + a[2,1]*YG[i,j] + a
41            [2,2]*ZG[i,j])
42
43    return DG

```

Let's apply this function to the map of Fig. 5.5. On the western half of this map, the contact between units B and C outcrops at point 2 and has an orientation 020/22 (RHR). On the eastern half of the map, the same contact

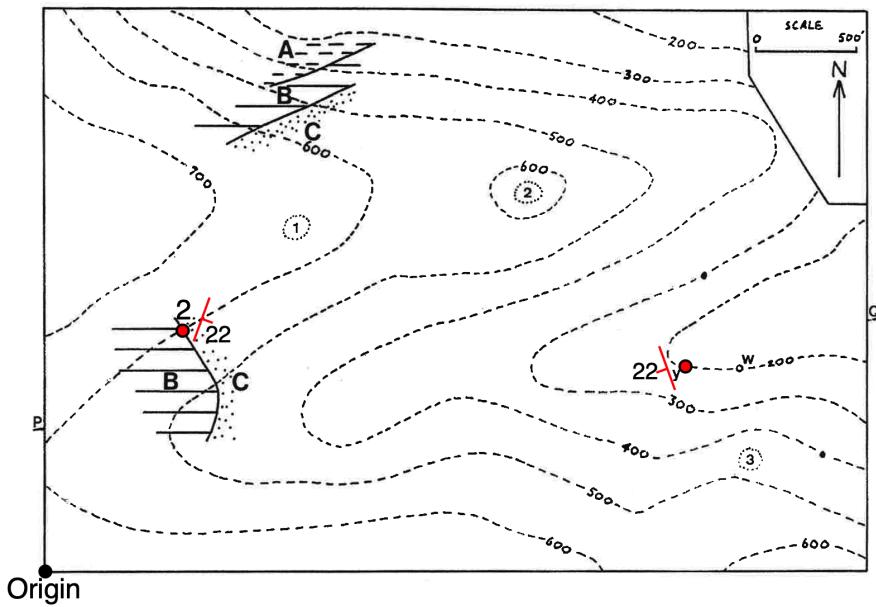


Figure 5.5: The contact between units B and C outcrops at point 2 with orientation 020/22 (RHR), and at point y with orientation 160/22 (RHR). From this information and a DEM of the terrain, we can determine the outcrop trace of the contact.

outcrops at point y and has an orientation 160/22 (RHR). The notebook [ch5-3](#) draws the outcrop trace of the contact. Notice that the ENU coordinates of the points of the DEM grid are input from the text files `XG`, `YG`, and `ZG`.

```

1 # Import libraries
2 import numpy as np
3 import matplotlib.pyplot as plt
4
5 # Import function OutcropTrace
6 import sys, os
7 sys.path.append(os.path.abspath('../functions'))
8 from OutcropTrace import OutcropTrace as OutcropTrace
9
10 # Read the DEM grid
11 XG = np.loadtxt(os.path.abspath('../data/ch5-3/XG.txt'))
12 YG = np.loadtxt(os.path.abspath('../data/ch5-3/YG.txt'))
13 ZG = np.loadtxt(os.path.abspath('../data/ch5-3/ZG.txt'))
14
15 # Contour the terrain
16 cval = np.linspace(200,700,6)
17 cp = plt.contour(XG,YG,ZG,cval)

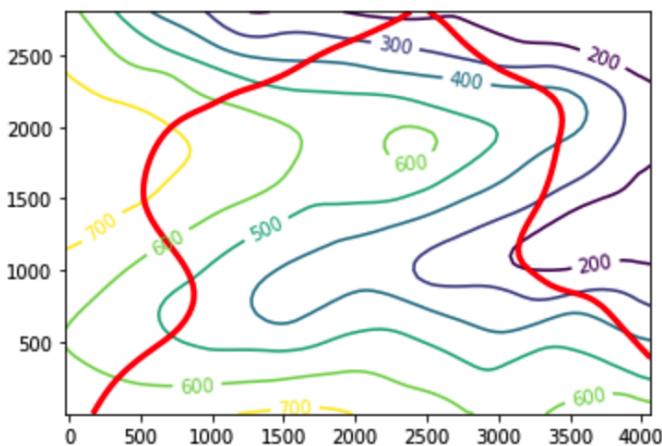
```

```

18 plt.clabel(cp, inline=True, fontsize=10, fmt="%d")
19
20 # Western contact
21 pi = np.pi
22 strike = 20*pi/180
23 dip = 22*pi/180
24 point2 = np.array([692, 1212, 600])
25 DG = OutcropTrace(strike,dip,point2,XG,YG,ZG)
26 cval = 0 # Contour only CG zero value
27 cp = plt.contour(XG,YG,DG,cval,colors='red',linewidths=3)
28
29 # Eastern contact
30 strike = 160*pi/180
31 dip = 22*pi/180
32 pointy = np.array([3203, 1031, 200])
33 DG = OutcropTrace(strike,dip,pointy,XG,YG,ZG)
34 cp = plt.contour(XG,YG,DG,cval,colors='red',linewidths=3)
35
36 # Make axes equal
37 plt.axis('equal');

```

Output:



### 5.2.3 Down-Plunge projection

Folded rock layers normally have a cylindrical symmetry; the layers are bent about a single axis or direction, called the fold axis. The fold axis is a line of minimum, zero curvature, and the lines of maximum, non-zero curvature are perpendicular to it (Suppe, 1985). The least distorted view of such structure

is in the plane perpendicular to the fold axis, which is called the profile plane (Fig. 5.6). Projecting the fold data to this profile plane is called a *Down-Plunge* projection.

Constructing a Down-Plunge projection by hand typically involves an orthographic projection, and this problem is complicated (and tedious), particularly if points on the fold are not at the same elevation. Fortunately, we can solve this problem as a coordinate transformation, where points on the fold referenced in an **ENU** coordinate system, are transformed to a new  $\mathbf{X}'_1 \mathbf{X}'_2 \mathbf{X}'_3$  coordinate system, with  $\mathbf{X}'_3$  parallel to the fold axis, and  $\mathbf{X}'_1 \mathbf{X}'_2$  defining the profile plane (Fig. 5.6).

We will again derive the matrix  $\mathbf{a}$  for this transformation using linear algebra. The direction cosines of the **ENU** coordinate system with respect to the **NED** coordinate system are given by Eq. 5.7. The direction cosines of the  $\mathbf{X}'_1 \mathbf{X}'_2 \mathbf{X}'_3$  coordinate system with respect to the **NED** coordinate system can be found using Table 4.1. If the trend and plunge of the fold axis are  $T$  and  $P$ , these direction cosines are (Fig. 5.6):

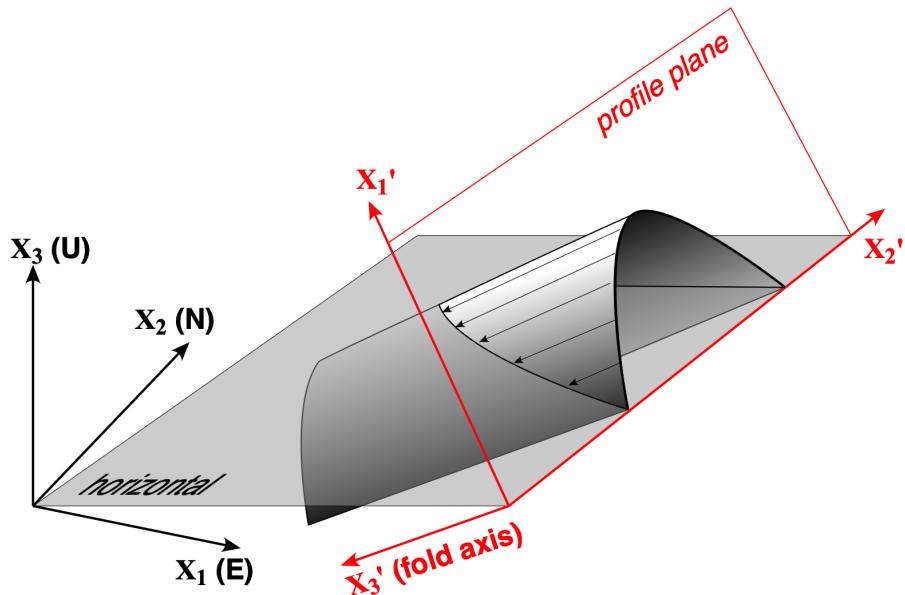


Figure 5.6: The two coordinate systems involved in a Down-Plunge projection of a fold. Modified from Allmendinger et al. (2012).

$$\begin{aligned}\mathbf{X}_1' &= [\cos(T) \cos(P - 90), \sin(T) \cos(P - 90), \sin(P - 90)] \\ \mathbf{X}_2' &= [\cos(T + 90), \sin(T + 90), 0] \\ \mathbf{X}_3' &= [\cos(T) \cos(P), \sin(T) \cos(P), \sin(P)]\end{aligned}$$

which simplifies to:

$$\begin{aligned}\mathbf{X}_1' &= [\cos(T) \sin(P), \sin(T) \sin(P), -\cos(P)] \\ \mathbf{X}_2' &= [-\sin(T), \cos(T), 0] \\ \mathbf{X}_3' &= [\cos(T) \cos(P), \sin(T) \cos(P), \sin(P)]\end{aligned}\tag{5.14}$$

The direction cosines of the new  $\mathbf{X}_1'\mathbf{X}_2'\mathbf{X}_3'$  axes into the old ENU axes are the dot product between the new and old axes:

$$\mathbf{a} = \begin{pmatrix} \mathbf{X}_1' \cdot \mathbf{E} & \mathbf{X}_1' \cdot \mathbf{N} & \mathbf{X}_1' \cdot \mathbf{U} \\ \mathbf{X}_2' \cdot \mathbf{E} & \mathbf{X}_2' \cdot \mathbf{N} & \mathbf{X}_2' \cdot \mathbf{U} \\ \mathbf{X}_3' \cdot \mathbf{E} & \mathbf{X}_3' \cdot \mathbf{N} & \mathbf{X}_3' \cdot \mathbf{U} \end{pmatrix}$$

which is equal to:

$$\mathbf{a} = \begin{pmatrix} \sin(T) \sin(P) & \cos(T) \sin(P) & \cos(P) \\ \cos(T) & -\sin(T) & 0 \\ \sin(T) \cos(P) & \cos(T) \cos(P) & -\sin(P) \end{pmatrix}\tag{5.15}$$

This is the transformation matrix  $\mathbf{a}$  for the Down-Plunge projection. To project  $i$  points on the fold with coordinates  $[E_i, N_i, U_i]$ , we just need to do the following:

$$\begin{aligned}X'_{1i} &= \sin(T) \sin(P) E_i + \cos(T) \sin(P) N_i + \cos(P) U_i \\ X'_{2i} &= \cos(T) E_i - \sin(T) N_i\end{aligned}\tag{5.16}$$

and then plot  $X'_{2i}$  against  $X'_{1i}$  (Fig. 5.6) to draw the Down-Plunge projection of the fold.

The function *DownPlunge* computes the Down-Plunge projection of a bed from the ENU coordinates of points on the bed, and the fold axis orientation:

```

1 import numpy as np
2
3 def DownPlunge(bedseg, trd, plg):
4     """
5         DownPlunge constructs the down plunge projection of a bed
6
7         bedseg is a nptes x 3 array, which holds nptes
8         on the digitized bed, each point defined by
9         3 coordinates: X1 = East, X2 = North, X3 = Up
10
11    trd and plg are the trend and plunge of the fold axis
12
13    NOTE: trd and plg should be entered in radians
14
15    Python function translated from the Matlab function
16    DownPlunge in Allmendinger et al. (2012)
17    """
18
19    # Number of points in bed
20    nvtx = bedseg.shape[0]
21
22    # Allocate some arrays
23    a=np.zeros((3,3))
24    dpbedseg = np.zeros((np.shape(bedseg)))
25
26    # Calculate the transformation matrix a(i,j) Eq. 5.15
27    a[0,0] = np.sin(trd)*np.sin(plg)
28    a[0,1] = np.cos(trd)*np.sin(plg)
29    a[0,2] = np.cos(plg)
30    a[1,0] = np.cos(trd)
31    a[1,1] = -np.sin(trd)
32    a[2,0] = np.sin(trd)*np.cos(plg)
33    a[2,1] = np.cos(trd)*np.cos(plg)
34    a[2,2] = -np.sin(plg)
35
36    # Perform transformation
37    for nv in range(0,nvtx,1):
38        for i in range(0,3,1):
39            dpbedseg[nv,i] = 0.0
40            for j in range(0,3,1):
41                dpbedseg[nv,i] = a[i,j]*bedseg[nv,j] + dpbedseg[nv,
42                i]
43
44    return dpbedseg

```

Let's use this function to draw the Down-Plunge projection of the Big Elk

anticline in southeastern Idaho, USA (Fig. 5.7; Albee and Cullins, 1975; Allmendinger et al., 2012). Text files contain the digitized contacts (**ENU**) of three tops along the fold: the Jurassic Twin Creek Limestone (*jtc.txt*), the Jurassic Stump Sandstone (*js.txt*), and the Cretaceous Peterson Limestone (*kp.txt*). The trend and plunge of the folds axis is 125/126 (in the next chapter we will see how to compute this axis). The notebook **ch5-4** shows the solution to this problem:

```

1 # Import libraries
2 import numpy as np
3 import matplotlib.pyplot as plt
4
5 # Import function DownPlunge
6 import sys, os
7 sys.path.append(os.path.abspath('../functions'))
8 from DownPlunge import DownPlunge as DownPlunge
9
10 # Trend and plunge of the fold axis in radians
11 trend = 125 * np.pi/180
12 plunge = 26 * np.pi/180
13
14 # Read the tops from the text files
15 jtc = np.loadtxt(os.path.abspath('../data/ch5-4/jtc.txt'))
16 js = np.loadtxt(os.path.abspath('../data/ch5-4/js.txt'))
17 kp = np.loadtxt(os.path.abspath('../data/ch5-4/kp.txt'))
18
19 # Transform the points
20 jtcdp = DownPlunge(jtc,trend,plunge)
21 jsdp = DownPlunge (js,trend,plunge)
22 kpdp = DownPlunge(kp,trend,plunge)
23
24 # Plot the down plunge section
25 plt.plot(jtcdp[:,1],jtcdp[:,0], 'k-')
26 plt.plot(jsdp[:,1],jsdp[:,0], 'r-')
27 plt.plot(kpdp[:,1],kpdp[:,0], 'b-')
28
29 # Display the section's orientation
30 # Notice that the fold axis plunges SE
31 # Therefore the left side of the section is NE
32 # and the right side is SW
33 plt.text(-2.1e4,12e3,'NE')
34 plt.text(-0.6e4,12e3,'SW')
35
36 # Make axes equal
37 plt.axis('equal');
```

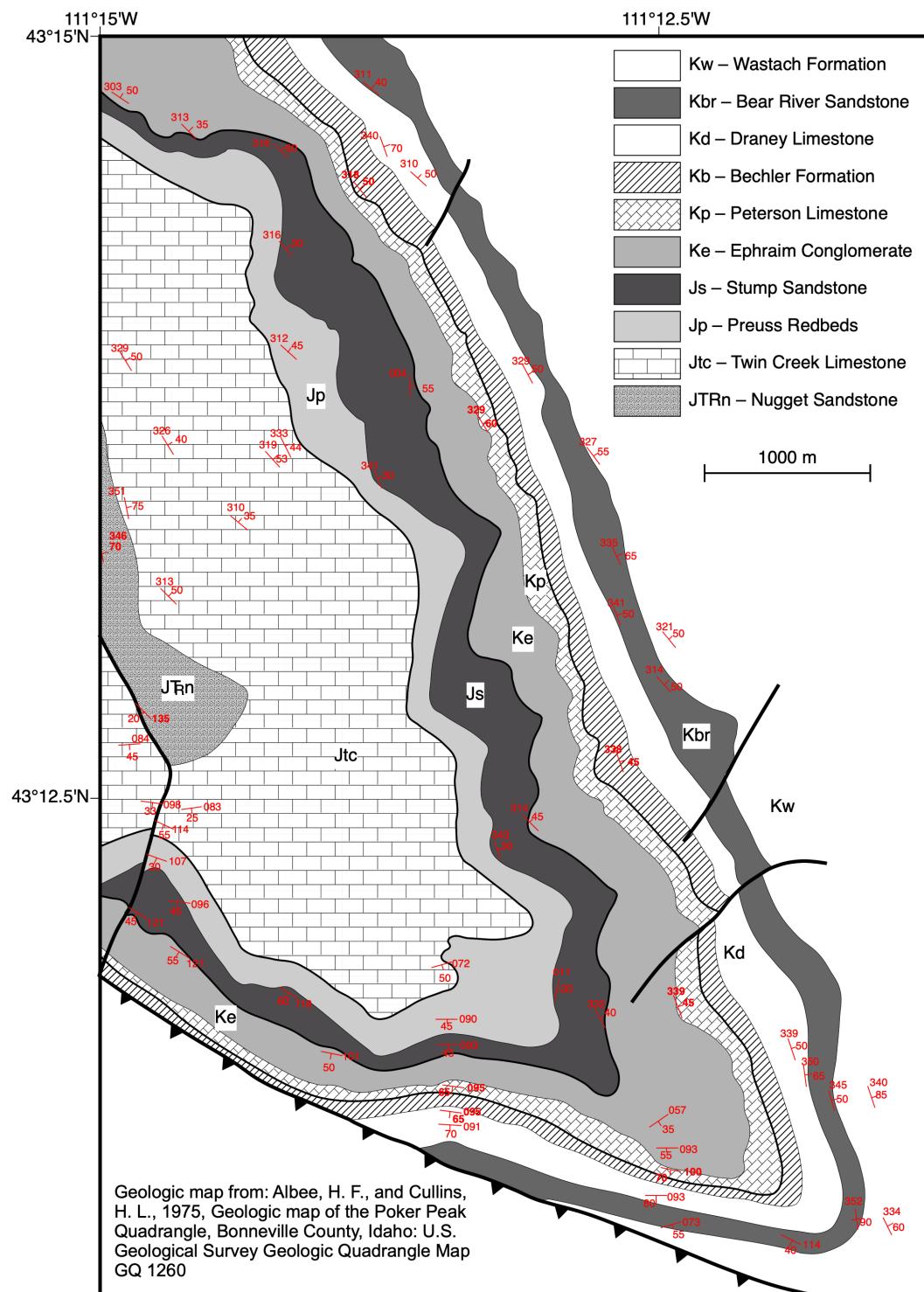
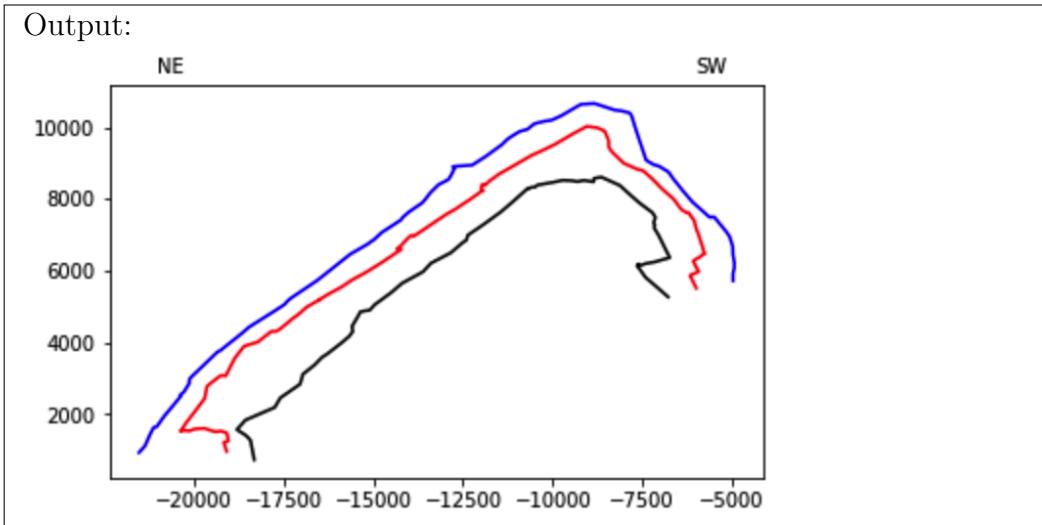


Figure 5.7: Simplified geologic map of the Big Elk anticline in southeastern Idaho. Modified from Allmendinger et al. (2012).



The thrust verges to the NE (the direction of transport is towards the NE), yet the fold verges to the SW in the opposite direction. Unit J<sub>p</sub>, between J<sub>tc</sub> and J<sub>s</sub>, contains evaporites (Fig. 5.7). Could this explain the observed fold geometry?

#### 5.2.4 Rotations

Rotations are essential in geology. For example, when we measure the orientation of current lineations on tilted beds, and we want to estimate the orientation of the paleocurrent that deposited these beds, we need to rotate or unfold the beds (and the lineations) back to their pre-tilting orientation. The stereonet is a convenient device to rotate data around a horizontal axis or a vertical axis, but is rather difficult to rotate data around an axis of a different orientation (Marshak and Mitra, 1988).

A rotation is also a coordinate transformation from an old coordinate system  $\mathbf{X}_1 \mathbf{X}_2 \mathbf{X}_3$  to a new coordinate system  $\mathbf{X}'_1 \mathbf{X}'_2 \mathbf{X}'_3$  (Fig. 5.8). The rotation axis is specified by its trend and plunge, and the magnitude of rotation is given as an angle  $\omega$  that is positive if the rotation is clockwise about the given axis and vice versa (Fig. 5.8). The difficult part is that the rotation axis may not coincide with the axes of either the old or the new coordinate system (unlike the Down-Plunge projection).

The components of the transformation matrix  $\mathbf{a}$  defining the rotation, which

are the direction cosines of the new coordinate system  $\mathbf{X}_1'\mathbf{X}_2'\mathbf{X}_3'$  with regards to the old coordinate system  $\mathbf{X}_1\mathbf{X}_2\mathbf{X}_3$ , can be found using spherical trigonometry (Allmendinger et al., 2012) or linear algebra as we did before. Here, we give them without proof. If  $\cos \alpha$ ,  $\cos \beta$  and  $\cos \gamma$  are the direction cosines of the rotation axis in the **NED** coordinate system (Table 4.1), and  $\omega$  is the amount of rotation, the elements of matrix  $\mathbf{a}$  are:

$$\begin{aligned}
 a_{11} &= \cos \omega + \cos^2 \alpha (1 - \cos \omega) \\
 a_{12} &= -\cos \gamma \sin \omega + \cos \alpha \cos \beta (1 - \cos \omega) \\
 a_{13} &= \cos \beta \sin \omega + \cos \alpha \cos \gamma (1 - \cos \omega) \\
 a_{21} &= \cos \gamma \sin \omega + \cos \beta \cos \alpha (1 - \cos \omega) \\
 a_{22} &= \cos \omega + \cos^2 \beta (1 - \cos \omega) \\
 a_{23} &= -\cos \alpha \sin \omega + \cos \beta \cos \gamma (1 - \cos \omega) \\
 a_{31} &= -\cos \beta \sin \omega + \cos \gamma \cos \alpha (1 - \cos \omega) \\
 a_{32} &= \cos \alpha \sin \omega + \cos \gamma \cos \beta (1 - \cos \omega) \\
 a_{33} &= \cos \omega + \cos^2 \gamma (1 - \cos \omega)
 \end{aligned} \tag{5.17}$$

The function *Rotate* rotates a line (*trd* and *plg*) about a rotation axis (*rtrd* and *rplg*), an amount  $\omega$  (*rot*):

```

1 import numpy as np
2 from SphToCart import SphToCart as SphToCart
3 from CartToSph import CartToSph as CartToSph
4
5 def Rotate(rtrd,rplg,rot,trd,plg,ans0):
6     """
7         Rotate rotates a line by performing a coordinate
8         transformation. The algorithm was originally written
9         by Randall A. Marrett
10
11     rtrd = trend of rotation axis
12     rplg = plunge of rotation axis
13     rot = magnitude of rotation
14     trd = trend of the vector to be rotated
15     plg = plunge of the vector to be rotated
16     ans0 = A character indicating whether the line to be
17         rotated is an axis (ans0 = 'a') or a vector
18         (ans0 = 'v')
19     trdr and plgr are the trend and plunge of the
20         rotated line
21

```

```

22 NOTE: All angles are in radians
23
24 Rotate uses functions SphToCart and CartToSph
25
26 Python function translated from the Matlab function
27 Rotate in Allmendinger et al. (2012)
28 '''
29 # Allocate some arrays
30 a = np.zeros((3,3)) #Transformation matrix
31 pole = np.zeros(3) #Dir. cosines of rotation axis
32 plotr = np.zeros(3) #Dir. cosines of rotated vector
33 temp = np.zeros(3) #Dir. cosines of unrotated vector
34
35 # Convert rotation axis to direction cosines. The
36 # convention here is X1 = North, X2 = East, X3 = Down
37 pole[0] , pole[1] , pole[2] = SphToCart(rtrd,rplg,0)
38
39 # Calculate the transformation matrix a for the rotation
40 # Eq. 5.17
41 x = 1.0 - np.cos(rot)
42 sinRot = np.sin(rot)
43 cosRot = np.cos(rot)
44 a[0,0] = cosRot + pole[0]*pole[0]*x
45 a[0,1] = -pole[2]*sinRot + pole[0]*pole[1]*x
46 a[0,2] = pole[1]*sinRot + pole[0]*pole[2]*x
47 a[1,0] = pole[2]*sinRot + pole[1]*pole[0]*x
48 a[1,1] = cosRot + pole[1]*pole[1]*x
49 a[1,2] = -pole[0]*sinRot + pole[1]*pole[2]*x
50 a[2,0] = -pole[1]*sinRot + pole[2]*pole[0]*x
51 a[2,1] = pole[0]*sinRot + pole[2]*pole[1]*x
52 a[2,2] = cosRot + pole[2]*pole[2]*x
53
54 # Convert trend and plunge of vector to be rotated into
55 # direction cosines
56 temp[0] , temp[1] , temp[2] = SphToCart(trd,plg,0)
57
58 # Perform the coordinate transformation
59 for i in range(0,3,1):
60     plotr[i] = 0.0
61     for j in range(0,3,1):
62         plotr[i] = a[i,j]*temp[j] + plotr[i]
63
64 # Convert to lower hemisphere projection if data are
65 # axes (ans0 = 'a')
66 if plotr[2] < 0.0 and ans0 == 'a' :
67     plotr[0] = -plotr[0]
68     plotr[1] = -plotr[1]
69     plotr[2] = -plotr[2]
70

```

```

71 # Convert from direction cosines back to trend and plunge
72 trdr , plgr = CartToSph(plotr[0] , plotr[1] , plotr[2])
73
74 return trdr , plgr

```

The notebook [ch5-5](#) illustrates the use of the function *Rotate* to solve the following problem from Leyshon and Lisle (1996): An overturned bed oriented 305/60 (RHR) has sedimentary lineations which indicate the palaeocurrent direction. These pitch at 60NW, with the current flowing up the plunge. Calculate the original trend of the palaeocurrents.

Besides rotating the lineations back to their pre-tilted orientation, there is an additional challenge in this problem. We need to figure out the orientation of the lineations from their pitch on the bed. We will do this as well using a rotation.

```

1 import math
2 pi = math.pi
3
4 # Import function Rotate and related functions
5 import sys, os
6 sys.path.append(os.path.abspath('../functions'))
7 from Pole import Pole as Pole
8 from Rotate import Rotate as Rotate
9 from ZeroTwoPi import ZeroTwoPi as ZeroTwoPi
10
11 # Strike and dip of bed in radians
12 strike = 305*pi/180
13 dip = 60*pi/180
14
15 # Pole of bed
16 rtrd, rplg = Pole(strike, dip, 1)
17
18 # To find the orientation of the lineations
19 # rotate the strike line clockwise about the
20 # pole an amount equal to the pitch
21
22 # strike line
23 trd = strike
24 plg = 0
25
26 # rotation = pitch in radians
27 rot = 60 * pi/180
28
29 # orientation of lineations

```

```

30 trdr, plgr = Rotate(rtrd,rplg,rot,trd,plg,'a')
31
32 # Now we need to rotate the lineations about
33 # the strike line to their pre-tilted orientation
34
35 # The bed is overturned, so it has been rotated
36 # pass the vertical. The amount of rotation
37 # required to restore the bed to its pre-tilted
38 # orientation is 180- 60 = 120 deg, and it
39 # should be clockwise
40 rot = 120 * pi/180 # rotation in radians
41
42 # rotate lineations to their pre-tilted orientation
43 trdl, plgl = Rotate(trd,plg,rot,trdr,plgr,'a')
44
45 # The current flows up the plunge,
46 # so the trend of the paleocurrents is:
47 trdl = ZeroTwoPi(trdl + pi)
48 print('Original trend of the paleocurrents = {:.1f}'.format(
      trdl*180/pi))

```

Output:

Original trend of the paleocurrents = 65.0

### 5.2.5 Plotting great and small circles using rotations

The transformation matrix **a** that describes the rotation (Eq. 5.17), provides a simple and elegant way to draw great and small circles on a stereonet. As you may suspect from the previous notebook, to draw a great circle, we just need to rotate the strike line of the plane in fixed increments (e.g. 1°) around the pole to the plane until completing 180°. This is the same as drawing lines on the plane of incrementally larger rake from 0 to 180°. To draw a small circle, we just need to incrementally rotate (e.g. 1°increments) a line around the axis of the conic section until completing 360°. Any line making an angle less than 90°with the axis of rotation will trace out a cone, which plots on the stereonet as a small circle. The functions *GreatCircle* and *SmallCircle* return the path of great and small circles on an equal angle or equal area stereonet:

```

1 import numpy as np
2 from Pole import Pole as Pole
3 from Rotate import Rotate as Rotate
4 from StCoordLine import StCoordLine as StCoordLine
5
6 def GreatCircle(strike,dip,ststype):
7     '''
8         GreatCircle computes the great circle path of a plane
9         in an equal angle or equal area stereonet of unit radius
10
11    strike = strike of plane
12    dip = dip of plane
13    ststype = type of stereonet: 0 = equal angle, 1 = equal area
14    path = x and y coordinates of points in great circle path
15
16    NOTE: strike and dip should be entered in radians.
17
18    GreatCircle uses functions StCoordLine, Pole and Rotate
19
20    Python function translated from the Matlab function
21    GreatCircle in Allmendinger et al. (2012)
22    '''
23
24    pi = np.pi
25    # Compute the pole to the plane. This will be the axis of
26    # rotation to make the great circle
27    trda, plga = Pole(strike,dip,1)
28
29    # Now pick the strike line at the intersection of the
30    # great circle with the primitive of the stereonet
31    trd = strike
32    plg = 0.0
33
34    # To make the great circle, rotate the line 180 degrees
35    # in increments of 1 degree
36    rot = np.arange(0,181,1)*pi/180
37    path = np.zeros((rot.shape[0],2))
38
39    for i in range(rot.shape[0]):
40        # Avoid joining ends of path
41        if rot[i] == pi:
42            rot[i] = rot[i]*0.9999
43        # Rotate line
44        rtrd, rplg = Rotate(trda,plga,rot[i],trd,plg,'a')
45        # Calculate stereonet coordinates of rotated line
46        # and add to great circle path
47        path[i,0], path[i,1] = StCoordLine(rtrd,rplg,ststype)
48
49    return path

```

```

1 import numpy as np
2 from Rotate import Rotate as Rotate
3 from StCoordLine import StCoordLine as StCoordLine
4 from ZeroTwoPi import ZeroTwoPi as ZeroTwoPi
5
6 def SmallCircle(trda,plga,coneAngle,sttype):
7     '''
8         SmallCircle computes the paths of a small circle defined
9         by its axis and cone angle, for an equal angle or equal
10        area stereonet of unit radius
11
12        trda = trend of axis
13        plga = plunge of axis
14        coneAngle = cone angle
15        sttype = type of stereonet. 0 = equal angle, 1 = equal area
16        path1 and path2 = vectors with the x and y coordinates of
17            the points in the small circle paths
18        np1 and np2 = Number of points in path1 and path2
19
20        NOTE: All angles should be in radians
21
22        SmallCircle uses functions ZeroTwoPi, StCoordLine and
23        Rotate
24
25        Python function translated from the Matlab function
26        SmallCircle in Allmendinger et al. (2012)
27        '''
28        pi = np.pi
29        # Find where to start the small circle
30        if (plga - coneAngle) >= 0.0:
31            trd = trda
32            plg = plga - coneAngle
33        else:
34            if plga == pi/2.0:
35                plga = plga*0.9999
36            angle = np.arccos(np.cos(coneAngle)/np.cos(plga))
37            trd = ZeroTwoPi(trda+angle)
38            plg = 0.0
39
40        # To make the small circle, rotate the starting line
41        # 360 degrees in increments of 1 degree
42        rot = np.arange(0,361,1)*pi/180
43        path1 = np.zeros((rot.shape[0],2))
44        path2 = np.zeros((rot.shape[0],2))
45        np1 = 0
46        np2 = 0
47        for i in range(rot.shape[0]):
48            # Rotate line: Notice that the line is considered as

```

```

49     # a vector
50     rtrd , rplg = Rotate(trda,plga,rot[i],trd,plg,'v')
51     # Calculate stereonet coordinates and add to the
52     # right path
53     # If plunge of rotated line is positive add to
54     # first path
55     if rplg >= 0.0:
56         path1[np1,0] , path1[np1,1] = StCoordLine(rtrd,rplg,
57         sttype)
57         np1 = np1 +1
58     # Else add to the second path
59     else:
60         path2[np2,0] , path2[np2,1] = StCoordLine(rtrd,rplg,
61         sttype)
61         np2 = np2 +1
62
63     return path1, path2, np1, np2

```

Normally, stereonets are displayed with the primitive equal to the horizontal (i.e. looking straight down). However, sometimes is convenient to look at the stereonet in another orientation. For example, one may want to plot data in the plane of a cross section (the view direction is perpendicular to the cross section), or in a down-plunge projection of a fold (the view direction is parallel to the fold axis). The function *GeogrToView* enables to plot great and small circles on a stereonet of any view direction, by transforming the poles of rotation from **NED** coordinates to the view direction coordinates:

```

1 import numpy as np
2 from SphToCart import SphToCart as SphToCart
3 from CartToSph import CartToSph as CartToSph
4 from ZeroTwoPi import ZeroTwoPi as ZeroTwoPi
5
6 def GeogrToView(trd,plg,trdv,plgv):
7     '''
8     GeogrToView transforms a line from NED to View Direction
9     coordinates
10    trd = trend of line
11    plg = plunge of line
12    trdv = trend of view direction
13    plgv = plunge of view direction
14    rtrd and rplg are the new trend and plunge of the line
15    in the view direction.
16
17    NOTE: Input/Output angles are in radians
18

```

```

19 GeogrToView uses functions ZeroTwoPi, SphToCart and
20 CartToSph
21
22 Python function translated from the Matlab function
23 GeogrToView in Allmendinger et al. (2012)
24 '''
25 #some constants
26 east = np.pi/2.0
27
28 #Make transformation matrix between NED and View Direction
29 a = np.zeros((3,3))
30 a[2,0], a[2,1], a[2,2] = SphToCart(trdv,plgv,0)
31 temp1 = trdv + east
32 temp2 = 0.0
33 a[1,0], a[1,1], a[1,2] = SphToCart(temp1,temp2,0)
34 temp1 = trdv
35 temp2 = plgv - east
36 a[0,0], a[0,1], a[0,2] = SphToCart(temp1,temp2,0)
37
38 #Direction cosines of line
39 dirCos = np.zeros(3)
40 dirCos[0], dirCos[1], dirCos[2] = SphToCart(trd,plg,0)
41
42 # Transform line
43 nDirCos = np.zeros(3)
44 for i in range(0,3,1):
45     nDirCos[i] = a[i,0]*dirCos[0] + a[i,1]*dirCos[1]+ a[i,2]*
46     dirCos[2]
47
48 # Compute line from new direction cosines
49 rtrd, rplg = CartToSph(nDirCos[0],nDirCos[1],nDirCos[2])
50
51 # Take care of negative plunges
52 if rplg < 0.0 :
53     rtrd = ZeroTwoPi(rtrd+np.pi)
54     rplg = -rplg
55
56 return rtrd, rplg

```

We put these three functions together in a function called *Stereonet*, that plots an equal angle or equal area stereonet in any view direction:

```

1 import numpy as np
2 import matplotlib.pyplot as plt
3 from Pole import Pole as Pole
4 from GeogrToView import GeogrToView as GeogrToView

```

```

5 from SmallCircle import SmallCircle as SmallCircle
6 from GreatCircle import GreatCircle as GreatCircle
7
8 def Stereonet(trdv,plgv,intrad,ststype):
9     '''
10    Stereonet plots an equal angle or equal area stereonet
11    of unit radius in any view direction
12
13    trdv = trend of view direction
14    plgv = plunge of view direction
15    intrad = interval in radians between great or small circles
16    ststype = type of stereonet. 0 = equal angle, 1 = equal area
17
18    NOTE: All angles should be entered in radians
19
20    Stereonet uses functions Pole, GeogrToView,
21    SmallCircle and GreatCircle
22
23    Python function translated from the Matlab function
24    Stereonet in Allmendinger et al. (2012)
25    '''
26
27    pi = np.pi
28    # some constants
29    east = pi/2.0
30    west = 3.0*east
31
32    # Plot stereonet reference circle
33    r = 1.0 # radius pf stereonet
34    TH = np.arange(0,360,1)*pi/180
35    X = r * np.cos(TH)
36    Y = r * np.sin(TH)
37
38    # Make a larger figure
39    plt.rcParams['figure.figsize'] = [15, 7.5]
40    plt.plot(X,Y, 'k')
41    plt.axis([-1, 1, -1, 1])
42    plt.axis ('equal')
43    plt.axis('off')
44
45    # Number of small circles
46    nCircles = int(pi/(intrad*2.0))
47
48    # small circles
49    # start at the North
50    trd = 0.0
51    plg = 0.0
52
53    # If view direction is not the default (trdv=0,plgv=90)
      # transform line to view direction

```

```

54 if trdv != 0.0 and plgv != east:
55     trd, plg = GeogrToView(trd,plg,trdv,plgv)
56
57 # Plot small circles
58 for i in range(1,nCircles+1):
59     coneAngle = i*intrad
60     path1, path2, np1, np2 = SmallCircle(trd,plg,coneAngle,
61                                         sttype)
62     plt.plot(path1[np.arange(0,np1),0], path1[np.arange(0,np1),
63                                         1], color='gray', linewidth=0.5)
64     if np2 > 0:
65         plt.plot(path2[np.arange(0,np2),0], path2[np.arange(0,
66                                         np2),1], color='gray', linewidth=0.5)
67
68 # Great circles
69 for i in range(0,nCircles*2+1):
70     # Western half
71     if i <= nCircles:
72         # Pole of great circle
73         trd = west
74         plg = i*intrad
75         # Eastern half
76     else:
77         # Pole of great circle
78         trd = east
79         plg = (i-nCircles)*intrad
80     # If pole is vertical shift it a little bit
81     if plg == east:
82         plg = plg * 0.9999
83     # If view direction is not the default
84     # (trdv = 0,plgv = 90)
85     # transform line to view direction
86     if trdv != 0.0 and plgv != east:
87         trd, plg = GeogrToView(trd,plg,trdv,plgv)
88     # Compute plane from pole
89     strike, dip = Pole(trd,plg,0)
90     # Plot great circle
91     path = GreatCircle(strike,dip,sttype)
92     plt.plot(path[:,0],path[:,1],color='gray', linewidth=0.5)

```

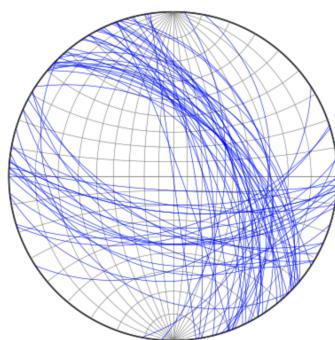
Now, let's use all these functions to plot the bedding data of the Big Elk anticline (Fig. 5.7) in an equal angle stereonet, looking down and also along the fold axis. The notebook [ch5-6](#) illustrates this. Notice that we read the strike and dips from the file [\*beasd.txt\*](#):

```

1 # Import libraries
2 import numpy as np
3 import matplotlib.pyplot as plt
4 %matplotlib inline
5 pi = np.pi
6
7 # Import function Stereonet and related functions
8 import sys, os
9 sys.path.append(os.path.abspath('../functions'))
10 from Pole import Pole as Pole
11 from GreatCircle import GreatCircle as GreatCircle
12 from GeogrToView import GeogrToView as GeogrToView
13 from Stereonet import Stereonet as Stereonet
14
15 # Draw a lower hemisphere equal angle stereonet
16 trdv = 0
17 plgv = 90 * pi/180
18 intrad = 10 * pi/180
19 Stereonet(trdv,plgv,intrad,0)
20
21 # Read the strike-dip data from the Big Elk anticline
22 beasd = np.loadtxt('beasd.txt')
23
24 # Plot the great circles
25 for i in range(beasd.shape[0]):
26     path = GreatCircle(beasd[i,0]*pi/180,beasd[i,1]*pi/180,0)
27     plt.plot(path[:,0], path[:,1], 'b', linewidth=0.5)

```

Output:



```

1 # Draw the same data in an equal angle stereonet,
2 # but make the view direction = fold axis
3 trdv = 125*pi/180
4 plgv = 26*pi/180
5 Stereonet(trdv,plgv,intrad,0)
6

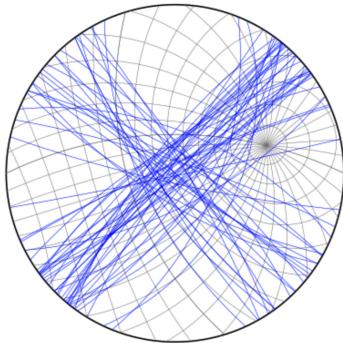
```

```

7 # Plot the great circles
8 for i in range(beasd.shape[0]):
9     # pole to bed
10    trdp, plgp = Pole(beasd[i,0]*pi/180,beasd[i,1]*pi/180,1)
11    # transform pole
12    trdpt, plgpt = GeogrToView(trdp,plgp,trdv,plgv)
13    # bed from transformed pole
14    striket, dipt = Pole(trdpt,plgpt,0)
15    # plot great circle
16    path = GreatCircle(striket,dipt,0)
17    plt.plot(path[:,0], path[:,1], 'b', linewidth=0.5)

```

Output:



What do these plots tell you about the geometry of the fold?

### 5.3 Exercises

- Figure 5.8 is a satellite image of the Sheep Mountain anticline, Wyoming, USA (Rioux, 1994). At 75 localities along the anticline in the Jurassic Sundance Formation (gray-green sandstone, siltstone and shale; Rioux, 1994), the ENU coordinates of points on the base and top of the unit (Fig. 5.8a, green and red points), and three points on a bed inside the unit (Fig. 5.8b, blue points), were recorded in Google Earth. You can visualize these points in Google Earth using the file [sdtp.kml](#).

The file [sdtp.txt](#) contains the ENU coordinates (UTM in meters) of the points. Each row is one locality, and it contains 15 columns corresponding to the ENU coordinates of points 1 to 5. Points 1 to 3 are on a bed inside the unit, and points 4 and 5 are on the base and top

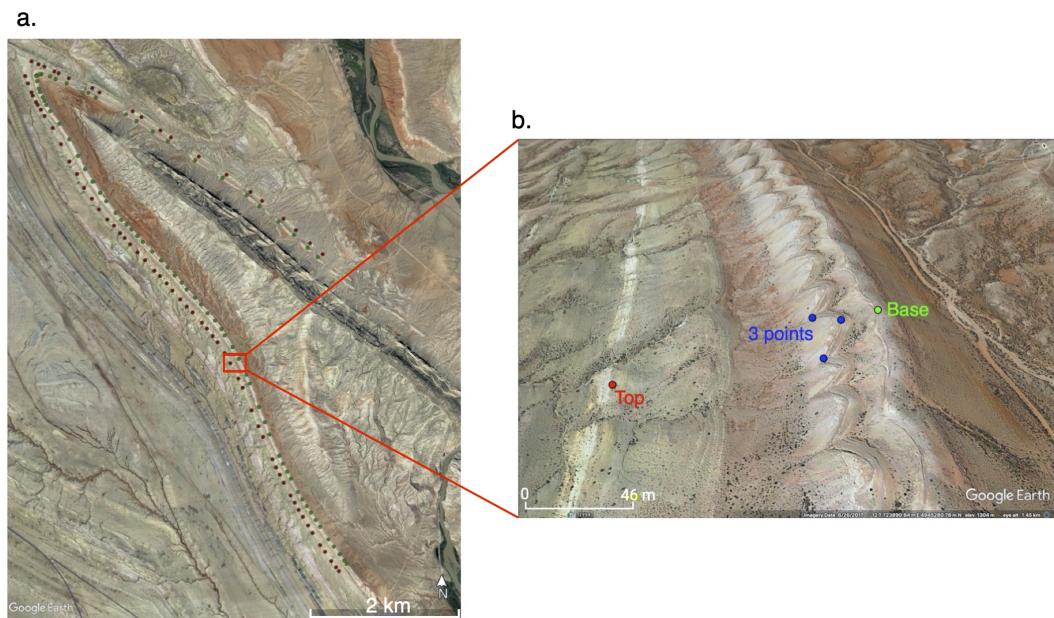


Figure 5.8: **a.** Base (green) and top (red) locations of the Jurassic Sundance Formation along the Sheep Mountain anticline, Wyoming, for exercise 1. **b.** Closeup of one of the localities (red rectangle in a) showing as well the three points (blue) used to determine strike and dip.

of the unit, respectively. Columns 1 to 3 are the **ENU** coordinates of point 1, columns 4 to 6 those of point 2, and so on.

- Compute the thickness of the Sundance Formation at the 75 localities. Notice that at each locality you will need to compute the strike and dip using points 1-3 and the *ThreePoint* function, and the thickness using points 4 and 5 and the *TrueThickness* function.
- Plot the bedding data along the anticline in an equal area, lower hemisphere stereonet. Plot these data as great circles.
- Suppose that the error in horizontal (**EN**) coordinates is  $\pm 3$  m and in the vertical is  $\pm 1.5$  m. These are conservative error estimates for Google Earth. What are the errors in strike and dip and thickness at the 75 localities? *Hint:* Use functions *ThreePointU* and *TrueThicknessU*.
- Make a plot of computed thickness versus computed dip, and another plot of computed thickness versus north (**N**) for the 75 lo-

calities. Include the thickness and dip error bars. Do you see any correlation between thickness and bedding dip? Is there a systematic variation of thickness along the anticline?

- (e) The axis of the anticline is oriented 306/11. This is approximately the location where the bedding planes on the stereonet intersect. In the next chapter we will see how to compute this axis. Make a Down-Plunge projection of the base and top of the Jurassic Sundance Formation. *Hint:* Project the 75 base and top locations using the function *DownPlunge*.
2. Allmendinger and Judge (2013) discuss the uncertainty in thickness measurements and its implication for estimating the shortening of fold and thrust belts. Figure 5.9 is a geologic map of the Canmore east half area in Alberta, Canada (Price, 1970). The yellow dots are the points used by these authors to estimate the thickness of the Devonian Palliser (Dpa) and Mississippian Livingstone (Mlv) formations. These are in a homoclinal dip package in a thrust sheet.

The files *dpa.txt* and *mlv.txt* contain the **ENU** coordinates (UTM in meters) of the points in the Palliser (Dpa) and Livingstone (Mlv) formations, respectively. Each row in the files is one locality, and it contains 12 columns corresponding to the **ENU** coordinates of points 1 to 4. Points 1-3 are either on the top or the base of the unit, and point 4 is on the other contact. Columns 1 to 3 are the **ENU** coordinates of point 1, columns 4 to 6 those of point 2, and so on.

- (a) Compute the thickness of the Palliser and Livingstone formations at the localities shown in Figure 5.9. What is the mean value of thickness of these two units? What is the standard deviation? *Hint:* Use the functions *ThreePoint* and *TrueThickness*. The NumPy functions *mean* and *std* compute the mean and standard deviation of an array.
- (b) Consider that the uncertainty in horizontal and vertical coordinates is  $\pm 15.24$  m. Compute again the mean value and standard deviation of the thickness of the units. This time these values will have uncertainties. *Hint:* Use the functions *ThreePointU* and *TrueThicknessU*. Notice that you can use the NumPy functions *mean* and *std* on arrays made of numbers with uncertainties (*uFloat*).
- (c) How do your results compare to those of Allmendinger and Judge (2013, their Table 1)?

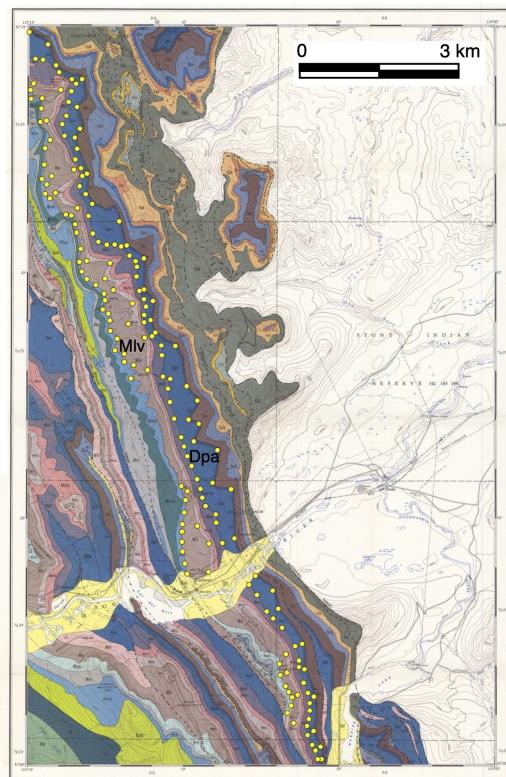


Figure 5.9: Geologic map of the Canmore east half area, Alberta, Canada (Price, 1970) for exercise 2. The yellow dots are points used to determine the thickness of the Devonian Palliser (Dpa) and Mississippian Livingstone (Mlv) formations.

3. The following exercise is from Ragan (2009): With the following information and the topographic map of Fig. 5.10, construct a geological map. The base of a 100 m thick sandstone unit of early Triassic age is exposed at point A; its attitude is 110/25 (RHR). Point B is on the east boundary of a 50 m thick, vertical diabase dike of Jurassic age; its trend is 020. At point C, the base of a horizontal Cretaceous sequence is exposed and at point D the base of a conformable sequence of Tertiary rocks is present.

This exercise is normally solved graphically (Fig. 3.9). Here, you are going to use computation. The files `XGE.txt`, `YGE.txt`, and `ZGE.txt` are the ENU coordinates of the points of the DEM grid (these arrays follow the format of the NumPy `meshgrid` function). Points A, B, C and D have the following coordinates ENU coordinates:

$$\begin{aligned}A &= [232, 428, 370] \\B &= [612, 322, 355] \\C &= [281.5, 239, 395] \\D &= [537, 183, 410]\end{aligned}$$

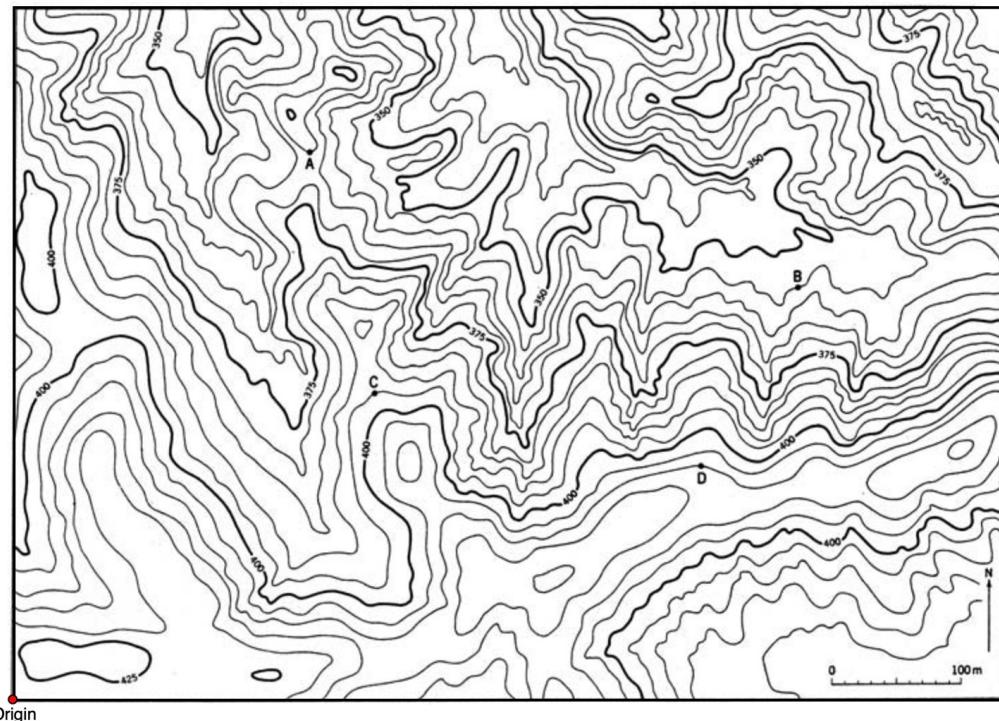


Figure 5.10: Topographic map for exercise 3. Notice that the origin is at the lower left corner of the map. This is exercise 2 in chapter 4 of Ragan (2009).

*Hint:* Use the function *OutcropTrace* to compute the contacts. Follow a procedure similar to notebook [ch5-3](#) to draw the topographic contours and the contacts. In this case though, some contacts will intersect. At contacts intersections you will need to use the principle of superposition to determine which contact cuts the other one: e.g. the Jurassic dyke will cut the Triassic sequence, but it will be covered by the Cretaceous and Tertiary sequences.

4. This exercise is from Marshak and Mitra (1988). It is probably one of the hardest exercises to solve using rotations on a stereonet. Here, you will use the function *Rotate* to solve this problem:

In eastern New York, there is an important unconformity called the Taconic unconformity. It separates Mid-Ordovician flysch from Devonian limestone. At a locality near the town of Catskill, the limestone (and the unconformity) is oriented  $195/44$  (RHR). An anticline occurs in the underlying flysch. One limb is presently oriented  $240/73$  (limb 1), and the other limb is presently oriented  $020/41$  (limb 2) (RHR). Flute

casts occur in the Ordovician strata on limb 1 (NW dipping limb) and they have an orientation of 037/52.

- (a) What was the orientation of each of the two fold limbs before tilting of the unconformity? *Hint:* Rotate the pole of the unconformity about the strike line of the unconformity to make the pole vertical (and the unconformity horizontal). Apply the same rotation to the poles of the limbs and the flute casts. Find the orientation of the limbs from their rotated poles.
- (b) What was the orientation of the fold axis prior to tilting? *Hint:* The fold axis is the intersection of the limbs before tilting of the unconformity. Use the function *Angles* to solve this.
- (c) What was the trend of the current direction responsible for the formation of the flute casts in Ordovician time? *Hint:* Rotate the fold axis computed in (b) about a horizontal line perpendicular to it, to bring the axis to the horizontal. Apply the same rotation to the poles of the limbs and the flute casts. Then, rotate the poles of the limbs about the horizontal fold axis to make them vertical (and the limbs horizontal). Apply the same rotation to the flute casts. If the rotations are correct, the flute casts should be horizontal and their trend is the orientation of the paleocurrent in the Ordovician.
- (d) What is the present orientation of the flute casts on limb 2 (SE dipping limb)? *Hint:* The trend of the flute casts on limb 2 in the Ordovician is the trend you got in (c) minus 180°. The plunge of the flute casts is of course zero. Apply to the flute casts on limb 2, the inverse of the rotations you applied to the pole of limb 2 to bring them back to their present orientation.
- (e) Plot the results of (a), (b), (c) and (d) as poles and lines on a stereonet. Use colors to indicate the different stages, and symbols to indicate the different elements: unconformity, limbs, fold axis, and flute casts.
- (f) Write a Python function to draw the arc of a rotation on a stereonet. Indicate the sense of rotation with an arrow at the end of the arc. Use this function to draw the arcs of the rotations in this problem.

## References

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# Chapter 6

## Tensors

A tensor is a physical entity that can be transformed from one coordinate system to another, changing its components in a predictable way, but without changing its fundamental nature, such that the tensor is independent of a particular coordinate system. Thus, scalars (e.g. mass, temperature and density), and vectors (e.g. velocity, force and poles to bedding) are tensors. More specifically, they are zero order (scalars) and first order (vectors) tensors. In this chapter, we will look at higher, second order tensors, which are commonly known as *tensors*. This is a short chapter, but it is fundamental to understand important concepts such as the Mohr Circle, the orientation tensor, and the mathematical background for important tensors in geology such as stress and strain.

### 6.1 Basic characteristics of a tensor

In three dimensions, a *tensor* is characterized by nine components:

$$\mathbf{T} = T_{ij} = \begin{bmatrix} T_{11} & T_{12} & T_{13} \\ T_{21} & T_{22} & T_{23} \\ T_{31} & T_{32} & T_{33} \end{bmatrix} \quad (6.1)$$

Notice that tensors are represented by capital bold letters and we use brackets to differentiate them from matrices such as the transformation matrix  $\mathbf{a}$  in chapter 5. The nine components of the tensor  $T_{ij}$  give the values of the tensor

with reference to the three axes of the specific coordinate system  $\mathbf{X}_1\mathbf{X}_2\mathbf{X}_3$ . If we change the axes orientations, then the nine components will change but, similar to a vector, the tensor itself will not change.

Like matrices, tensors can be symmetric, asymmetric, or antisymmetric. If the nine components  $T_{ij}$  have different values, the tensor is asymmetric. If  $T_{ij} = T_{ji}$ , the tensor is symmetric. In this case the components above the principal diagonal are the same as those below the diagonal and only six components are required to define the tensor. Finally, if  $T_{ij} = -T_{ji}$ , the tensor is antisymmetric. In this case the components along the diagonal are zero and only three components are required to define the tensor.

Any asymmetric tensor  $\mathbf{T}$  can be decomposed into a symmetric tensor  $\mathbf{S}$  plus an antisymmetric tensor  $\mathbf{A}$ :

$$T_{ij} = S_{ij} + A_{ij} \quad \text{where} \quad S_{ij} = \frac{T_{ij} + T_{ji}}{2} \quad \text{and} \quad A_{ij} = \frac{T_{ij} - T_{ji}}{2} \quad (6.2)$$

We will use this property when dealing with infinitesimal strain (chapter 8).

For all symmetric tensors, there is one orientation of the coordinate axes for which all the components except those along the principal diagonal, are zero:

$$\mathbf{T} = T_{ij} = \begin{bmatrix} T_{11} & 0 & 0 \\ 0 & T_{22} & 0 \\ 0 & 0 & T_{33} \end{bmatrix} = \begin{bmatrix} T_2 & 0 & 0 \\ 0 & T_1 & 0 \\ 0 & 0 & T_3 \end{bmatrix} \quad (6.3)$$

Under this condition, the values along the diagonal are the principal axes of the tensor. Based on their magnitude, these axes are ranked as the maximum ( $T_1$ ), intermediate ( $T_2$ ), and minimum ( $T_3$ ) principal axes. Notice that the indices of the principal axes do not have to coincide with the indices of the coordinate system, for example in Eq. 6.3  $T_1$  is parallel to the coordinate axis  $\mathbf{X}_2$ . The principal axes define the major, intermediate and minor axes of a three-dimensional surface known as the magnitude ellipsoid (Fig. 6.1). You have probably heard about this ellipsoid before in relation to stress or strain.

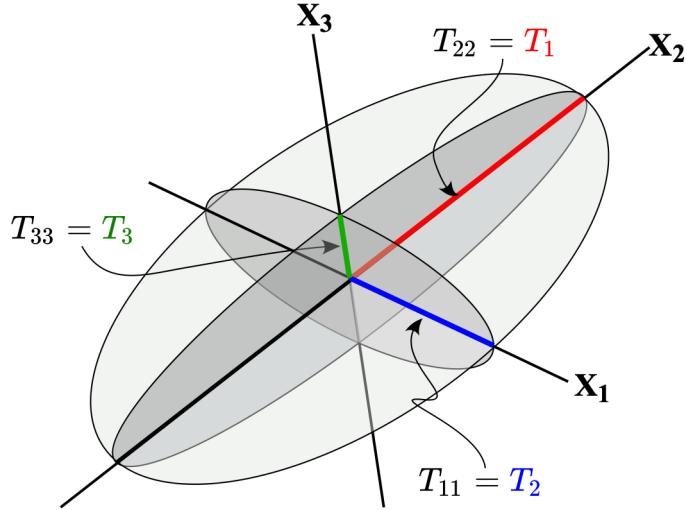


Figure 6.1: The magnitude ellipsoid and principal axes of a symmetric tensor  $\mathbf{T}$  for the case described by Eq. 6.3. Notice that  $T_1$ ,  $T_2$  and  $T_3$  define the major, intermediate and minor axes of the ellipsoid. Modified from Allmendinger et al. (2012).

## 6.2 Principal axes of a tensor

Determining the orientation of the coordinate system whose axes are parallel to the principal axes of a symmetric tensor involves solving the *eigenvalue* problem (Allmendinger et al., 2012). The mathematical solution to this problem gives a cubic polynomial:

$$\lambda^3 - I\lambda^2 - II\lambda - III = 0 \quad (6.4)$$

The three roots of  $\lambda$  are the three eigenvalues and they correspond to the magnitudes of the three principal axes. Once we know the eigenvalues, we can calculate the eigenvectors, which give the orientation of the three principal axes. Thus, we can find the principal axes of any symmetric tensor by finding its eigenvectors and eigenvalues. In Python, the NumPy `linalg.eigh` function computes the eigenvalues and eigenvectors of a symmetric array<sup>1</sup>. We will use this function later in the chapter when finding the principal axes of a tensor.

---

<sup>1</sup>`eigh` also sorts the eigenvalues in ascending order

The three coefficients  $I$ ,  $II$  and  $III$  in Eq. 6.4 are known as the invariants of the tensor. They have the same values regardless of the coordinate system we choose. As we will see later (e.g. stress invariants in Chapter 7), these invariants are very important. Their values are given by:

$$\begin{aligned} I &= T_{11} + T_{22} + T_{33} = T_1 + T_2 + T_3 \\ II &= \frac{(T_{ij}T_{ij} - I^2)}{2} = -(T_1T_2 + T_2T_3 + T_3T_1) \\ III &= \det \mathbf{T} = |T_{ij}| = T_1T_2T_3 \end{aligned} \quad (6.5)$$

### 6.3 Tensors as vector operators

A tensor commonly relates two vectors, or more formally we can say that a tensor is a linear vector operator because the components of the tensor are the coefficients of a set of linear equations that relate two vectors:

$$\mathbf{u} = \mathbf{T}\mathbf{v} \quad \text{or} \quad u_i = T_{ij}v_j \quad (6.6)$$

A nice example of this relation is Cauchy's law (Chapter 7), which says that the traction on a plane (a vector) is equal to the stress (a tensor) times the pole to the plane (another vector). Since in three dimensions the indices  $i$  and  $j$  change from 1 to 3, Eq. 6.6 corresponds to three equations, one for each of the components of  $\mathbf{u}$  in terms of the components of  $\mathbf{v}$ . In Python code this would look like:

```

1 # v (1 x 3 vector) and T (3 x 3 tensor) are declared before
2 u = np.zeros(3) # initialize u (1 x 3 vector)
3 for i in range(0,3,1): # free index
4     for j in range(0,3,1): # dummy index
5         u[i] = T[i,j]*v[j] + u[i]

```

An implication of Eq. 6.6 is that one can produce a tensor from a type of product of two vectors. This operation is known as the dyad product and it involves multiplying a column vector times a row vector, which gives a  $3 \times 3$  matrix:

$$\mathbf{T} = \mathbf{u} \otimes \mathbf{v} \quad \text{or} \quad T_{ij} = u_i v_j \quad (6.7)$$

This gives nine equations (one for each component of the tensor) in terms of the components of  $\mathbf{u}$  and  $\mathbf{v}$ . In Python code this would look like:

```

1 # u (1 x 3 vector) and v (1 x 3 vector) are declared before
2 T = np.zeros((3,3)) # initialize T (3 x 3 tensor)
3 for i in range(0,3,1): # free index
4     for j in range(0,3,1): # free index
5         T[i,j] = u[i]*v[j]

```

In section 6.5, we will use the dyad product to derive the orientation tensor.

## 6.4 Tensor transformations

If we know the components of a tensor in one coordinate system, we can determine what the components are in any other coordinate system, just as we did with vectors in section 5.1.2. All we need to know is the transformation matrix  $\mathbf{a}$ . The procedure, however, is more difficult because a second order tensor is more complicated than a vector. The new components of the tensor in terms of the old are given by (Allmendinger et al., 2012):

$$\mathbf{T}' = \mathbf{a}^T \mathbf{T} \mathbf{a} \quad \text{or} \quad T'_{ij} = a_{ik} a_{jl} T_{kl} \quad (6.8)$$

This equation represent nine equations (since there are two fixed indices  $i$  and  $j$ ) with nine terms each (since there are two dummy indices  $k$  and  $l$ ). It is tedious to expand and solve Eq. 6.8 by hand. Fortunately, we can solve this equation using code:

```

1 # T_old (3 x 3 tensor) and a (3 x 3 transf. matrix) are
2     declared before
3 T_new = np.zeros((3,3)) # initialize T_new (3 x 3 tensor)
4 for i in range(0,3,1): # free index
5     for j in range(0,3,1): # free index
6         for k in range(0,3,1): # dummy index
7             for l in range(0,3,1): # dummy index
8                 T_new[i,j] = a[i,k]*a[j,l]*T_old[k,l] + T_new
9                 [i,j]

```

Likewise, we can compute the old coordinates of the tensor in terms of the new coordinates:

$$\mathbf{T} = \mathbf{a}\mathbf{T}'\mathbf{a}^T \quad \text{or} \quad T_{ij} = a_{ki}a_{lj}T'_{kl} \quad (6.9)$$

In Python code this would look like:

```

1 # T_new (3 x 3 tensor) and a (3 x 3 transf. matrix) are
2     declared before
3 T_old = np.zeros((3,3)) # initialize T_old (3 x 3 tensor)
4 for i in range(0,3,1): # free index
5     for j in range(0,3,1): # free index
6         for k in range(0,3,1): # dummy index
7             for l in range(0,3,1): # dummy index
8                 T_old[i,j] = a[k,i]*a[l,j]*T_new[k,l] + T_old
9                 [i,j]

```

#### 6.4.1 The Mohr Circle

Let's consider the case where the axes of the old coordinate system are parallel to the principal axes of the tensor  $\mathbf{T}$ . Now, let's change the coordinate system to a different orientation by rotating it an angle  $\theta$  about one of the principal axes, for example the intermediate axis  $T_2$  (Fig. 6.2). The transformation matrix  $\mathbf{a}$  for this problem is:

$$\mathbf{a} = \begin{pmatrix} \cos \theta & \cos 90 & \cos(90 - \theta) \\ \cos 90 & \cos 0 & \cos 90 \\ \cos(90 + \theta) & \cos 90 & \cos \theta \end{pmatrix} = \begin{pmatrix} \cos \theta & 0 & \sin \theta \\ 0 & 1 & 0 \\ -\sin \theta & 0 & \cos \theta \end{pmatrix} \quad (6.10)$$

The tensor  $\mathbf{T}$  in the old coordinate system is:

$$\mathbf{T} = T_{ij} = \begin{bmatrix} T_1 & 0 & 0 \\ 0 & T_2 & 0 \\ 0 & 0 & T_3 \end{bmatrix} \quad (6.11)$$

Now, we can use Eq. 6.8 to calculate the components of the tensor in the new coordinate system. Substituting Eqs. 6.10 and 6.11 into Eq. 6.8 and carrying out the summation, we obtain:

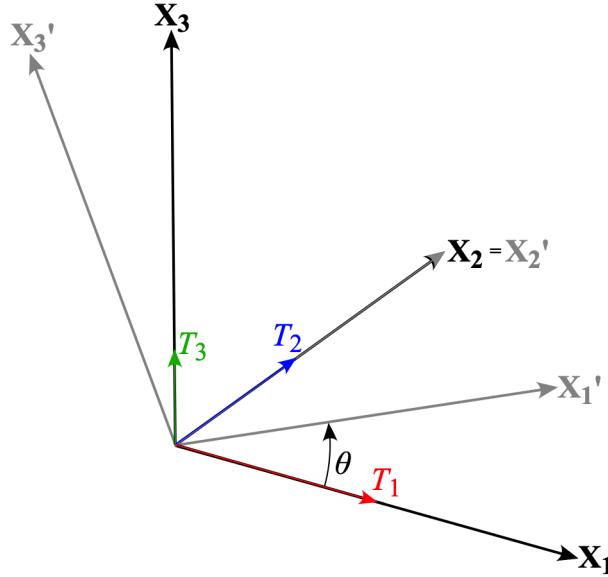


Figure 6.2: Rotation of principal coordinate system  $\mathbf{X}_1\mathbf{X}_2\mathbf{X}_3$  about the principal axis  $T_2$  an amount  $\theta$ . Modified from Allmendinger (2019).

$$\mathbf{T}' = T'_{ij} = \begin{bmatrix} T_1 \cos^2 \theta + T_3 \sin^2 \theta & 0 & -(T_1 - T_3) \sin \theta \cos \theta \\ 0 & T_2 & 0 \\ -(T_1 - T_3) \sin \theta \cos \theta & 0 & T_1 \sin^2 \theta + T_3 \cos^2 \theta \end{bmatrix} \quad (6.12)$$

The components of  $\mathbf{T}'$  can be expressed in a nicer way using the following trigonometric identities for double angles:

$$\sin 2\theta = 2 \sin \theta \cos \theta \quad \sin^2 \theta = \frac{1 - \cos 2\theta}{2} \quad \cos^2 \theta = \frac{1 + \cos 2\theta}{2} \quad (6.13)$$

Substituting these equations into Eq. 6.12 and rearranging, we get the following equations for the components of the tensor in the new coordinate system:

$$\begin{aligned} T'_{11} &= \frac{T_1 + T_3}{2} + \frac{T_1 - T_3}{2} \cos 2\theta \\ T'_{33} &= \frac{T_1 + T_3}{2} - \frac{T_1 - T_3}{2} \cos 2\theta \\ T'_{13} = T'_{31} &= -\frac{T_1 - T_3}{2} \sin 2\theta \end{aligned} \quad (6.14)$$

If you recall, the equation of a circle of center  $(c, 0)$  and radius  $r$  is:

$$\begin{aligned} x &= c - r \cos \alpha \\ y &= r \sin \alpha \end{aligned} \quad (6.15)$$

We can see that these equations are similar to Eq. 6.14. In fact, Eq. 6.14 describes a circle with center  $c$  and radius  $r$  (Fig. 6.3):

$$c = \left( \frac{T_1 + T_3}{2}, 0 \right) \quad r = \left( \frac{T_1 - T_3}{2}, 0 \right) \quad (6.16)$$

This circle is known as the *Mohr Circle*, because it was devised by the German engineer Otto Mohr in the late 1800s. The Mohr Circle is basically a graphical device to rotate a symmetric tensor about one of its principal axes. It is commonly associated with stress, but it can be applied to any symmetric tensor (strain and permeability for example). We will see the application of the Mohr Circle in chapters 7 and 8.

## 6.5 The orientation tensor

The concepts discussed so far in this chapter are the mathematical basis for the following two chapters on stress and strain. We will now focus on a relatively simple yet important problem that relies on the concept of eigenvalues and eigenvectors: How do we find the best-fit fold axis to a group of bedding poles? And similarly, how do we find the best-fit plane to a group of lines?

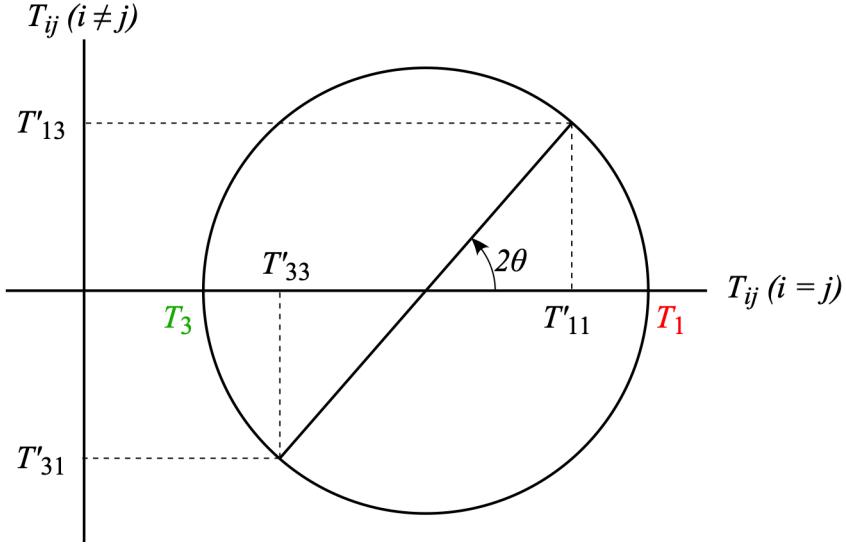


Figure 6.3: The Mohr Circle is the graphical representation of the rotation of a symmetric tensor about one of its principal axes. Modified from Allmendinger et al. (2012).

### 6.5.1 Best-fit fold axis

The solution to this problem is based on the least squares method (Charlesworth et al., 1976; Allmendinger et al., 2012). Suppose we are trying to calculate the axis  $\mathbf{f}$  of a fold. If the fold is truly cylindrical, then all the bedding poles  $\mathbf{p}_{[n]}$  should be perpendicular to  $\mathbf{f}$ , i.e. the angle  $\theta_i$  between any pole  $\mathbf{p}_{[i]}$  and  $\mathbf{f}$  should be  $90^\circ$ , and  $\cos \theta_i$  should be zero (Fig. 6.4).  $\cos \theta_i$  is equal to the dot product between  $\mathbf{f}$  and  $\mathbf{p}_{[i]}$ . Treating these lines as row vectors, the dot product can be written as:

$$\cos \theta_i = \mathbf{p}_{[i]} \mathbf{f}^T \quad (6.17)$$

We can use the value of  $\cos \theta_i$  to represent the deviation of a pole  $\mathbf{p}_{[i]}$  from  $\mathbf{f}$ . The sum of the squares of the deviations of all the poles is:

$$S = \sum_{i=1}^n \cos^2 \theta_i = \sum_{i=1}^n (\mathbf{p}_{[i]} \mathbf{f}^T)^2 \quad (6.18)$$

Since the dot product is commutative ( $\mathbf{p}_{[i]} \mathbf{f}^T = \mathbf{f} \mathbf{p}_{[i]}^T$ ), we can write Eq. 6.18

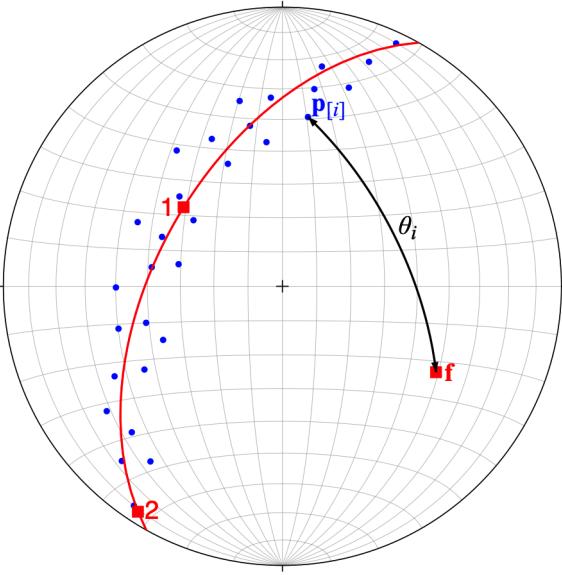


Figure 6.4: Best-fit fold axis to a group of bedding poles. A perfectly oriented pole  $\mathbf{p}_{[i]}$  should be perpendicular to the fold axis  $\mathbf{f}$ , and  $\theta_i$  should be  $90^\circ$  and  $\cos \theta_i$  should be zero. Modified from Allmendinger (2019).

as:

$$S = \sum_{i=1}^n \mathbf{f} \mathbf{p}_{[i]}^T \mathbf{p}_{[i]} \mathbf{f}^T = \mathbf{f} \mathbf{T} \mathbf{f}^T \quad (6.19)$$

$\mathbf{T}$  is a symmetric tensor known as the *orientation tensor* and it is composed of the sum of the dyad products of each pole  $\mathbf{p}_{[i]}$  ( $[\cos \alpha_i \cos \beta_i \cos \gamma_i]$ ) with itself (Eq. 6.7):

$$\begin{aligned} \mathbf{T} &= \sum_{i=1}^n \mathbf{p}_{[i]}^T \mathbf{p}_{[i]} = \sum_{i=1}^n (p_i p_j)_{[i]} \\ &= \begin{bmatrix} \sum \cos^2 \alpha_{[i]} & \sum \cos \alpha_{[i]} \cos \beta_{[i]} & \sum \cos \alpha_{[i]} \cos \gamma_{[i]} \\ \sum \cos \beta_{[i]} \cos \alpha_{[i]} & \sum \cos^2 \beta_{[i]} & \sum \cos \beta_{[i]} \cos \gamma_{[i]} \\ \sum \cos \gamma_{[i]} \cos \alpha_{[i]} & \sum \cos \gamma_{[i]} \cos \beta_{[i]} & \sum \cos^2 \gamma_{[i]} \end{bmatrix} \end{aligned} \quad (6.20)$$

You can think of  $\mathbf{T}$  as describing an ellipsoid in three-dimensions. To find

the principal axes of this ellipsoid, we need to calculate the eigenvalues and eigenvectors of  $\mathbf{T}$ . The smallest eigenvalue of  $\mathbf{T}$  is the minimization of the deviations  $S$  in Eqs. 6.18 and 6.19. If the fold were perfectly cylindrical, the lowest eigenvalue would be zero. Thus, the eigenvector corresponding to the lowest eigenvalue is the best-fit fold axis  $\mathbf{f}$ .

The function *Bingham* computes and plots a cylindrical best-fit to a distribution of bedding poles. It returns the eigenvalues and eigenvectors of  $\mathbf{T}$ , the uncertainty cones for the *Bingham* statistics, and the best-fit plane to the bedding poles. For more information on the Bingham statistics, please read Fisher et al. (1987):

```

1 import numpy as np
2 import matplotlib.pyplot as plt
3
4 from SphToCart import SphToCart as SphToCart
5 from CartToSph import CartToSph as CartToSph
6 from ZeroTwoPi import ZeroTwoPi as ZeroTwoPi
7 from Stereonet import Stereonet as Stereonet
8 from GreatCircle import GreatCircle as GreatCircle
9 from StCoordLine import StCoordLine as StCoordLine
10
11
12 def Bingham(T,P):
13     '''
14         Bingham calculates and plots a cylindrical best fit to
15         a distribution of poles to bedding. The statistical
16         routine is based on algorithms in Fisher et al. (1988)
17
18     USE: eigVec, confCone, bestFit = Bingham(T,P)
19
20     T and P = Vectors of lines trends and plunges
21     respectively
22
23     eigVec = 3 x 3 matrix with eigenvalues (column 1), trends
24     (column 2) and plunges (column 3) of the eigenvectors.
25     Maximum eigenvalue and corresponding eigenvector are
26     in row 1, intermediate in row 2, and minimum in row 3.
27
28     confCone = 2 x 2 matrix with the maximum (column 1) and
29     minimum (column 2) radius of the 95% elliptical
30     confidence cone around the eigenvector corresponding
31     to the largest (row 1), and lowest (row 2) eigenvalue
32
33     besFit = 1 x 2 vector containing the strike and dip
34     (right hand rule) of the best fit great circle to
35     the distribution of lines

```

```

36
37 NOTE: Input/Output trends and plunges, as well as
38 confidence cones are in radians. Bingham plots the
39 input poles, eigenvectors and best fit great circle
40 in an equal area stereonet.
41
42 Bingham uses functions ZeroTwoPi, Pole, StCoordLine
43 SphToCart, CartToSph, Rotate, GreatCircle, SmallCircle,
44 GeogrToView, and Stereonet
45
46 Python function translated from the Matlab function
47 Bingham in Allmendinger et al. (2012)
48 '''
49 # Some constants
50 pi = np.pi
51 east = pi/2
52 twopi = pi*2
53
54 # Number of lines
55 nlines = len(T)
56
57 # Initialize the orientation matrix
58 a = np.zeros((3,3))
59
60 # Fill the orientation matrix with the sums of the
61 # squares (for the principal diagonal) and the products
62 # of the direction cosines of each line. cn, ce and cd
63 # are the north, east and down direction cosines
64 for i in range(nlines):
65     cn,ce,cd = SphToCart(T[i],P[i],0)
66     a[0,0] = a[0,0] + cn*cn
67     a[0,1] = a[0,1] + cn*ce
68     a[0,2] = a[0,2] + cn*cd
69     a[1,1] = a[1,1] + ce*ce
70     a[1,2] = a[1,2] + ce*cd
71     a[2,2] = a[2,2] + cd*cd
72
73 # The orientation matrix is symmetric so the off-diagonal
74 # components can be equated
75 a[1,0] = a[0,1]
76 a[2,0] = a[0,2]
77 a[2,1] = a[1,2]
78
79 # Calculate the eigenvalues and eigenvectors of the
80 # orientation matrix using function eigh.
81 # D is a vector of eigenvalues and V is a full matrix
82 # whose columns are the corresponding eigenvectors
83 D, V = np.linalg.eigh(a)
84

```

```

85 # Normalize the eigenvalues by the number of lines and
86 # convert the corresponding eigenvectors to the lower
87 # hemisphere
88 for i in range(3):
89     D[i] = D[i]/nlines
90     if V[2,i] < 0:
91         V[0,i] = -V[0,i]
92         V[1,i] = -V[1,i]
93         V[2,i] = -V[2,i]
94
95 # Initialize eigVec
96 eigVec = np.zeros((3,3))
97 #Fill eigVec
98 eigVec[0,0] = D[2]      # Maximum eigenvalue
99 eigVec[1,0] = D[1]      # Intermediate eigenvalue
100 eigVec[2,0] = D[0]      # Minimum eigenvalue
101 # Trend and plunge of largest eigenvalue: column 3 of V
102 eigVec[0,1], eigVec[0,2] = CartToSph(V[0,2], V[1,2], V
103 [2,2])
104 # Trend and plunge of interm. eigenvalue: column 2 of V
105 eigVec[1,1], eigVec[1,2] = CartToSph(V[0,1], V[1,1], V
106 [2,1])
107 # Trend and plunge of minimum eigenvalue: column 1 of V
108 eigVec[2,1], eigVec[2,2] = CartToSph(V[0,0], V[1,0], V
109 [2,0])
110
111 # Initialize confCone
112 confCone = np.zeros((2,2))
113 # If there are more than 25 lines, calculate confidence
114 # cones at the 95% confidence level. The algorithm is
115 # explained in Fisher et al. (1987)
116 if nlines >= 25:
117     e11 = 0
118     e22 = 0
119     e12 = 0
120     d11 = 0
121     d22 = 0
122     d12 = 0
123     en11 = 1/(nlines*(eigVec[2,0] - eigVec[0,0])**2)
124     en22 = 1/(nlines*(eigVec[1,0] - eigVec[0,0])**2)
125     en12 = 1/(nlines*(eigVec[2,0] - eigVec[0,0])*(eigVec[1,0]
126 - eigVec[0,0]))
127     dn11 = en11
128     dn22 = 1/(nlines*(eigVec[2,0] - eigVec[1,0])**2)
129     dn12 = 1/(nlines*(eigVec[2,0] - eigVec[1,0])*(eigVec[2,0]
130 - eigVec[0,0]))
131     vec = np.zeros((3,3))
132     for i in range(3):
133         vec[i,0] = np.sin(eigVec[i,2] + east)*np.cos(twopi -

```

```

129     eigVec[i,1])
130     vec[i,1] = np.sin(eigVec[i,2] + east)*np.sin(twopi -
131     eigVec[i,1])
132     vec[i,2] = np.cos(eigVec[i,2] + east)
133     for i in range(nlines):
134         c1 = np.sin(P[i]+east)*np.cos(twopi-T[i])
135         c2 = np.sin(P[i]+east)*np.sin(twopi-T[i])
136         c3 = np.cos(P[i]+east)
137         u1x = vec[2,0]*c1 + vec[2,1]*c2 + vec[2,2]*c3
138         u2x = vec[1,0]*c1 + vec[1,1]*c2 + vec[1,2]*c3
139         u3x = vec[0,0]*c1 + vec[0,1]*c2 + vec[0,2]*c3
140         e11 = u1x*u1x * u3x*u3x + e11
141         e22 = u2x*u2x * u3x*u3x + e22
142         e12 = u1x*u2x * u3x*u3x + e12
143         d11 = e11
144         d22 = u1x*u1x * u2x*u2x + d22
145         d12 = u2x*u3x * u1x*u1x + d12
146         e22 = en22*e22
147         e11 = en11*e11
148         e12 = en12*e12
149         d22 = dn22*d22
150         d11 = dn11*d11
151         d12 = dn12*d12
152         d = -2*np.log(.05)/nlines
153         # initialize f
154         f = np.zeros((2,2))
155         if abs(e11*e22-e12*e12) >= 0.000001:
156             f[0,0] = (1/(e11*e22-e12*e12)) * e22
157             f[1,1] = (1/(e11*e22-e12*e12)) * e11
158             f[0,1] = -(1/(e11*e22-e12*e12)) * e12
159             f[1,0] = f[0,1]
160             # Calculate the eigenvalues and eigenvectors
161             # of the matrix f using function eigh
162             # The next lines follow steps 1-4 outlined
163             # on pp. 34-35 of Fisher et al. (1987)
164             DD, _ = np.linalg.eigh(f)
165             if DD[0] > 0 and DD[1] > 0:
166                 if d/DD[0] <= 1 and d/DD[1] <= 1:
167                     confCone[0,1] = np.arcsin(np.sqrt(d/DD[1]))
168                     confCone[0,0] = np.arcsin(np.sqrt(d/DD[0]))
169             # Repeat the process for the eigenvector
170             # corresponding to the smallest eigenvalue
171             if abs(d11*d22-d12*d12) >= 0.000001:
172                 f[0,0] = (1/(d11*d22-d12*d12)) * d22
173                 f[1,1] = (1/(d11*d22-d12*d12)) * d11
174                 f[0,1] = -(1/(d11*d22-d12*d12)) * d12
175                 f[1,0] = f[0,1]
176                 DD, _ = np.linalg.eigh(f)
177                 if DD[0] > 0.0 and DD[1] > 0.0:

```

```

176     if d/DD[0] <= 1 and d/DD[1] <= 1:
177         confCone[1,1] = np.arcsin(np.sqrt(d/DD[1]))
178         confCone[1,0] = np.arcsin(np.sqrt(d/DD[0]))
179
180     # Calculate the best fit great circle
181     # to the distribution of points
182     bestFit = np.zeros(2)
183     bestFit[0] = ZeroTwoPi(eigVec[2,1] + east)
184     bestFit[1] = east - eigVec[2,2]
185
186     # Plot stereonet
187     Stereonet(0, 90*pi/180, 10*pi/180, 1)
188
189     # Plot lines
190     for i in range(nlines):
191         xp,yp = StCoordLine(T[i],P[i],1)
192         plt.plot(xp,yp,'k.')
193
194     # Plot eigenvectors
195     for i in range(3):
196         xp,yp = StCoordLine(eigVec[i,1],eigVec[i,2],1)
197         plt.plot(xp,yp,'rs')
198
199     # Plot best fit great circle
200     path = GreatCircle(bestFit[0],bestFit[1],1)
201     plt.plot(path[:,0],path[:,1],'r')
202
203     # Show plot
204     plt.show()
205
206     return eigVec, confCone, bestFit

```

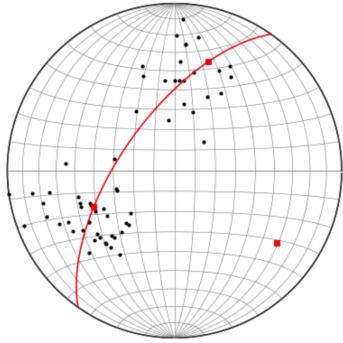
Let's use this function to compute the best-fit fold axis for the Big Elk anticline (southeastern Idaho), using the bedding data in Fig. 5.7. The notebook [ch6-1](#) illustrates this. Notice that the bedding data (strike and dips) are read from the file [\*beasd.txt\*](#):

```

1 # Import libraries
2 import numpy as np
3 import matplotlib.pyplot as plt
4 pi = np.pi
5
6 # Import functions Pole and Bingham
7 import sys, os
8 sys.path.append(os.path.abspath('../functions'))
9 from Pole import Pole as Pole
10 from Bingham import Bingham as Bingham
11
12 # Read the bedding data from the Big Elk anticline
13 beasd = np.loadtxt(os.path.abspath('../data/ch6-1/beasd.txt'))
14
15 # Initialize poles
16 T = np.zeros(len(beasd))
17 P = np.zeros(len(beasd))
18
19 # Compute poles to bedding
20 for i in range(len(T)):
21     T[i],P[i] = Pole(beasd[i,0]*pi/180,beasd[i,1]*pi/180,1)
22
23 # Compute cylindrical best fit
24 eigVec,confCone,bestFit = Bingham(T,P)
25
26 # Print best-fit fold axis
27 print('Best-fit fold axis: trend = {:.1f}, plunge {:.1f}'.format(eigVec[2,1]*180/pi,eigVec[2,2]*180/pi))
28 # Print best-fit plane
29 print('Best-fit plane: strike = {:.1f}, dip {:.1f}\n'.format(bestFit[0]*180/pi,bestFit[1]*180/pi))
30 # Print confidence cone
31 print('95% elliptical confidence cones:')
32 print('Axis 1 (largest eigenvalue): Max = {:.1f}, Min {:.1f}'.format(confCone[0,0]*180/pi,confCone[0,1]*180/pi))
33 print('Axis 3 (lowest eigenvalue): Max = {:.1f}, Min {:.1f}'.format(confCone[1,0]*180/pi,confCone[1,1]*180/pi))

```

Output:



Best-fit fold axis: trend = 125.3, plunge 26.1

Best-fit plane: strike = 215.3, dip 63.9

95% elliptical confidence cones:

Axis 1 (largest eigenvalue): Max = 16.9, Min 5.9

Axis 3 (lowest eigenvalue): Max = 8.2, Min 5.8

### 6.5.2 Line distributions

The orientation tensor  $\mathbf{T}$  (Eq. 6.20) is also useful for characterizing line distributions. Figure 6.5 shows three end-members of line distributions. The bipolar distribution (Fig. 6.5a) consists of a group of lines that are parallel or sub-parallel to each other and plunge in opposite directions, with some limited scatter. In this case, the lines define an elongate ellipsoid (a cigar), with a large (near 1.0) eigenvalue (long axis of the ellipsoid) and two small (near zero) eigenvalues (short axes of the ellipsoid). Also, the eigenvector of the largest eigenvalue describes well the preferred orientation of the lines (Fig. 6.5a). Notice that in this case, the mean vector calculation (section 4.4.1) will fail since the lines plunging in opposite directions will cancel each other out.

In the girdle distribution (Fig. 6.5b), all the lines are close to being coplanar, and they define a flattened ellipsoid (or pancake) with one small (near zero) eigenvalue corresponding to the pole of the best-fit plane through the lines, and two large relatively equal eigenvalues (near 0.5) whose eigenvectors lie within the best-fit plane. Finally, in the random distribution (Fig. 6.5c), the lines define a sphere and the eigenvalues are relatively equal. Thus, in general, the eigenvalues of  $\mathbf{T}$  are a good way to characterize line distributions.

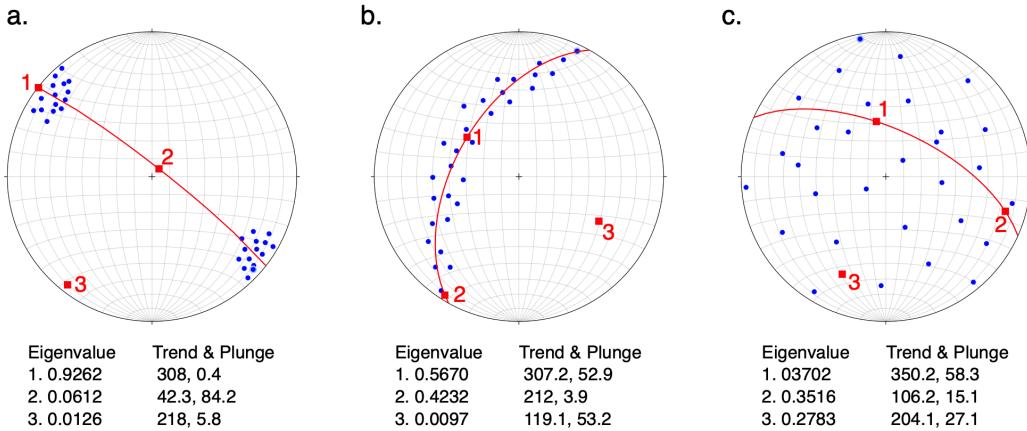


Figure 6.5: Three end members of line distributions. **a.** Bipolar, **b.** Girdle, and **c.** random. Each diagram has 30 lines. Modified from Allmendinger (2019).

### 6.5.3 Best-fit plane

In section 4.4.3 we look at the problem of calculating the orientation of a plane from three points on the plane. But what if we have more than three points on the plane? We can use the least squares approach above to solve this problem (Allmendinger, in press). This will also allow us to evaluate the goodness of fit of the plane to the data points. Let's assume the points are defined by position vectors  $\mathbf{p}_{[i]}$  in an east-north-up (**ENU**) coordinate system. First, the centroid  $\mathbf{c}$  of the position vectors  $\mathbf{p}_{[i]}$  is calculated:

$$\mathbf{c} = \frac{\sum_{i=1}^n \mathbf{p}_{[i]}}{n} \quad (6.21)$$

Then, the centroid  $\mathbf{c}$  is subtracted from the position vectors  $\mathbf{p}_{[i]}$ :

$$\mathbf{s}_{[i]} = \mathbf{p}_{[i]} - \mathbf{c} \quad (6.22)$$

And we use the vectors  $\mathbf{s}_{[i]}$  to construct a covariance matrix  $\mathbf{C}$  (which looks very similar to the orientation matrix  $\mathbf{T}$ ):

$$\mathbf{C} = \begin{bmatrix} \sum(s_E)_{[i]}^2 & \sum(s_E)_{[i]}(s_N)_{[i]} & \sum(s_E)_{[i]}(s_U)_{[i]} \\ \sum(s_N)_{[i]}(s_E)_{[i]} & \sum(s_N)_{[i]}^2 & \sum(s_N)_{[i]}(s_U)_{[i]} \\ \sum(s_U)_{[i]}(s_E)_{[i]} & \sum(s_U)_{[i]}(s_N)_{[i]} & \sum(s_U)_{[i]}^2 \end{bmatrix} \quad (6.23)$$

Finally, the eigenvalues and eigenvectors of the covariance matrix  $\mathbf{C}$  are determined. The eigenvector corresponding to the smallest eigenvalue is the pole to the best-fit plane, and the square root of the smallest eigenvalue is the standard deviation of the distance of each point from the best-fit plane.

The function *FitPlane* calculates the best-fit plane to a group of lines:

```

1 import numpy as np
2
3 from Pole import Pole as Pole
4 from CartToSph import CartToSph as CartToSph
5
6 def FitPlane(pts):
7     """
8         Fitplane computes the best-fit plane for a group of
9         points (position vectors) on the plane
10
11    USE: strike, dip, stdev = FitPlane(pts)
12
13    pts is a n x 3 matrix containing the East (column 1),
14    North (column 2), and Up (column 3) coordinates
15    of n points on the plane
16
17    strike and dip are returned in radians
18
19    stdev is the standard deviation of the distance of
20    each point from the best-fit plane
21
22    FitPlane uses functions Pole and CartToSph
23    """
24
25    # Compute the centroid of the selected points
26    avge = np.mean(pts[:,0])
27    avgn = np.mean(pts[:,1])
28    avgu = np.mean(pts[:,2])
29
30    # Compute the points vectors minus the centroid
31    pts[:,0] = pts[:,0] - avge
32    pts[:,1] = pts[:,1] - avgn
33    pts[:,2] = pts[:,2] - avgu
34
35    # Compute the covariance/orientation matrix
36    a = np.zeros((3,3))

```

```

36     for i in range(pts.shape[0]):
37         ce = pts[i,0]
38         cn = pts[i,1]
39         cu = pts[i,2]
40         # compute orientation matrix
41         a[0,0] = a[0,0] + ce*ce
42         a[0,1] = a[0,1] + ce*cn
43         a[0,2] = a[0,2] + ce*cu
44         a[1,1] = a[1,1] + cn*cn
45         a[1,2] = a[1,2] + cn*cu
46         a[2,2] = a[2,2] + cu*cu
47         # The orientation matrix is symmetric so the off-diagonal
48         # components can be equated
49         a[1,0] = a[0,1]
50         a[2,0] = a[0,2]
51         a[2,1] = a[1,2]
52
53         # calculate the eigenvalues and eigenvectors of the
54         # orientation matrix: use function eigh
55         D, V = np.linalg.eigh(a)
56
57         # Calculate pole to best-fit plane = lowest eigenvalue
58         # vector in N, E, D coordinates
59         cn = V[1,0]
60         ce = V[0,0]
61         cd = -V[2,0]
62
63         # Find trend and plunge of pole to best fit plane
64         trd, plg = CartToSph(cn,ce,cd)
65
66         # Find Best fit plane
67         strike, dip = Pole(trd,plg,0)
68
69         # Calculate standard deviation = square root of
70         # minimum eigenvalue
71         stdev = np.sqrt(D[0])
72
73     return strike, dip, stdev

```

Let's use this function to compute the orientation of the contact between the Jurassic Js and Cretaceous Ke in the northeastern part of the Poker Peak Quadrangle, Idaho (Albee et al., 1975) (yellow contact in Fig. 6.6). The notebook [ch6-2](#) shows the solution to this problem. Notice that the UTM ENU coordinates of the points on the Js-Ke contact are read from the file [jske.txt](#):

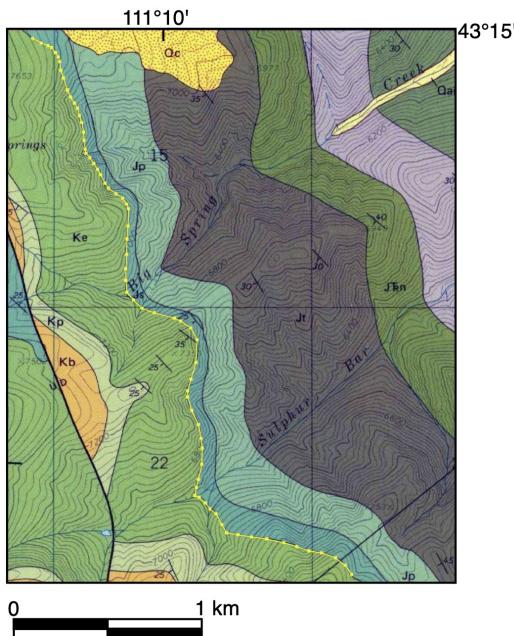


Figure 6.6: Northeastern portion of the Poker Peak Quadrangle, Idaho (Albee et al., 1975). The yellow dots are points on the Js-Ke contact.

```

1 # Import libraries
2 import numpy as np
3 pi = np.pi
4
5 # Import function FitPlane
6 import sys, os
7 sys.path.append(os.path.abspath('../functions'))
8 from FitPlane import FitPlane as FitPlane
9
10 # Read the points on the contact
11 # Coordinates are UTM (ENU) in meters
12 jske = np.loadtxt(os.path.abspath('../data/ch6-2/jske.txt'))
13
14 # Compute best-fit plane
15 strike, dip, stdev = FitPlane(jske)
16
17 # Print strike and dip of plane
18 print('Strike = {:.1f}, Dip = {:.1f}'.format(strike*180/pi,
19     dip*180/pi))
20
21 # Print standard deviation of the distance of each point
22 # from the best-fit plane
23 print('Standard deviation = {:.1f} m'.format(stdev))

```

Output:

Strike = 153.3, Dip = 29.9  
Standard deviation = 246.8 m

This orientation is not far from the strike and dip symbols shown close to the Js-Ke contact in Fig. 6.6. To learn more about fitting a plane to a distribution of lines in three-dimensions, you can read Fernandez (2005).

## 6.6 Exercises

1. The file `csdtp.txt` contains the strikes and dips (RHR) of the Jurassic Sundance Formation around the Sheep Mountain Anticline, Wyoming (Fig. 5.8). You can visualize these bedding orientations in Google Earth using the file `csdtp.kml`. Compute the anticline's best-fit fold axis using the function `Bingham`.
2. The file `biaxial.txt`, `girdle.txt`, and `random.txt` contain the lines (trend and plunge) of the distributions shown in Fig. 6.5. Compute the eigenvalues and eigenvectors, and the 95% confidence cones of these line distributions using the function `Bingham`.
3. Trede et al. (2019) published an interesting article about the appropriate sample size for strike and dip measurements. Figure 6.7 shows the Lidar scan of one of their test surfaces, a two meter-sized foliation in Cambro-Ordovician mica schists of the Svarthola Cave, SW Norway. The file `fol.txt` contains the ENU coordinates of the scanned points (grey points, Fig. 6.7), and the file `kfol.txt` contains the ENU coordinates of regularly spaced points on the foliation (red circles, Fig. 6.7).
  - (a) On each of the points of the regularly spaced grid (red circles, Fig. 6.7), compute the strike and dip of the foliation using the Lidar scanned points (grey points, Fig. 6.7) within a radius  $r$  of 0.1 m from the grid point. Do this only if there are more than 3 points within the search radius  $r$ .
  - (b) Repeat the procedure in *a* for larger search radii  $r$  of 0.3, 0.5, 0.7 and 0.9 m.
  - (c) Plot a histogram of the strike, and another histogram of the dip distribution, for the different search radii. Use different colors to

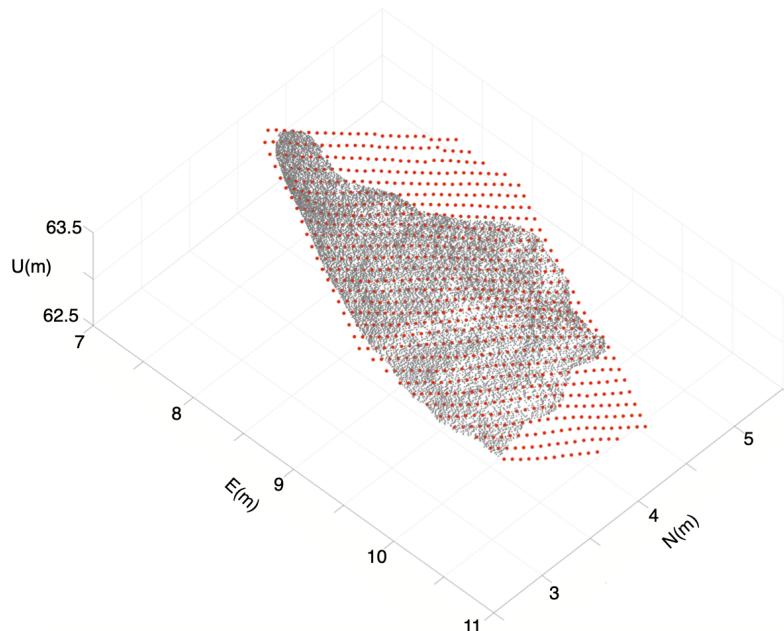


Figure 6.7: Two-metre size foliation plane in Cambro-Ordovician mica schists of the Svarthole Cave, SW Norway. The grey points are Lidar scanned points on the foliation. The red circles are points on a regular grid covering the foliation. The Lidar scan frequency is 300 kHz, and vertical and horizontal point spacing are 0.013 and 0.022, respectively. From Trede et al. (2019).

denote the different radii (see Fig. 8 of Trede et al., 2019 for an example).

- (d) At what search radius  $r$ , does the orientation of the foliation stabilize? What is the best sample size to measure the foliation?

*Hint:* Use function [FitPlane](#).

## References

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Allmendinger, R.W. 2019. Modern Structural Practice: A structural geology laboratory manual for the 21st century. [Online]. [Accessed January, 2020].

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Charlesworth, H.A.K., Langenberg, C.W. and Ramsden, J. 1976. Determining axes, axial planes, and sections of macroscopic folds using computer-based methods. *Canadian Journal of Earth Science* 13, 54-65.

Fernandez, O. 2005. Obtaining a best fitting plane through 3D georeferenced data. *Journal of Structural Geology* 27, 855–858.

Fisher, N.I., Lewis, T. and Embleton, B.J.J. 1987. Statistical analysis of spherical data. Cambridge University Press.

Trede, C., Cardozo, N. and Watson, L. 2019. What is the appropriate sample size for strike and dip measurements? An evaluation from compass, smartphone and LIDAR measurements. *Norwegian Journal of Geology* 99, 1-14.

# Chapter 7

## Stress

Geoscientists and engineers are familiar with the concept of stress. Stress describes the forces per unit area, i.e. the tractions, acting on imaginary planes of varied orientations inside a body. These tractions and the stress occur at a particular instant of time.

### 7.1 The stress tensor

A traction is defined as a force,  $\mathbf{f}$ , divided by the area of the plane,  $A$ , on which it acts:

$$\mathbf{t} = \frac{\mathbf{f}}{A} \quad (7.1)$$

A force of one Newton acting on one square meter is one pascal ( $1 \text{ N/m}^2 = 1 \text{ Pa}$ ). A pascal is very small, the atmospheric pressure is about  $10^5 \text{ Pa}$ . Therefore, we use a more convenient unit called megapascal ( $1 \text{ MPa} = 10^6 \text{ Pa}$ ).

In the subsurface, the vertical traction due to the weight of the overburden ( $\sigma_v$ ) is equal to:

$$\sigma_v = \rho g h \quad (7.2)$$

where  $\rho$  is the rock density,  $g$  is gravity, and  $h$  is depth. The rock density increases with depth, but assuming an average rock density of  $2400 \text{ kg/m}^3$ ,  $\sigma_v$  is about  $24 \text{ MPa}$  at  $1 \text{ km}$  depth.  $24\text{-}25 \text{ MPa/km}$  is a reasonable value for the gradient of  $\sigma_v$  with depth.

If we now consider a point in space and a Cartesian coordinate system  $\mathbf{X}_1\mathbf{X}_2\mathbf{X}_3$  centered at this point (Fig. 7.1), the components of the stress tensor,  $\boldsymbol{\sigma}$ , are just the tractions on planes that are perpendicular to the axes of the coordinate system:

$$\sigma_{ij} = \begin{bmatrix} \sigma_{11} & \sigma_{12} & \sigma_{13} \\ \sigma_{21} & \sigma_{22} & \sigma_{23} \\ \sigma_{31} & \sigma_{32} & \sigma_{33} \end{bmatrix} \quad (7.3)$$

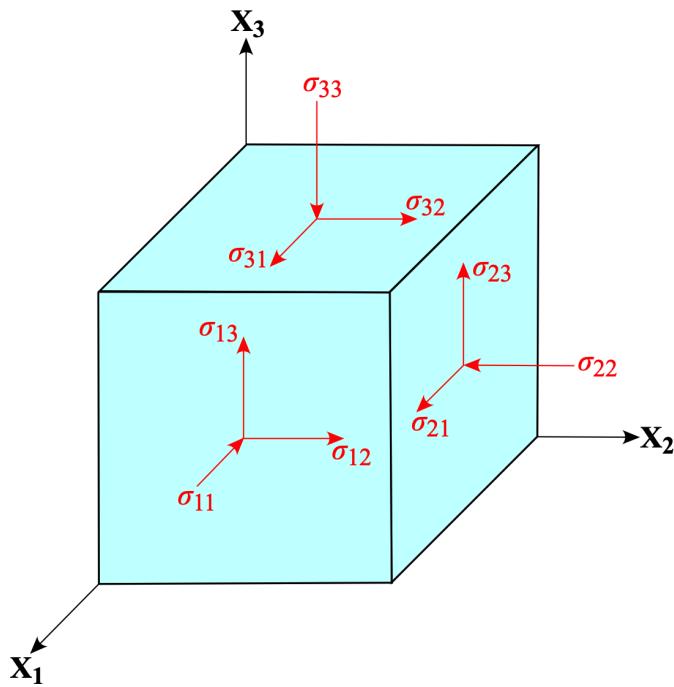


Figure 7.1: The components of the stress tensor are the normal and shear tractions on planes perpendicular to the coordinate axes.

For each component, the first index indicates the axis perpendicular to the plane, and the second index the axis to which the traction is parallel (Fig. 7.1). Traction with equal indices (e.g.  $\sigma_{11}$ ) act perpendicular to the plane and are called normal tractions, while tractions with different indices (e.g.

$\sigma_{12}$ ) act parallel to the plane and are called shear tractions. Because normal tractions are predominantly compressive within the earth (Eq. 7.2), in geology we consider compressive normal tractions as positive and tensional normal tractions as negative. This is opposite to material science, where tensional normal tractions are considered positive.

From Fig. 7.1 it is also clear that if the cube is in equilibrium (it does not rotate about one of the coordinates axis), the stress tensor must be symmetric ( $\sigma_{ij} = \sigma_{ji}$ ).

### 7.1.1 Cauchy's law

The stress tensor relates two vectors, the traction on a plane,  $\mathbf{p}$ , and the pole to the plane,  $\mathbf{n}$  (Fig. 7.2). This is nicely expressed by Cauchy's law (for a proof of this law see Allmendinger et al., 2012):

$$p_i = \sigma_{ij}n_j \quad (7.4)$$

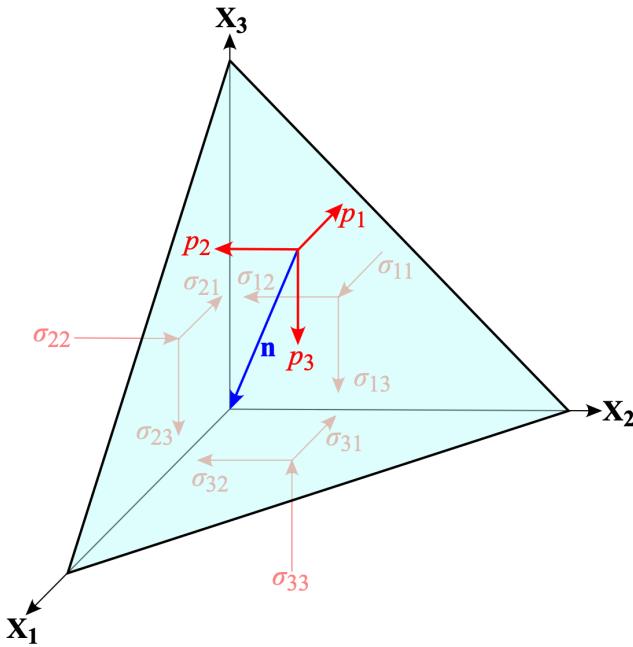


Figure 7.2: Tensions  $p_i$  on a plane oblique to the coordinate axes.  $\mathbf{n}$  is the pole to the plane.

Notice that  $p_i$  are tractions parallel to the axes of the coordinate system and  $\mathbf{n}$  is defined by its direction cosines with respect to these axes (Fig. 7.2).

The function *Cauchy* calculates the tractions  $p_i$  on a plane of any orientation in any coordinate system. *Cauchy* uses function *DirCosAxes* which calculates the direction cosines of the  $\mathbf{X}_1\mathbf{X}_2\mathbf{X}_3$  axes. To define the orientation of these axes, it is just necessary to give the trend and plunge of  $\mathbf{X}_1$  and the trend of  $\mathbf{X}_3$ :

```

1 import numpy as np
2
3 from DirCosAxes import DirCosAxes as DirCosAxes
4 from SphToCart import SphToCart as SphToCart
5
6 def Cauchy(stress,tX1,pX1,tX3,strike,dip):
7     '''
8         Given the stress tensor in a X1X2X3 coordinate system,
9         Cauchy computes the X1X2X3 tractions on an arbitrarily
10        oriented plane
11
12    USE: T,pT = Cauchy(stress,tX1,pX1,tX3,strike,dip)
13
14    stress = 3 x 3 stress tensor
15    tX1 = trend of X1
16    pX1 = plunge of X1
17    tX3 = trend of X3
18    strike = strike of plane
19    dip = dip of plane
20    T = 1 x 3 vector with X1, X2 and X3 tractions
21    pT = 1 x 3 vector with direction cosines of pole
22        to plane with respect to X1X2X3
23
24    NOTE = Plane orientation follows the right hand rule
25    Input/Output angles are in radians
26
27    Cauchy uses functions DirCosAxes and SphToCart
28
29    Python function translated from the Matlab function
30    Cauchy in Allmendinger et al. (2012)
31    '''
32    # Compute direction cosines of X1X2X3 with respect
33    # to NED
34    dC = DirCosAxes(tX1,pX1,tX3)
35
36    # Calculate direction cosines of pole to plane
37    p = np.zeros(3)
38    p[0],p[1],p[2] = SphToCart(strike,dip,1)
39
```

```

40 # Transform pole to plane to stress coordinates X1X2X3
41 # The transformation matrix is the direction cosines of
42 # X1X2X3
43 pT = np.zeros(3)
44 for i in range(3):
45     for j in range(3):
46         pT[i] = dC[i,j]*p[j] + pT[i]
47
48 # Calculate the tractions in stress coordinates X1X2X3
49 T = np.zeros(3)
50 # Compute tractions using Cauchy's law: Eq. 7.4
51 for i in range(3):
52     for j in range(3):
53         T[i] = stress[i][j]*pT[j] + T[i]
54
55 return T, pT

```

```

1 import numpy as np
2
3 from SphToCart import SphToCart as SphToCart
4
5 def DirCosAxes(tX1,pX1,tX3):
6     '''
7     DirCosAxes calculates the direction cosines of a right
8     handed, orthogonal X1X2X3 cartesian coordinate system
9     of any orientation with respect to NED
10
11 USE: dC = DirCosAxes(tX1,pX1,tX3)
12
13 tX1 = trend of X1
14 pX1 = plunge of X1
15 tX3 = trend of X3
16 dC = 3 x 3 matrix containing the direction cosines
17     of X1 (row 1), X2 (row 2), and X3 (row 3)
18
19 Note: Input angles should be in radians
20
21 DirCosAxes uses function SphToCart
22
23 Python function translated from the Matlab function
24 DirCosAxes in Allmendinger et al. (2012)
25
26 # Some constants
27 east = np.pi/2.0
28 west = 3.0*east
29 # tolerance for near zero values
30 tol = 1e-6
31

```

```

32 # Initialize matrix of direction cosines
33 dC = np.zeros((3,3))
34
35 # Direction cosines of X1
36 dC[0,0],dC[0,1],dC[0,2] = SphToCart(tX1,pX1,0)
37
38 # Calculate plunge of axis 3
39 # If axis 1 is horizontal
40 if abs(pX1) < tol:
41     dt = abs(tX1-tX3)
42     if abs(dt - east) < tol or abs(dt - west) < tol:
43         pX3 = 0.0
44     else:
45         pX3 = east
46 # Else
47 else:
48     # From dot product, theta = 90, cos(theta) = 0
49     pX3 = np.arctan(-(dC[0,0]*np.cos(tX3)+dC[0,1]*np.sin(tX3))/dC[0,2])
50
51 # Direction cosines of X3
52 dC[2,0],dC[2,1],dC[2,2] = SphToCart(tX3,pX3,0)
53
54 # X2 is the cross product of X3 and X1
55 dC[1,:] = np.cross(dC[2,:],dC[0,:])
56 # Make it a unit vector
57 dC[1,:] = dC[1,:]/np.linalg.norm(dC[1,:])
58
59 return dC

```

### 7.1.2 Stress transformation

If we know the components of the stress tensor in one coordinate system  $\mathbf{X}_1\mathbf{X}_2\mathbf{X}_3$ , we can calculate the components of the tensor in another coordinate system  $\mathbf{X}'_1\mathbf{X}'_2\mathbf{X}'_3$  (section 6.4):

$$\boldsymbol{\sigma}' = \mathbf{a}^T \boldsymbol{\sigma} \mathbf{a} \quad \text{or} \quad \sigma'_{ij} = a_{ik} a_{jl} \sigma_{kl} \quad (7.5)$$

where  $\mathbf{a}$  is the transformation matrix between the new and the old coordinate system. The function *TransformStress* transforms the stress tensor from one coordinate system to another:

```
1 import numpy as np
2
3 from DirCosAxes import DirCosAxes as DirCosAxes
4
5 def TransformStress(stress,tX1,pX1,tX3,ntX1,npX1,ntX3):
6     '''
7         TransformStress transforms a stress tensor from
8         old X1X2X3 to new X1'X2'X3' coordinates
9
10    USE: nstress = TransformStress(stress,tX1,pX1,tX3,ntX1,npX1
11        ,ntX3)
12
13    stress = 3 x 3 stress tensor
14    tX1 = trend of X1
15    pX1 = plunge of X1
16    tX3 = trend of X3
17    ntX1 = trend of X1'
18    npX1 = plunge of X1'
19    ntX3 = trend of X3'
20    nstress = 3 x 3 stress tensor in new coordinate system
21
22    NOTE: All input angles should be in radians
23
24    TransformStress uses function DirCosAxes
25
26    Python function translated from the Matlab function
27    TransformStress in Allmendinger et al. (2012)
28    '''
29
30    # Direction cosines of axes of old coordinate system
31    odC = DirCosAxes(tX1,pX1,tX3)
32
33    # Direction cosines of axes of new coordinate system
34    ndC = DirCosAxes(ntX1,npX1,ntX3)
35
36    # Transformation matrix between old and new
37    # coordinate systems
38    a = np.zeros((3,3))
39    for i in range(3):
40        for j in range(3):
41            # Use dot product
42            a[i,j] = np.dot(ndC[i,:],odC[j,:])
43
44    # Transform stress: Eq. 7.5
45    nstress = np.zeros((3,3))
46    for i in range(3):
47        for j in range(3):
48            for k in range(3):
49                for l in range(3):
```

```

48     nstress[i,j] = a[i,k] * a[j,l] * stress[k,l] +
49     nstress[i,j]
50
return nstress

```

### 7.1.3 Principal axes of stress

Since stress is a symmetric tensor, there is one orientation of the coordinate system for which the non-diagonal components of the tensor are zero, and only normal tractions act on the planes perpendicular to the coordinate axes (Fig. 7.3). These normal tractions are the principal stresses:  $\sigma_1$  is the maximum,  $\sigma_2$  is the intermediate, and  $\sigma_3$  is the minimum principal stress.

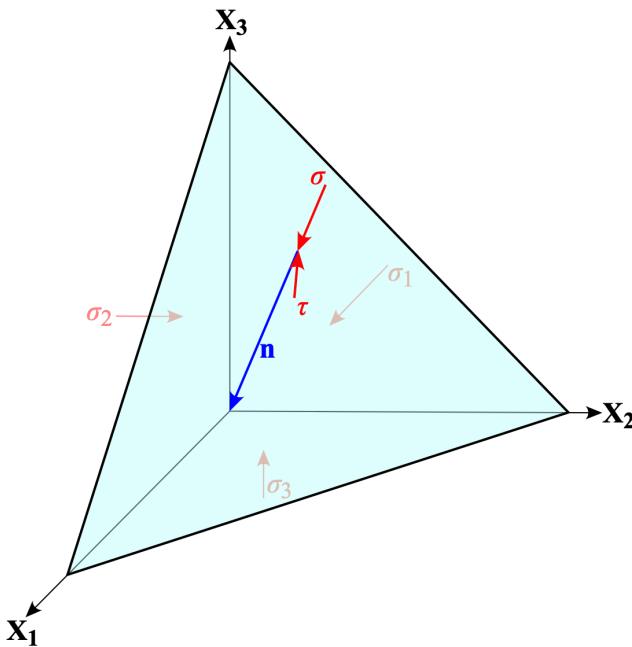


Figure 7.3: Plane oblique to the principal stress coordinate system  $\mathbf{X}_1\mathbf{X}_2\mathbf{X}_3$ .  $\sigma_1$ ,  $\sigma_2$  and  $\sigma_3$  are the principal stresses, and  $\sigma$  and  $\tau$  are the normal and maximum shear tractions on the plane.

As we saw in section 6.2, finding the principal stresses is an eigenvalue problem. The function [PrincipalStress](#) calculates the principal stresses and their orientations for a given stress tensor in a Cartesian coordinate system of any orientation:

```
1 import numpy as np
2
3 from DirCosAxes import DirCosAxes as DirCosAxes
4 from CartToSph import CartToSph as CartToSph
5
6 def PrincipalStress(stress,tX1,pX1,tX3):
7     """
8         Given the stress tensor in a X1X2X3 coordinate system
9         PrincipalStress calculates the principal stresses and
10        their orientations (trend and plunge)
11
12    USE: pstress,dCp = PrincipalStress(stress,tX1,pX1,tX3)
13
14    stress = Symmetric 3 x 3 stress tensor
15    tX1 = trend of X1
16    pX1 = plunge of X1
17    tX3 = trend of X3
18    pstress = 3 x 3 matrix containing the magnitude
19        (column 1), trend (column 2), and plunge
20        (column 3) of the maximum (row 1),
21        intermediate (row 2), and minimum (row 3)
22        principal stresses
23    dCp = 3 x 3 matrix with direction cosines of the
24        principal stress directions: Max. (row 1),
25        Int. (row 2), and Min. (row 3) with respect
26        to North-East-Down
27
28    NOTE: Input/Output angles are in radians
29
30    PrincipalStress uses functions DirCosAxes and CartToSph
31
32    Python function translated from the Matlab function
33    PrincipalStress in Allmendinger et al. (2012)
34    """
35    # Compute direction cosines of X1X2X3
36    dC = DirCosAxes(tX1,pX1,tX3)
37
38    # Initialize pstress
39    pstress = np.zeros((3,3))
40
41    # Calculate the eigenvalues and eigenvectors
42    # of the stress tensor
43    D, V = np.linalg.eigh(stress)
44
45    # Fill principal stress magnitudes
46    pstress[0,0] = D[2] # Maximum principal stress
47    pstress[1,0] = D[1] # Interm. principal stress
48    pstress[2,0] = D[0] # Minimum principal stress
```

```

49
50
51 # The direction cosines of the principal stresses are
52 # with respect to the X1X2X3 stress coordinate system,
53 # so they need to be transformed to the NED coordinate
54 # system
55 tV = np.zeros((3,3))
56 for i in range(3):
57     for j in range(3):
58         for k in range(3):
59             tV[j,i] = dC[k,j]*V[k,i] + tV[j,i]
60
61 # Initialize dCp
62 dCp = np.zeros((3,3))
63
64 # Direction cosines of principal stresses
65 for i in range(3):
66     for j in range(3):
67         dCp[i,j] = tV[j,2-i]
68 # Avoid precision issues
69 # Make sure the principal axes are unit vectors
70 dCp[i,:] = dCp[i,:]/np.linalg.norm(dCp[i,:])
71
72 # Trend and plunge of principal stresses
73 for i in range(3):
74     pstress[i,1],pstress[i,2] = CartToSph(dCp[i,0],dCp[i,1],
75 dCp[i,2])
76
77 return pstress,dCp

```

If we know the principal stresses, and the direction cosines of the pole to the plane **n** with respect to them (Fig. 7.3), it is possible to compute the normal,  $\sigma$ , and maximum shear,  $\tau$ , tractions acting on the plane (Ramsay, 1967):

$$\begin{aligned}\sigma &= \sigma_1 l^2 + \sigma_2 m^2 + \sigma_3 n^2 \\ \tau^2 &= (\sigma_1 - \sigma_2)^2 l^2 m^2 + (\sigma_2 - \sigma_3)^2 m^2 n^2 + (\sigma_3 - \sigma_1)^2 n^2 l^2\end{aligned}\quad (7.6)$$

where  $l$ ,  $m$  and  $n$  are the direction cosines of **n** with respect to  $\sigma_1$ ,  $\sigma_2$  and  $\sigma_3$ , respectively. Notice that this equation just tells us about the magnitude of the maximum shear traction. It does not say anything about the direction and sense of it. In section 7.4.1 we will see a more comprehensive way to solve this problem.

Let's use the functions introduced so far to solve the following problem: The maximum, intermediate and minimum principal stresses are 40, 30, and 20 MPa, respectively.  $\sigma_1$  is vertical and  $\sigma_3$  is horizontal and trends N-S:

1. Compute the tractions parallel to the principal stress directions, acting on a plane with orientation (RHR) 040/65.
2. Compute the normal and maximum shear tractions acting on the same plane
3. Compute the stress tensor on a new coordinate system with  $\mathbf{X}_1$  030/45 and  $\mathbf{X}_3$  trending 210.
4. Demonstrate that these new components represent still the same tensor, by computing the principal stresses from the new components.

The notebook [ch7-1](#) shows the solution to this problem:

```

1 # Import libraries
2 import numpy as np
3 pi = np.pi
4
5 # Import Cauchy, TransformStress and PrincipalStress
6 import sys, os
7 sys.path.append(os.path.abspath('../functions'))
8 from Cauchy import Cauchy as Cauchy
9 from TransformStress import TransformStress as
    TransformStress
10 from PrincipalStress import PrincipalStress as
    PrincipalStress
11
12 # Stress tensor in principal stress coordinate system
13 stress = np.array([[40, 0, 0],[ 0, 30, 0],[ 0, 0, 20]])
14
15 # trend and plunge of X1, and trend of X3
16 tX1 = 0*pi/180
17 pX1 = 90*pi/180
18 tX3 = 0*pi/180
19
20 # plane orientation
21 strike = 40*pi/180
22 dip = 65*pi/180
23
24 # X1, X2 and X3 tractions on the plane
25 T,pT = Cauchy(stress,tX1,pX1,tX3,strike,dip)

```

```

26 print('X1, X2 and X3 tractions = ', T.round(3), '\n')
27
28 # Compute the normal and maximum shear tractions
29 # on the plane: Eq. 7.6
30 l2 = pT[0]*pT[0]
31 m2 = pT[1]*pT[1]
32 n2 = pT[2]*pT[2]
33 s1 = stress[0,0]
34 s2 = stress[1,1]
35 s3 = stress[2,2]
36 s12 = s1 - s2
37 s23 = s2 - s3
38 s31 = s3 - s1
39 sigma = s1*l2 + s2*m2 + s3*n2
40 tau = np.sqrt(s12*s12*l2*m2 + s23*s23*m2*n2 + s31*s31*n2*l2)
41 print('Sigma = {:.3f}, Tau = {:.3f}\n'.format(sigma,tau))
42
43 # New coordinate system
44 # trend and plunge of X'1, and trend of X'3
45 ntX1 = 30*np.pi/180
46 npX1 = 45*np.pi/180
47 ntX3 = 210*np.pi/180
48
49 # Transform stress to new coordinate system
50 nstress = TransformStress(stress,tX1,pX1,tX3,ntX1,npX1,ntX3)
51 print('Stress in new coordinate system = \n', nstress.round
      (3), '\n')
52
53 # Principal stresses from new components
54 pstress, dCp = PrincipalStress(nstress,ntX1,npX1,ntX3)
55 pstress[:,1:3] = pstress[:,1:3]*180/pi
56 print('Sigma1 = {:.3f}, Trend = {:.1f}, Plunge = {:.1f}'.
      format(pstress[0,0],pstress[0,1],pstress[0,2]))
57 print('Sigma2 = {:.3f}, Trend = {:.1f}, Plunge = {:.1f}'.
      format(pstress[1,0],pstress[1,1],pstress[1,2]))
58 print('Sigma3 = {:.3f}, Trend = {:.1f}, Plunge = {:.1f}'.
      format(pstress[2,0],pstress[2,1],pstress[2,2]))

```

Output:

X1, X2 and X3 tractions = [16.905 20.828 11.651]

Sigma = 28.392, Tau = 7.015

Stress in new coordinate system =

[[31.25 3.062 8.75]

[3.062 27.5 -3.062]

[8.75 -3.062 31.25]]

Sigma1 = 40.000, Trend = 149.0, Plunge = -90.0

Sigma2 = 30.000, Trend = 270.0, Plunge = -0.0

Sigma3 = 20.000, Trend = 180.0, Plunge = 0.0

The principal stresses computed from the new components of the stress tensor are the same as the input principal stresses. Try changing the orientations of the principal stresses in the notebook (e.g.  $tX1 = 45$ ,  $pX1 = 0$ ). Check how the results change. This is a great way to understand the concepts introduced so far.

## 7.2 Mohr Circle for stress

As discussed in section 6.4.1, the Mohr Circle is derived by making a rotation about one of the principal axes of a symmetric tensor. In the case of stress, the rotation is about one of the principal stresses. In Figure 7.4a, the old axes are parallel to the principal axes of the stress tensor, and the rotation is about the  $\sigma_2$  axis. If the amount of rotation  $\theta$  is such that the new  $X'_1$  axis is parallel to the pole to the plane (Fig. 4.7b), the components  $\sigma'_{11}$  and  $\sigma'_{13}$  are the normal ( $\sigma$ ) and shear ( $\tau$ ) tractions on the plane, respectively. These tractions are given by:

$$\begin{aligned}\sigma &= \frac{\sigma_1 + \sigma_3}{2} + \frac{\sigma_1 - \sigma_3}{2} \cos 2\theta \\ \tau &= \frac{\sigma_1 - \sigma_3}{2} \sin 2\theta\end{aligned}\tag{7.7}$$

which are similar to Eq. 6.14<sup>1</sup> and define the Mohr Circle for stress.

---

<sup>1</sup>The sign change in the equation for  $\tau$  is due to our convention of considering compressional tractions as positive.

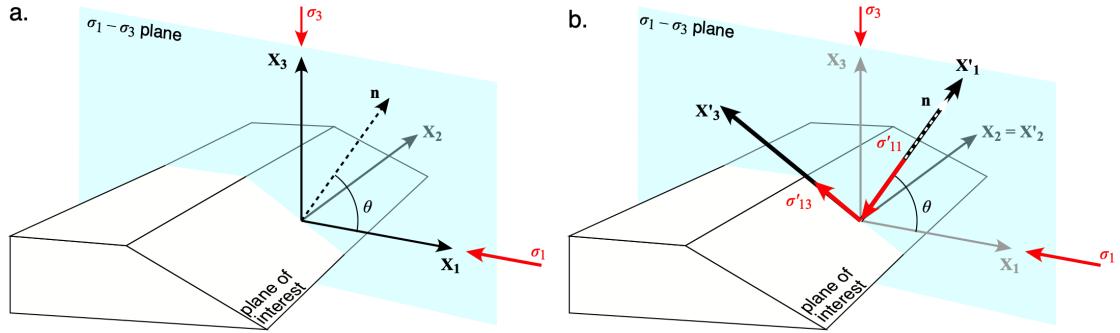


Figure 7.4: Rotation of the stress tensor about  $\sigma_2$ . **a.** The old coordinate system is parallel to the principal axes of the tensor. **b.** In the new coordinate system  $\mathbf{X}'_1$  is parallel to the pole to the plane of interest. Modified from Allmendinger et al. (2012).

The horizontal axis of the Mohr Circle for stress is  $\sigma$  and the vertical axis is  $\tau$ .  $\sigma$  is positive if compressional, and  $\tau$  is positive if the sense of shear is anticlockwise (e.g. Fig. 7.4b). The center,  $C$ , of the Mohr Circle is  $(\sigma_1 + \sigma_3)/2$ , and the radius,  $r$ , is  $(\sigma_1 - \sigma_3)/2$  (Fig. 7.5).

If the pole to the plane makes an angle  $\theta$  with respect to  $\sigma_1$  (Fig. 7.4), the normal and shear tractions on the plane can be found by drawing in the Mohr Circle a radius  $CP$  at an angle  $2\theta$  with respect to  $\sigma_1$  (Fig. 7.5). The coordinates of point  $P$  are the normal and shear tractions on the plane.

If we draw lines from  $\sigma_1$  and  $\sigma_3$  parallel to the planes on which these tractions act, the lines will intersect at a point  $Op$  (Fig. 7.5). This point is known as the pole for planes (Ragan, 2009) and it has a very useful property: A line drawn from  $Op$  to any point  $P$  on the Mohr Circle circumference is parallel to the plane on which the tractions given by  $P$  act (Fig. 7.5). Thus, from the pole for planes, we can rapidly find out the tractions on any plane parallel to  $\sigma_2$ .

Notice that we can rotate the stress tensor about anyone of the three principal axes. Thus in 3D, the Mohr Circle for stress consists of three circles, each one describing the rotation about one of the principal stresses. In section 7.4.2 we will see how to plot the Mohr Circle for stress in 3D.

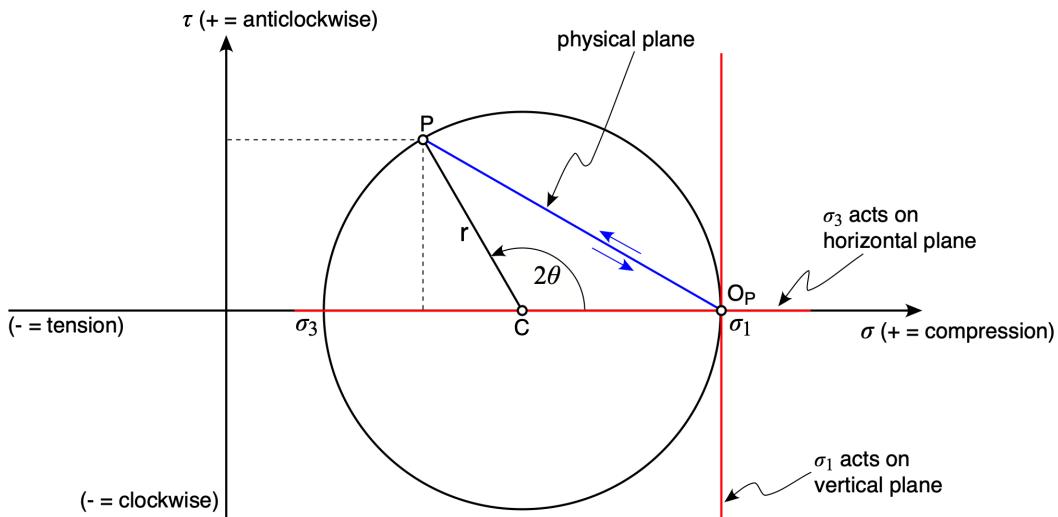


Figure 7.5: Mohr Circle for stress for the situation shown in Fig. 7.4. The normal and shear tractions on the plane (point  $P$ ) can be found by either measuring  $2\theta$  from  $\sigma_1$  or by tracing the plane from  $O_P$ .

### 7.2.1 Special states of stress

There are some special states of stress that can be nicely illustrated with the Mohr Circle:

- Biaxial stress: Two of the principal stresses are non-zero and are different (Fig. 7.6a).
- Triaxial stress: This is the most general type of stress. It has three non-zero, different principal stresses (Fig. 7.6b).
- Cylindrical stress: When two of the principal stresses are equal and the third is different (Fig. 7.6c). If the two equal principal stresses are zero, the stress is known as uniaxial.
- Hydrostatic stress: All three principal stresses have the same value (Fig. 7.6d). In this case, any direction is a principal axis (the stress tensor is a sphere), and there are no shear tractions on the body. This condition is typical of static fluids.
- Pure shear stress: Two of the principal stresses are equal in magnitude

but opposite in sign (one is compressional and the other is tensional), and the third is zero (Fig. 7.6e).

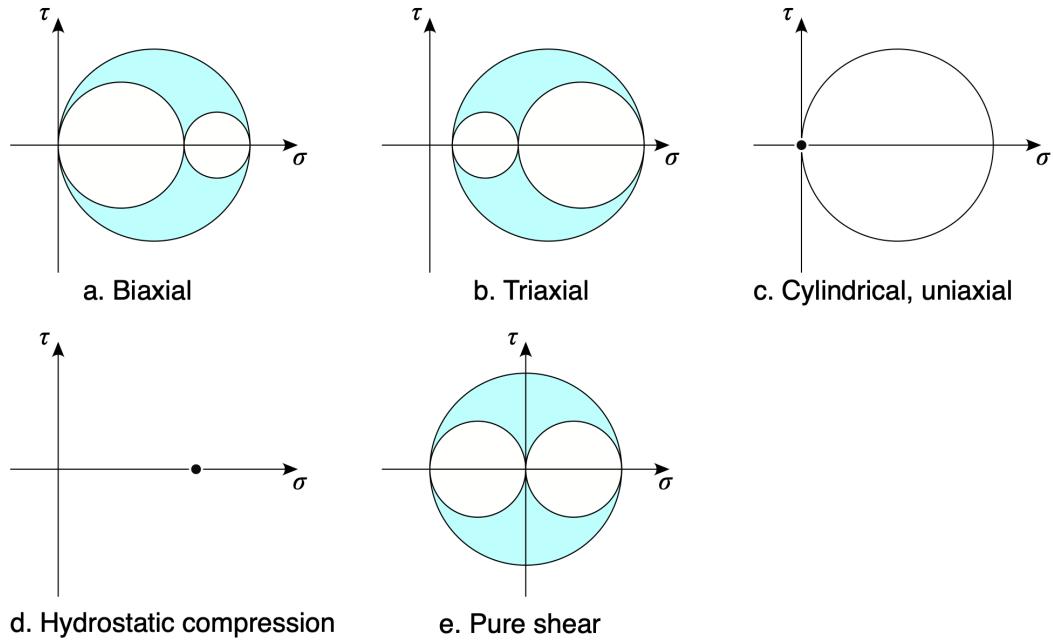


Figure 7.6: Mohr Circle for several special states of stress. **a.** Biaxial:  $\sigma_3 = 0$ ,  $\sigma_1$  and  $\sigma_2 \neq 0$ ; **b.** Triaxial:  $\sigma_1$ ,  $\sigma_2$  and  $\sigma_3 \neq 0$ ; **c.** Cylindrical uniaxial:  $\sigma_2$  and  $\sigma_3 = 0$ ,  $\sigma_1 \neq 0$ ; **d.** Hydrostatic:  $\sigma_1 = \sigma_2 = \sigma_3$ ; **e.** Pure shear:  $\sigma_3 = -\sigma_1$ ,  $\sigma_2 = 0$ . Modified from Allmendinger et al. (2012).

### 7.3 Mean and deviatoric stress

The special states of stress above allow us to introduce two fundamental types of stress tensors, the mean and the deviatoric stress. The mean traction is the average of the three normal tractions (the elements in the diagonal of the stress tensor):

$$\sigma_m = \frac{\sigma_{11} + \sigma_{22} + \sigma_{33}}{3} \quad (7.8)$$

Notice that the mean traction is the same regardless of the coordinate system because the sum of the normal tractions is the first invariant of the stress

tensor (section 6.2). Knowing the mean traction, we can express the stress tensor as the sum of two tensors:

$$\sigma_{ij} = \begin{bmatrix} \sigma_m & 0 & 0 \\ 0 & \sigma_m & 0 \\ 0 & 0 & \sigma_m \end{bmatrix} + \begin{bmatrix} \sigma_{11} - \sigma_m & \sigma_{12} & \sigma_{13} \\ \sigma_{21} & \sigma_{22} - \sigma_m & \sigma_{23} \\ \sigma_{31} & \sigma_{32} & \sigma_{33} - \sigma_m \end{bmatrix} \quad (7.9)$$

The tensor on the left is the mean stress tensor. It is a hydrostatic state of stress that may cause a body to shrink or expand but, on first glance, it is difficult to see how it would change the shape of the body, unless the body is heterogeneous in strength. The tensor on the right is the deviatoric stress tensor. It is the part of the stress tensor that is viewed as causing distortion of the body. For a cylindrical state of stress (Fig. 7.6c), it is easy to visualize these tensors. The mean stress is represented by the center of the Mohr Circle, while the deviatoric stress is represented by the same circle but centered at the origin.

## 7.4 Applications

In this section we will look at a problem involving stress, namely calculating the magnitude and orientation of the normal and maximum shear tractions on a plane. This problem is crucial to any question involving faulting and fracturing in the upper crust. We will also use the proposed solution to draw the Mohr Circle for stress in 3D.

### 7.4.1 Normal and shear tractions on a plane

Figure 7.7 illustrates the problem. We want to determine the normal and maximum shear tractions on a plane of any orientation, under a stress with principal axes of any orientation. There are three coordinate systems involved: 1. The geographic coordinate system **NED** where the data are input and the results are output, 2. The principal stress coordinate system which is defined by the orientation of the principal stresses  $\sigma_1$ ,  $\sigma_2$  and  $\sigma_3$ , and 3. A coordinate system defined by the fault plane, with the pole to the plane,  $\mathbf{n}$ , as the first axis, the line of zero shear traction on the fault plane,

**b**, as the second axis, and the line of maximum shear traction on the fault plane, **s**, as the third axis.

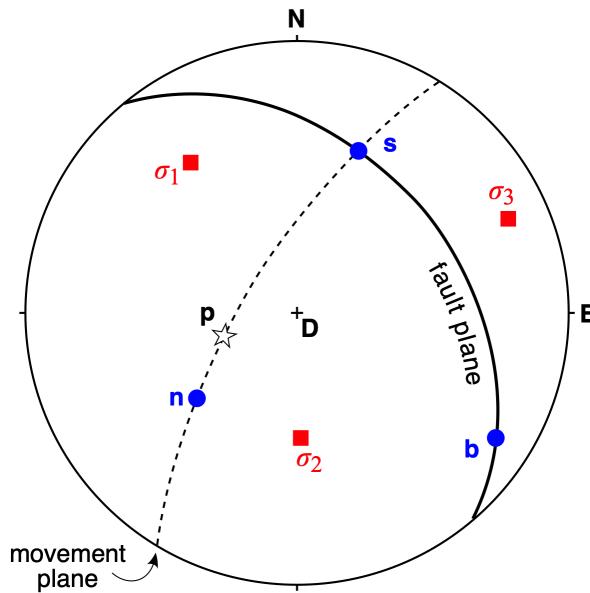


Figure 7.7: Lower hemisphere, equal area stereonet illustrating the three coordinate systems involved in determining the maximum shear traction on a fault plane with pole **n**. These coordinate systems are: **NED**,  $\sigma_1\sigma_2\sigma_3$ , and **nbs**. **b** and **s** are the directions of zero and maximum shear traction, respectively. Modified from Allmendinger et al. (2012).

The solution to this problem consists of the following steps:

1. Compute the principal stresses and their directions. Here we can use function *PrincipalStress*.
2. Transform the pole to the plane **n** to principal stress coordinates.
3. Compute the traction vector **p** (Fig. 7.7) in principal stress coordinates using Cauchy's law (Eq. 7.4).
4. **n**, **p** and the maximum shear traction **s** fall along the same plane (Fig. 7.7). This plane is known as the *movement plane* (Marshak and Mitra, 1988). The pole to the movement plane is the line of zero shear traction **b**. Therefore, we can calculate **b** by the cross product of **p** and **n**, and **s** by the cross product of **n** and **b**. Obviously after doing this, we need to make **b** and **s** unit vectors by dividing them by their magnitude.

5. Make a transformation matrix **a** between the principal stress coordinates and the fault plane coordinates. This matrix has as the first row **n**, the second row **b**, and the third row **s**.
6. Transform the stress tensor from principal stress coordinates to fault plane coordinates. For the transformed tensor,  $\mathbf{X}'_1$  is the pole to the plane, and  $\mathbf{X}'_3$  is the direction of the maximum shear traction **s**. Therefore,  $\sigma'_{11}$  is the normal traction on the plane, and  $\sigma'_{13}$  is the maximum shear traction on the plane.
7. Transform **n**, **b** and **s** from principal stress coordinates to NED coordinates and find their orientations (trend and plunge).

The function *ShearOnPlane* follows these steps and computes the normal and maximum shear tractions on a plane of any orientation, and under a stress with principal axes of any orientation:

```

1 import numpy as np
2 from PrincipalStress import PrincipalStress as
   PrincipalStress
3 from SphToCart import SphToCart as SphToCart
4 from CartToSph import CartToSph as CartToSph
5
6 def ShearOnPlane(stress ,tx1,pX1,tX3,strike,dip):
7     ''
8     ShearOnPlane calculates the direction and magnitudes of
9     the normal and maximum shear tractions on an arbitrarily
10    oriented plane
11
12 USE: TT,dCTT,R = ShearOnPlane(stress ,tx1,pX1,tX3,strike,dip
13 )
14
15 stress = 3 x 3 stress tensor
16 tx1 = trend of X1
17 pX1 = plunge of X1
18 tX3 = trend of X3
19 strike = strike of plane
20 dip = dip of plane
21 TT = 3 x 3 matrix with the magnitude (column 1),
22     trend (column 2) and plunge (column 3) of the:
23     normal traction on the plane (row 1), zero shear
24     traction (row 2), and max. shear traction (row 3)
25 dCTT = 3 x 3 matrix with the direction cosines of unit
26     vectors parallel to: normal traction on the plane
     (row 1), zero shear traction (row 2), and maximum

```

```

27     shear traction (row 3) with respect to NED
28     R = Stress ratio
29
30 NOTE = Input stress tensor does not need to be along
31     principal stress directions
32     Plane orientation follows the right hand rule
33     Input/Output angles are in radians
34
35 ShearOnPlane uses functions PrincipalStress, Cauchy and
36 CartToSph
37
38 Python function translated from the Matlab function
39 ShearOnPlane in Allmendinger et al. (2012)
40 '''
41 # Compute principal stresses and their orientations
42 pstress, dCp = PrincipalStress(stress,tX1,pX1,tX3)
43
44 # Update stress tensor to principal stress directions
45 stress = np.zeros((3,3))
46 for i in range(3):
47     stress[i,i] = pstress[i,0]
48
49 # Calculate stress ratio
50 R = (stress[1,1] - stress[0,0])/(stress[2,2]-stress[0,0])
51
52 # Calculate direction cosines of pole to plane
53 p = np.zeros(3)
54 p[0], p[1], p[2] = SphToCart(strike,dip,1);
55
56 # Transform pole to plane to principal stress coordinates
57 pT = np.zeros(3);
58 for i in range(3):
59     for j in range(3):
60         pT[i] = dCp[i,j]*p[j] + pT[i]
61
62 # Calculate the tractions in principal stress coordinates
63 T = np.zeros(3)
64 # Compute tractions using Cauchy's law
65 for i in range(3):
66     for j in range(3):
67         T[i] = stress[i,j]*pT[j] + T[i]
68
69 # Find the B axis by the cross product of T and pT
70 B = np.cross(T,pT)
71
72 # Find the max. shear traction orientation
73 # by the cross product of pT and B
74 S = np.cross(pT,B)
75

```

```

76 # Convert B and S to unit vectors
77 B = B/np.linalg.norm(B)
78 S = S/np.linalg.norm(S)
79
80 # Now we can write the transformation matrix from
81 # principal stress coordinates to plane coordinates
82 a = np.zeros((3,3))
83 a[0,:] = pT
84 a[1,:] = B
85 a[2,:] = S
86
87 # Transform stress from principal to plane coordinates
88 # Do it only for the first row since we are just
89 # interested in the plane: sigma'11 = normal traction,
90 # sigma'12 = zero, and sigma'13 = max. shear traction
91 TT = np.zeros((3,3))
92 for i in range(3):
93     TT[i,0] = stress[0,0]*a[0,0]*a[i,0] + stress[1,1]*a[0,1]*
94         a[i,1] +stress[2,2]*a[0,2]*a[i,2]
95
96 # Transform normal traction, zero shear
97 # and max. shear traction to NED coords
98 dCTT = np.zeros((3,3))
99 for i in range(3):
100     for j in range(3):
101         dCTT[0,i] = dCp[j,i]*pT[j] + dCTT[0,i]
102         dCTT[1,i] = dCp[j,i]*B[j] + dCTT[1,i]
103         dCTT[2,i] = dCp[j,i]*S[j] + dCTT[2,i]
104
105 # Compute trend and plunge of normal traction,
106 # zero shear, and max. shear traction on plane
107 for i in range(3):
108     TT[i,1],TT[i,2] = CartToSph(dCTT[i,0],dCTT[i,1],dCTT[i
109         ,2])
110
111 return TT, dCTT, R

```

Function *ShearOnPlane* also computes an important parameter called the *principal stress ratio*,  $R$ :

$$R = \frac{(\sigma_2 - \sigma_1)}{(\sigma_3 - \sigma_1)} \quad (7.10)$$

when  $R$  is 1,  $\sigma_2$  is equal to  $\sigma_3$ ; when  $R$  is 0,  $\sigma_2$  is equal to  $\sigma_1$ . This ratio is of key importance for predicting faulting and fracturing in the crust (Gephart,

1990; Morris and Ferrill, 2009). Let's look at the influence of this parameter for the case illustrated in Figure 7.7. Let's assume  $\sigma_1 = 50$  MPa and  $\sigma_3 = 10$  MPa, and let's vary  $\sigma_2$  between  $\sigma_3$  ( $R = 1$ ) and  $\sigma_1$  ( $R = 0$ ). The notebook [ch7-2](#) shows the solution to this problem:

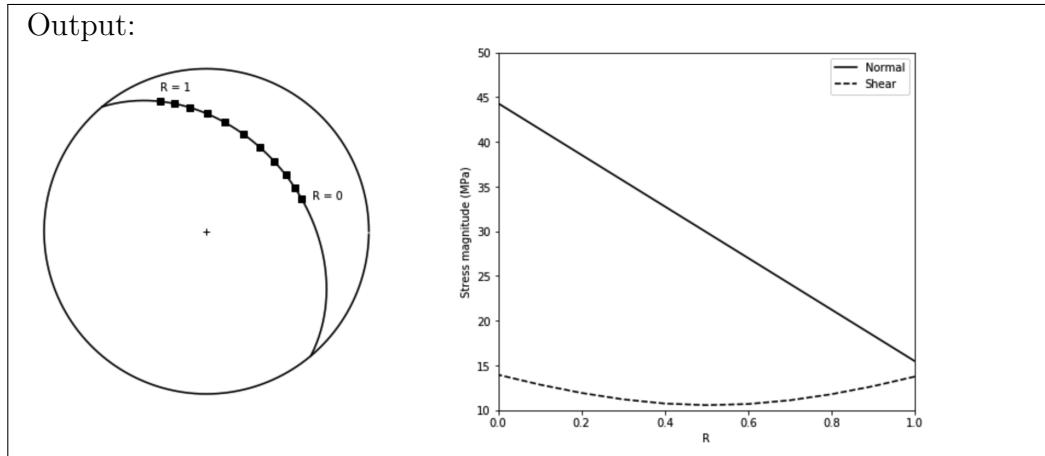
```

1 # Import libraries
2 import numpy as np
3 import matplotlib.pyplot as plt
4 pi = np.pi
5
6 # Import ShearOnPlane, GreatCircle and StCoordLine
7 import sys, os
8 sys.path.append(os.path.abspath('../functions'))
9 from ShearOnPlane import ShearOnPlane as ShearOnPlane
10 from GreatCircle import GreatCircle as GreatCircle
11 from StCoordLine import StCoordLine as StCoordLine
12
13 # Stress tensor in principal stress coordinate system
14 # start with R = 1, sigma2 = sigma3
15 stress = np.array([[50, 0, 0],[ 0, 10, 0],[ 0, 0, 10]])
16
17 # Trend and plunge of sigma1, and trend of sigma3
18 tX1 = 325*pi/180
19 pX1 = 33*pi/180
20 tX3 = 66*pi/180
21
22 # Plane orientation
23 strike = 320*pi/180
24 dip = 40*pi/180
25
26 # Number of R increments
27 rinc = 11
28
29 # sigma2 increment
30 sstep = (stress[0,0] - stress[2,2])/(rinc-1)
31
32 # Initialize array
33 nort = np.zeros(rinc) # normal tractions
34 sht = np.zeros(rinc) # max. shear traction
35 tsht = np.zeros(rinc) # trend max. shear traction
36 psht = np.zeros(rinc) # plunge max. shear traction
37 rval = np.zeros(rinc) # R value
38
39 # Compute normal and shear tractions for all Rs
40 for i in range(rinc):
41     stress[1,1] = stress[2,2] + sstep*i
42     # Compute normal and maximum shear tractions on plane
43     TT,dCTT,R = ShearOnPlane(stress,tX1,pX1,tX3,strike,dip)
```

```

44 # Extract values
45 nort[i] = TT[0,0]
46 sht[i] = TT[2,0]
47 tsht[i] = TT[2,1]
48 psht[i] = TT[2,2]
49 rval[i] = R
50
51 # Make a larger figure
52 plt.rcParams['figure.figsize'] = [15, 6]
53
54 # Plot fault plane and max. shear tractions
55 # orientations in a lower hemisphere, equal
56 # area stereonet
57 plt.subplot(1,2,1)
58 # Plot the primitive of the stereonet
59 r = 1; # unit radius
60 TH = np.arange(0,360,1)*pi/180
61 x = r * np.cos(TH)
62 y = r * np.sin(TH)
63 plt.plot(x,y,'k')
64 # Plot center of circle
65 plt.plot(0,0,'k+')
66 # Make axes equal and remove them
67 plt.axis('equal')
68 plt.axis('off')
69 # Plot fault plane
70 path = GreatCircle(strike,dip,1)
71 plt.plot(path[:,0], path[:,1], 'k')
72 # Plot max. shear tractions orientations
73 for i in range(rinc):
74     x, y = StCoordLine(tsht[i],psht[i],1)
75     plt.plot(x,y,'ks')
76     if i == 0:
77         plt.annotate('R = 1',(x,y),textcoords='offset points'
78 ,xytext=(0,10))
78     if i == rinc-1:
79         plt.annotate('R = 0',(x,y),textcoords='offset points'
80 ,xytext=(10,0))
81 # Plot normal and shear tractions versus R
82 plt.subplot(1,2,2)
83 plt.plot(rval,nort,'k')
84 plt.plot(rval,sht,'k--')
85 plt.axis([0, 1, 10, 50])
86 plt.xlabel('R')
87 plt.ylabel('Stress magnitude (MPa)')
88 plt.legend(['Normal', 'Shear']);

```



This is essentially Figure 6.9 of Allmendinger et al. (2012). In one of the exercises of section 7.5, you will explore more the significance of the principal stress ratio,  $R$ .

#### 7.4.2 The Mohr Circle for stress in 3D

We can also use the solution above to draw a Mohr Circle for stress in 3D. Here it is also important to determine the sense of the maximum shear traction. According to our convention, anticlockwise shear is positive, and clockwise shear is negative in the Mohr Circle. The function `StressMohrCircle` draws the Mohr Circle in 3D for a give stress tensor and stress coordinate system. It also plots and delivers the normal and maximum shear tractions on a group of input planes.

```

1 import numpy as np
2 import matplotlib.pyplot as plt
3 from PrincipalStress import PrincipalStress as
   PrincipalStress
4 from SphToCart import SphToCart as SphToCart
5 from CartToSph import CartToSph as CartToSph
6
7 def StressMohrCircle(stress,tX1,pX1,tX3,planes):
8     ''
9     Given the stress tensor in a X1X2X3 coordinate system,
10    and a group of n planes, StressMohrCircle draws the Mohr
11    Circle for stress (including the planes). It
12    also returns the normal and max. shear tractions on the
13    planes and their orientations

```

```

14 USE: ns, ons = StressMohrCircle(stress,tX1,pX1,tX3,planes)
15
16 stress = 3 x 3 stress tensor
17 tX1 = trend of X1
18 pX1 = plunge of X1
19 tX3 = trend of X3
20 planes = n x 2 vector with strike and dip of planes
21 ns = n x 2 vector with the normal and max. shear
22 tractions on the planes
23 ons = n x 4 vector with the trend and plunge of the
24 normal traction (columns 1 and 2), and the
25 max. shear traction (columns 3 and 4)
26
27 NOTE = Planes orientation follows the right hand rule
28 Input and output angles are in radians
29
30 StressMohrCircle uses functions PrincipalStress
31 '''
32 # tolerance for near zero values
33 tol = 1e-6
34
35 # Compute principal stresses and their orientations
36 pstress, dCp = PrincipalStress(stress,tX1,pX1,tX3)
37
38 # Update stress tensor to principal stresses
39 stress = np.zeros((3,3))
40 for i in range(3):
41     stress[i,i] = pstress[i,0]
42
43 # Draw sigma1-sigma3 circle
44 c = (stress[0,0] + stress[2,2])/2.0
45 r = (stress[0,0] - stress[2,2])/2.0
46 th = np.arange(0,2*np.pi,np.pi/50)
47 x = r * np.cos(th)+c
48 y = r*np.sin(th)
49 fig, ax = plt.subplots()
50 plt.plot(x,y,'k-')
51
52 # Draw sigma1-sigma2 circle
53 c = (stress[0,0] + stress[1,1])/2.0
54 r = (stress[0,0] - stress[1,1])/2.0
55 th = np.arange(0,2*np.pi,np.pi/50)
56 x = r * np.cos(th)+c
57 y = r*np.sin(th)
58 plt.plot(x,y,'k-')
59
60 # Draw sigma2-sigma3 circle
61 c = (stress[1,1] + stress[2,2])/2.0

```

```

63 r = (stress[1,1] - stress[2,2])/2.0
64 th = np.arange(0,2*np.pi,np.pi/50)
65 x = r * np.cos(th)+c
66 y = r*np.sin(th)
67 plt.plot(x,y,'k-')

68
69
70 # Initialize pole to plane
71 p = np.zeros(3)

72
73 # Initialize vectors with normal and
74 # max. shear tractions
75 ns = np.zeros((np.size(planes,0),2))
76 ons = np.zeros((np.size(planes,0),4))

77
78 # Compute normal and max. shear tractions
79 for i in range(np.size(planes,0)):

80
81     # Calculate direction cosines of pole to plane
82     p[0],p[1],p[2] = SphToCart(planes[i,0],planes[i,1],1)

83
84     # Trend and plunge of pole = dir. normal traction
85     ons[i,0],ons[i,1] = CartToSph(p[0],p[1],p[2])

86
87     # Transform pole to principal stress coordinates
88     pT = np.zeros(3)
89     for j in range(3):
90         for k in range(3):
91             pT[j] = dCp[j,k]*p[k] + pT[j]

92
93     # Calculate the tractions in principal stress
94     # coordinates
95     T = np.zeros(3)
96     for j in range(3):
97         for k in range(3):
98             T[j] = stress[j,k]*pT[k] + T[j]

99
100    # Find the B and S axes
101    B = np.cross(T,pT);
102    S = np.cross(pT,B);
103    B = B/np.linalg.norm(B);
104    S = S/np.linalg.norm(S);

105
106    # Transformation matrix from principal
107    # stress coordinates to plane coordinates
108    a = np.zeros((3,3))
109    a[0,:] = pT
110    a[1,:] = B
111    a[2,:] = S

```

```

112
113     # normal and max. shear tractions
114     ns[i,0] = stress[0,0]*a[0,0]*a[0,0] + stress[1,1]*a[0,1]*
115         a[0,1]+ stress[2,2]*a[0,2]*a[0,2]
116     ns[i,1] = stress[0,0]*a[0,0]*a[2,0] + stress[1,1]*a[0,1]*
117         a[2,1]+ stress[2,2]*a[0,2]*a[2,2]
118
119     # Calculate direction cosines of max.
120     # shear traction with respect to NED
121     ds = np.zeros(3)
122     for j in range(3):
123         for k in range(3):
124             ds[j] = dCp[k,j]*S[k] + ds[j]
125
126     # Trend and plunge of max. shear traction
127     ons[i,2],ons[i,3] = CartToSph(ds[0],ds[1],ds[2])
128
129     # Cross product of pole and max. shear traction
130     ps = np.cross(p,ds)
131
132     # Make clockwise shear traction negative
133     if np.abs(ps[2]) < tol: # Dip slip
134         if ds[2] > 0.0: # Normal slip
135             if pT[0]*pT[2] < 0.0:
136                 ns[i,1] *= -1.0
137             else: # Reverse slip
138                 if pT[0]*pT[2] >= 0.0:
139                     ns[i,1] *= -1.0
140             else: # Oblique slip
141                 if ps[2] < 0.0:
142                     ns[i,1] *= -1.0
143
144     # Plot planes
145     plt.plot(ns[:,0],ns[:,1],'ks')
146
147     # Make axes equal and plot grid
148     plt.axis('equal')
149     plt.grid()
150
151     # Move x-axis to center and y-axis to origin
152     ax.spines['bottom'].set_position('center')
153     ax.spines['left'].set_position('zero')
154
155     # Eliminate upper and right axes
156     ax.spines['right'].set_color('none')
157     ax.spines['top'].set_color('none')
158
159     # Show ticks in the left and lower axes only
160     ax.xaxis.set_ticks_position('bottom')

```

```

159     ax.yaxis.set_ticks_position('left')
160
161     # Add labels at end of axes
162     ax.set_xlabel('σ',x=1)
163     ax.set_ylabel('τ',y=1,rotation=0)
164
165     # Show plot
166     plt.show()
167
168     return ns, ons

```

Let's use this function to plot the Mohr Circle for the following condition: The maximum, intermediate and minimum principal stresses are 50, 30, and 10 MPa, respectively.  $\sigma_1$  is horizontal and trends E-W, while  $\sigma_3$  is vertical. Plot on the Mohr Circle the normal and maximum shear tractions on planes with the following orientation (RHR): 000/30, 000/45, 000/60, 180/30, 180/45, 180/60, 045/30, 045/45, 045/60, 225/30, 225/45 and 225/60. The notebook [ch7-3](#) shows the solution to this problem:

```

1 # Import libraries
2 import numpy as np
3 pi = np.pi
4
5 # Import StressMohrCircle
6 import sys, os
7 sys.path.append(os.path.abspath('../functions'))
8 from StressMohrCircle import StressMohrCircle as
    StressMohrCircle
9
10 # Stress tensor in principal stress coordinate system
11 stress = np.array([[50, 0, 0],[ 0, 30, 0],[ 0, 0, 10]])
12
13 # Trend and plunge of sigma1, and trend of sigma3
14 tX1 = 90*pi/180
15 pX1 = 0*pi/180
16 tX3 = 90*pi/180
17
18 # Planes orientations
19 planes = np.array
    ([[0,30],[0,45],[0,60],[180,30],[180,45],[180,60],[45,30],
     [45,45],[45,60],[225,30],[225,45],[225,60]])
20 planes = planes * pi/180 # radians
21
22 # Plot Mohr Circle
23 ns, ons = StressMohrCircle(stress,tX1,pX1,tX3,planes)

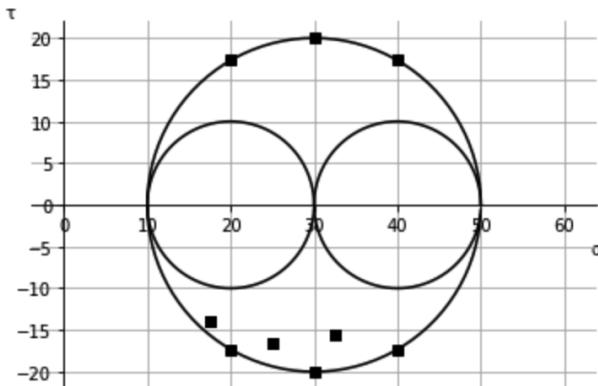
```

```

24 # Print normal and shear tractions
25 print('Strike\tDip\tNormal\tTrend\tPlunge\tShear\tTrend\t
26     \tPlunge\t')
27 # return to degrees
28 planes = planes*180/pi
29 ons = ons*180/pi
30 # print
31 for i in range(np.size(planes,0)):
32     print('{:.1f}\t{:.1f}\t{:.3f}\t{:.1f}\t{:.1f}\t{:.3f}\t{:.1f}\t
33     \t{:.1f}'.format(planes[i,0],planes[i,1],ns[i,0],ons
34     [i,0],ons[i,1],ns[i,1],ons[i,2],ons[i,3]))

```

Output:



Strike	Dip	Normal	Trend	Plunge	Shear	Trend	Plunge
0.0	30.0	20.000	270.0	60.0	17.321	270.0	-30.0
0.0	45.0	30.000	270.0	45.0	20.000	270.0	-45.0
0.0	60.0	40.000	270.0	30.0	17.321	270.0	-60.0
180.0	30.0	20.000	90.0	60.0	-17.321	90.0	-30.0
180.0	45.0	30.000	90.0	45.0	-20.000	90.0	-45.0
180.0	60.0	40.000	90.0	30.0	-17.321	90.0	-60.0
45.0	30.0	17.500	315.0	60.0	-13.919	291.0	-27.8
45.0	45.0	25.000	315.0	45.0	-16.583	281.3	-39.8
45.0	60.0	32.500	315.0	30.0	-15.612	261.9	-46.1
225.0	30.0	17.500	135.0	60.0	-13.919	111.0	-27.8
225.0	45.0	25.000	135.0	45.0	-16.583	101.3	-39.8
225.0	60.0	32.500	135.0	30.0	-15.612	81.9	-46.1

N-S striking planes parallel to  $\sigma_2$  plot on the  $\sigma_1-\sigma_3$  circle. Planes dipping east show positive, anticlockwise shear, while those dipping west show negative, clockwise shear. Another way to visualize the N-S planes is by using the pole to planes,  $Op$ . With  $\sigma_1$  horizontal and  $\sigma_3$  vertical,  $Op$  is at  $\sigma_1$  (Fig. 7.5). From  $Op$  you can trace N-S planes of any dip to the E or W, and quickly verify that E dipping planes have anticlockwise shear, while W dipping planes

have clockwise shear. Planes non-parallel to  $\sigma_2$  are more difficult to visualize. On the NE-SW striking planes dipping both to the SE and NW, the shear tractions are clockwise and they plot inside the  $\sigma_1$ - $\sigma_3$  circle but outside the  $\sigma_2$ - $\sigma_3$  and  $\sigma_1$ - $\sigma_2$  circles (in fact no plane orientation can plot inside these two internal circles).

## 7.5 Exercises

1. This is exercise 6 in chapter 6 of Allmendinger et al. (2012): In the Oseberg field, North Sea, the principal stresses are oriented  $\sigma_1 = 080/00$ ,  $\sigma_2 = 000/90$ , and  $\sigma_3 = 170/00$ . If at 2 km depth,  $\sigma_1 = 50$  MPa,  $\sigma_2 = 40$  MPa, and  $\sigma_3 = 30$  MPa, what are the normal and shear tractions on a plane oriented (RHR) 040/65? *Hint:* Use function `ShearOnPlane`.
2. Morris and Ferrill (2009) discuss the importance of the intermediate principal stress,  $\sigma_2$ , for faulting. Let's look at their first example: The maximum and minimum principal stresses are 95 and 25 MPa, respectively.  $\sigma_1$  is vertical and  $\sigma_3$  is horizontal and trends E-W. Compute the normal and maximum shear tractions acting on three planes with orientation (RHR) 180/45, 090/45 and 135/45, and for principal stress ratios,  $R$ , between 1 and 0. Display your results graphically in a lower hemisphere equal area stereonet showing the maximum shear directions on the planes, and a plot of  $R$  versus normal and maximum shear tractions. How do the normal and maximum shear tractions vary on the N-S and E-W planes? How do they vary in the SE-NW plane? *Hint:* This problem is similar to the notebook `ch7-2`. Modify the notebook to include the new stress and the three planes. Use colors to indicate the different planes.
3. The slip tendency is the ratio between the maximum shear and normal tractions on a plane ( $T_s = \tau/\sigma$ ). It is a proxy for the tendency of a surface to undergo slip under a given stress field (Morris et al., 1996). Write a Python function that for a given stress with coordinate axes of any orientation, plots a lower hemisphere equal area stereonet and a Mohr Circle colored by slip tendency. The function should work as follows:

`SlipTendency(stress,tX1,pX1,tX3)`

where  $\text{stress}$  is the stress tensor,  $tX1$  and  $pX1$  are the trend and plunge of  $\mathbf{X}_1$ , and  $tX3$  is the trend of  $\mathbf{X}_3$ . Figure 7.8 shows how the output of the function would look like for the stress tensor in the notebook [ch7-3](#).

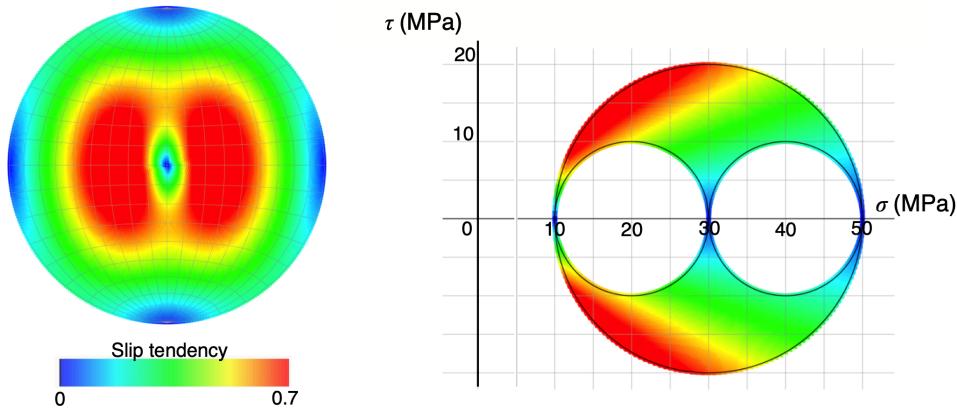


Figure 7.8: Slip tendency for the state of stress in the notebook [ch7-3](#). Left is lower hemisphere equal area stereonet, and right is Mohr Circle. Figure made with the program [GeoKalk](#) by Nestor Cardozo.

*Hint:* Use the function [\*StressMohrCircle\*](#) as the base of your new function. In the new function, calculate the normal and shear tractions on a set of planes varying in strike from 0 to  $360^\circ$  and dip from 0 to  $90^\circ$ . A  $1^\circ$  increment in strike and dip would be sufficient. Plot each pole (not the plane itself) colored by slip tendency on a stereonet and a Mohr Circle. Use a color scale bar similar to Fig. 7.8. Since you will be plotting about 35,000 poles and since in this case the direction of the maximum shear traction is not relevant, you may consider calculating the normal and maximum shear tractions using Eq. 7.6.

Based on your new function, at which dip angle would you expect the N-S oriented planes in the notebook [ch7-3](#) to slip? Will the planes slip at the possible maximum shear traction ( $\sigma_1 - \sigma_3$ )?

## References

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Marshak, S. and Mitra, G. 1988. Basic Methods of Structural Geology. Prentice Hall.

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Morris, A.P. and Ferrill, D.A. 2009. The importance of the effective intermediate principal stress ( $\sigma'_2$ ) to fault slip patterns. *Journal of Structural Geology* 31, 950-959.

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# Chapter 8

## Strain

Stresses within the Earth change through time, and these changes can lead to deformation. Deformation is more complicated than stress because it involves the comparison of states of the rock material at two different points in time. Therefore, one needs to establish both temporal and spatial reference frames. This chapter covers the basics of deformation and strain, including infinitesimal, finite, and progressive strain. This is a relatively long and complicated material, it comprises several chapters in classical books such as Ramsay (1967) and Means (1976). However, our purpose is not to discuss in detail the theory of strain, but rather to introduce some interesting strain problems in geosciences, and their computation.

### 8.1 Deformation and strain

Strictly speaking, deformation involves rigid body deformation (translation and rotation), and non-rigid body deformation (changes in shape and volume) or strain. In geology, rigid-body deformation is rather difficult to determine, with a few exceptions (e.g. paleolatitude of a continent from paleomagnetic pole). We often just focus on strain.

Consider the deformation shown in Fig. 8.1. The square and inscribed circle (Fig. 8.1a) are first translated, then rotated, and then sheared. The translation vector  $\mathbf{t}$  (Fig. 8.1b) and rotation  $\omega$  (Fig. 8.1c) describe the first stage of rigid body-deformation. Shear of the objects defines the second stage

of non-rigid body deformation or strain (Fig. 8.1d).

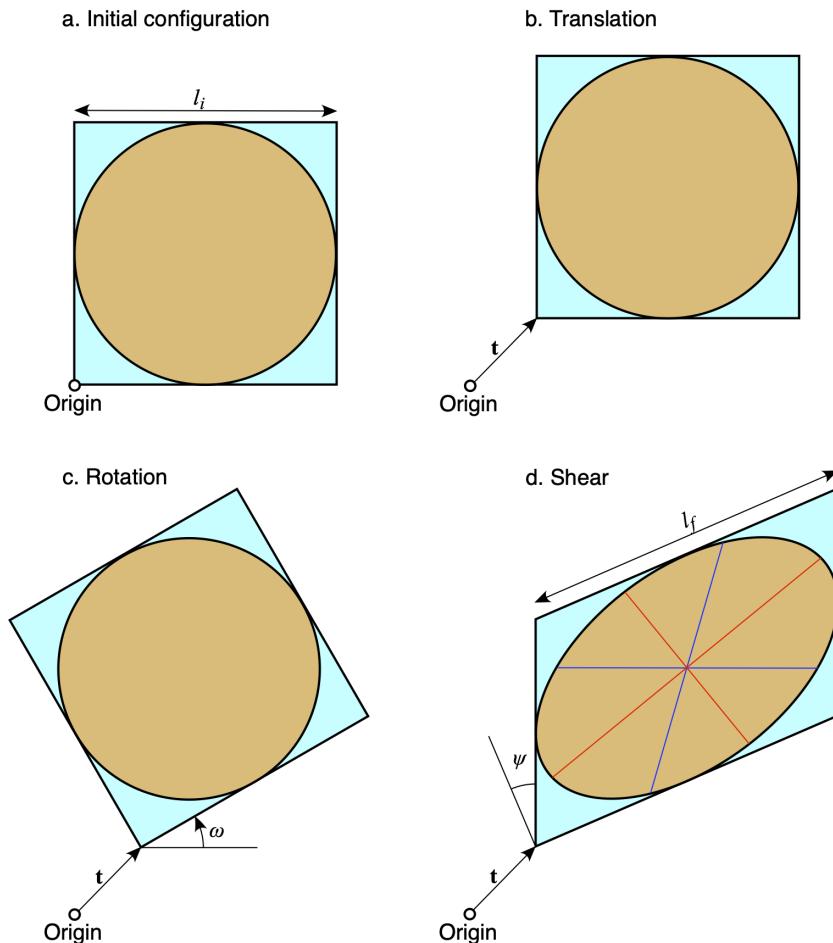


Figure 8.1: Deformation of a square of side  $l_i$  and inscribed circle. **a.** Initial configuration. **b.** Translation  $t$ . **c.** Rotation  $\omega$ . **d.** Shear.  $l_f$  and  $\psi$  are the final length and angular shear of the long side of the parallelogram. Red and blue lines in ellipse are principal axes and lines of no finite elongation (LNFE).

The changes in shape (distortion) of the bodies can be described by the changes in length and angle of lines in the bodies. If the initial length of a line is  $l_i$  and the deformed length of the line is  $l_f$ , the change in length of the line can be defined by either one of the following parameters:

$$\begin{aligned} e &= \frac{l_f - l_i}{l_i} \\ S &= \frac{l_f}{l_i} = 1 + e \\ \lambda &= S^2 = (1 + e)^2 \end{aligned} \tag{8.1}$$

where  $e$  is elongation,  $S$  is stretch, and  $\lambda$  is quadratic elongation. For the long side of the parallelogram in Fig. 8.1d,  $e$  is positive, and  $S$  and  $\lambda$  are larger than 1. For the short side,  $e$  is negative, and  $S$  and  $\lambda$  are lower than 1. Lines that have their original length have  $e = 0$ , and  $S$  and  $\lambda = 1$  (blue lines, Fig. 8.1d). Notice that  $e$  cannot be lower than  $-1$ , and  $S$  and  $\lambda$  cannot be lower than 0 (a line can't be shortened more than its original length).

Changes in angle are measured by the angular shear  $\psi$ , which is the change in angle between two originally perpendicular lines (Fig. 8.1d). From the angular shear, one can calculate the shear strain  $\gamma$ :

$$\gamma = \tan \psi \tag{8.2}$$

Changes in area or volume (dilation) can be described using the areal or volumetric stretch:

$$\begin{aligned} S_A &= \frac{A_f}{A_i} \\ S_V &= \frac{V_f}{V_i} \end{aligned} \tag{8.3}$$

where  $A_i$  and  $A_f$  are initial and final area, and  $V_i$  and  $V_f$  are initial and final volume. We can also determine areal or volumetric elongation.

In this chapter, we make two major assumptions about strain: Strain is continuous (it is distributed uniformly across the body), and strain is homogeneous (it is identical across the body). Clearly these assumptions are incorrect: Rocks are full of discontinuities, and geological structures (e.g. folds) exhibit heterogeneous strain. However at the appropriate scale, rocks can be described as continuum materials, and the heterogeneous strain of

geological structures can be represented by domains of homogeneous (yet compatible) strain. This makes possible applying homogeneous strain to geologic deformation.

For homogeneous strain, straight lines remain straight, parallel lines remain parallel, and circles become ellipses in 2D, or spheres become ellipsoids in 3D (Fig. 8.1d). The resultant ellipse (or ellipsoid) is called the strain ellipse (or ellipsoid). The stretches along the axes of this ellipse (or ellipsoid, red lines in Fig. 8.1d) are called the principal stretches, and they are denoted by the symbols  $S_1, S_2, S_3$ , for the major, intermediate, and minor principal stretch, respectively. The volumetric stretch can also be defined as:

$$S_V = S_1 S_2 S_3 \quad (8.4)$$

The deformation in Fig. 8.1 is volume and area constant ( $S_V$  and  $S_A = 1$ ). Under this condition, there are two lines in the strain ellipse that have their original length (blue lines, Fig. 8.1d). These lines are known as the lines of no finite elongation (LNFE).

## 8.2 Deformation and displacement gradients

Consider the deformation shown in Fig. 8.2. The cube is transformed into a brick-shaped body. It is shortened along the  $\mathbf{X}_2$  axis by half ( $e = -0.5$ ,  $S = 0.5$ ), and it is stretched along the  $\mathbf{X}_3$  axis twice ( $e = 1$ ,  $S = 2$ ).

We can express the deformed coordinates  $\mathbf{x}$  of any point in the cuboid in terms of the undeformed coordinates  $\mathbf{X}$  of the same point in the cube<sup>1</sup>:

$$\begin{aligned} x_1 &= 1X_1 + 0X_2 + 0X_3 \\ x_2 &= 0X_1 + 0.5X_2 + 0X_3 \\ x_3 &= 0X_1 + 0X_2 + 2X_3 \end{aligned} \quad (8.5)$$

Likewise, we can express the undeformed coordinates  $\mathbf{X}$  of any point in the cube in terms of the deformed coordinates  $\mathbf{x}$  of the same point in the cuboid:

---

<sup>1</sup>By convention, we use  $\mathbf{X}$  to refer to the undeformed coordinates, and  $\mathbf{x}$  to denote the deformed coordinates

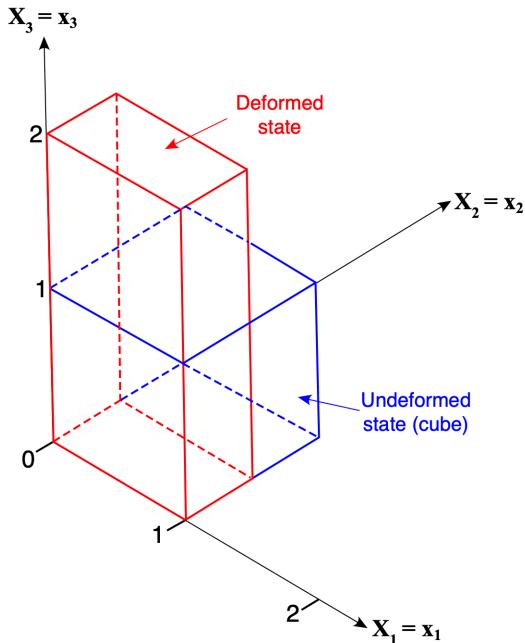


Figure 8.2: Deformation of a cube into a brick-shaped body. The principal axes of strain are parallel to the coordinate axes before  $\mathbf{X}$  and after  $\mathbf{x}$  deformation. Modified from Means (1976).

$$\begin{aligned} X_1 &= 1x_1 + 0x_2 + 0x_3 \\ X_2 &= 0x_1 + 2x_2 + 0x_3 \\ X_3 &= 0x_1 + 0x_2 + 0.5x_3 \end{aligned} \quad (8.6)$$

Equations 8.5 and 8.6 are called *coordinate transformations*, but they are fundamentally different from the transformation of coordinate axes in Chapter 5. The coordinate transformations here are between two different states in time. Eq. 8.5 is called a *Green* transformation (new in terms of old), while Eq. 8.6 is a *Cauchy* transformation (old in terms of new).

We can take the partial derivatives of these equations, which are just the coefficients of the equations:

$$\frac{\partial x_i}{\partial X_j} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0.5 & 0 \\ 0 & 0 & 2 \end{bmatrix} \quad (8.7)$$

and:

$$\frac{\partial X_i}{\partial x_j} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 0.5 \end{bmatrix} \quad (8.8)$$

These partial derivatives are known as the deformation gradients and unlike the coordinate transformations, they are homogeneous and independent of the coordinate axes (i.e. they are tensors). Eq. 8.7 is called the *Green* deformation gradient, while Eq. 8.8 is the *Cauchy* deformation gradient. Since in Fig. 8.2 the principal axes of strain are parallel to the coordinate axes, we can see one thing: The components of the Green deformation gradient are the stretches along the coordinate axes, and the components of the Cauchy deformation gradient are the inverse of the stretches along the coordinate axes. For other more complex situations this will not be the case, but in general the Green and Cauchy deformation gradient tensors are related to the stretch (Allmendinger et al., 2012).

Another way to study the deformation is to look at the displacement  $\mathbf{u}$  between the undeformed and deformed states (Fig. 8.2). The displacement can either be expressed in the undeformed configuration:

$$\begin{aligned} u_1 &= 0X_1 + 0X_2 + 0X_3 \\ u_2 &= 0X_1 - 0.5X_2 + 0X_3 \\ u_3 &= 0X_1 + 0X_2 + 1X_3 \end{aligned} \quad (8.9)$$

or in the deformed configuration:

$$\begin{aligned} u_1 &= 0x_1 + 0x_2 + 0x_3 \\ u_2 &= 0x_1 - 1x_2 + 0x_3 \\ u_3 &= 0x_1 + 0x_2 + 0.5x_3 \end{aligned} \quad (8.10)$$

Eq. 8.9 is known as the *Lagrangian* displacement (in terms of old coordinates), while Eq. 8.10 is the *Eulerian* displacement (in terms of new coordinates). We can take the partial derivatives of these equations, which are just the coefficients of the equations:

$$\frac{\partial u_i}{\partial X_j} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & -0.5 & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad (8.11)$$

and:

$$\frac{\partial u_i}{\partial x_j} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & -1 & 0 \\ 0 & 0 & 0.5 \end{bmatrix} \quad (8.12)$$

These partial derivatives are known as the displacement gradients and unlike the displacement, they are homogeneous and independent of the coordinate axes (i.e. they are tensors). Eq. 8.11 is called the *Lagrangian* displacement gradient, while Eq. 8.12 is the *Eulerian* displacement gradient. For the case of Fig. 8.2, we can see that the components of the Lagrangian displacement gradient are the elongations along the coordinate axes, while the components of the Eulerian displacement gradient are the elongations along the coordinate axes with respect to the deformed reference frame ( $\tilde{e} = (l_f - l_i)/l_f$ ). This will not be the case for more complicated situations, but in general the Lagrangian and Eulerian displacement gradient tensors are related to the elongation (Allmendinger et al., 2012).

Table 8.1 summarizes this section.

	Old coordinates	New coordinates
Coordinate transformations	Green $x_i = \frac{\partial x_i}{\partial X_j} X_j$	Cauchy $X_i = \frac{\partial X_i}{\partial x_j} x_j$
Displacement	Lagrangian $u_i = \frac{\partial u_i}{\partial X_j} X_j$	Eulerian $u_i = \frac{\partial u_i}{\partial x_j} x_j$

Table 8.1: Coordinate transformations and displacement via deformation and displacement gradient tensors. Rigid body deformation is not included.

### 8.3 Infinitesimal strain

Suppose that a line parallel to the  $\mathbf{X}_1$  axis is elongated 1% of its initial length. In this case the displacement gradient is:

$$\frac{\partial u_1}{\partial X_1} = \frac{0.01}{1.0} = 0.01 \quad \text{and} \quad \frac{\partial u_1}{\partial x_1} = \frac{0.01}{1.01} = 0.0099$$

Thus, when strains are small ( $e < 1\%$ ),  $\frac{\partial u_i}{\partial X_i} \approx \frac{\partial u_i}{\partial x_i}$ , and the difference between the displacement gradient in the initial or final state is insignificant. Small strains are called *infinitesimal strains*, and they are important in a number of fields in geosciences, particularly in geophysics.

For infinitesimal strain, the distinction between old and new coordinates is irrelevant, and therefore we can just use one column in Table 8.1. The displacement gradient  $\mathbf{e}$ <sup>2</sup> is an asymmetric tensor, and it can be decomposed into a symmetric and an antisymmetric tensor (Eq. 6.2):

$$e_{ij} = \varepsilon_{ij} + \omega_{ij} \tag{8.13}$$

where:

$$\varepsilon_{ij} = \frac{1}{2}(e_{ij} + e_{ji}) = \begin{bmatrix} e_{11} & \frac{e_{12}+e_{21}}{2} & \frac{e_{13}+e_{31}}{2} \\ \frac{e_{21}+e_{12}}{2} & e_{22} & \frac{e_{23}+e_{32}}{2} \\ \frac{e_{31}+e_{13}}{2} & \frac{e_{32}+e_{23}}{2} & e_{33} \end{bmatrix} \tag{8.14}$$

and:

$$\omega_{ij} = \frac{1}{2}(e_{ij} - e_{ji}) = \begin{bmatrix} 0 & \frac{e_{12}-e_{21}}{2} & \frac{e_{13}-e_{31}}{2} \\ \frac{e_{21}-e_{12}}{2} & 0 & \frac{e_{23}-e_{32}}{2} \\ \frac{e_{31}-e_{13}}{2} & \frac{e_{32}-e_{23}}{2} & 0 \end{bmatrix} \tag{8.15}$$

The symmetric tensor  $\boldsymbol{\varepsilon}$  is called the strain tensor. The diagonal,  $\varepsilon_{ii}$ , terms of this tensor correspond to the elongations along the axes of the reference system, and the off-diagonal terms,  $\varepsilon_{ij}$ , to half the shear strain ( $\varepsilon_{ij} = \frac{\gamma_{ij}}{2}$ ). Like

---

<sup>2</sup>We use  $\mathbf{e}$  to denote the displacement gradient. This is different than the non-bold italic letter  $e$  which is used for elongation.

any symmetric tensor, the strain tensor has three principal axes which can be determined by computing the eigenvalues and eigenvectors of the tensor (section 6.2). These principal axes define the infinitesimal strain ellipsoid.

The antisymmetric tensor  $\omega$  is also known as an axial vector. The Cartesian coordinates,  $r_i$ , of this vector give the orientation of the rotation axis:

$$r_1 = \frac{-(\omega_{23} - \omega_{32})}{2} \quad r_2 = \frac{-(-\omega_{13} + \omega_{31})}{2} \quad \text{and} \quad r_3 = \frac{-(\omega_{12} - \omega_{21})}{2} \quad (8.16)$$

The amount of rotation in radians is just the length of the vector  $\mathbf{r}$ :

$$\omega = |\mathbf{r}| = \sqrt{r_1^2 + r_2^2 + r_3^2} \quad (8.17)$$

The function *InfStrain* computes the infinitesimal strain and rotation tensors from a displacement gradient, as well as the principal strains, and the components and amount of rotation:

```

1 import numpy as np
2
3 from CartToSph import CartToSph as CartToSph
4 from ZeroTwoPi import ZeroTwoPi as ZeroTwoPi
5
6 def InfStrain(e):
7     """
8     InfStrain computes infinitesimal strain from an input
9     displacement gradient tensor
10
11    USE: eps,ome,pstrain,rotc,rot = InfStrain(e)
12
13    e = 3 x 3 displacement gradient tensor
14    eps = 3 x 3 strain tensor
15    ome = 3 x 3 rotation tensor
16    pstrain = 3 x 3 matrix with magnitude (column 1), trend
17        (column 2) and plunge (column 3) of maximum
18        (row 1), intermediate (row 2), and minimum
19        (row 3) principal strains
20    rotc = 1 x 3 vector with rotation components
21    rot = 1 x 3 vector with rotation magnitude and trend
22        and plunge of rotation axis
23
24    NOTE: Output trends and plunges of principal strains

```

```

25     and rotation axes are in radians
26
27 InfStrain uses function CartToSph and ZeroTwoPi
28
29 Python function translated from the Matlab function
30 InfStrain in Allmendinger et al. (2012)
31 '''
32 # Initialize variables
33 eps = np.zeros((3,3))
34 ome = np.zeros((3,3))
35 pstrain = np.zeros((3,3))
36 rotc = np.zeros(3)
37 rot = np.zeros(3)
38
39 # Compute strain and rotation tensors
40 # Eqs. 8.14 and 8.15
41 for i in range(3):
42     for j in range(3):
43         eps[i,j]=0.5*(e[i,j]+e[j,i])
44         ome[i,j]=0.5*(e[i,j]-e[j,i])
45
46 # Compute principal strains and orientations.
47 # Here we use the function eigh. D is a vector
48 # of eigenvalues (i.e. principal strains), and V is a
49 # full matrix whose columns are the corresponding
50 # eigenvectors (i.e. principal strain directions)
51 D,V = np.linalg.eigh(eps)
52
53 # Maximum principal strain
54 pstrain[0,0] = D[2]
55 pstrain[0,1],pstrain[0,2] = CartToSph(V[0,2],V[1,2],V[2,2])
56 # Intermediate principal strain
57 pstrain[1,0] = D[1]
58 pstrain[1,1],pstrain[1,2] = CartToSph(V[0,1],V[1,1],V[2,1])
59 # Minimum principal strain
60 pstrain[2,0] = D[0]
61 pstrain[2,1],pstrain[2,2] = CartToSph(V[0,0],V[1,0],V[2,0])
62
63 # Calculate rotation components, Eq. 8.16
64 rotc[0]=(ome[1,2]-ome[2,1])*-0.5
65 rotc[1]=(-ome[0,2]+ome[2,0])*-0.5
66 rotc[2]=(ome[0,1]-ome[1,0])*-0.5
67
68 # Compute rotation magnitude, Eq. 8.17
69 rot[0] = np.sqrt(rotc[0]**2+rotc[1]**2+rotc[2]**2)
70 # Compute trend and plunge of rotation axis
71 rot[1],rot[2] = CartToSph(rotc[0]/rot[0],rotc[1]/rot[0],
    rotc[2]/rot[0])
72 # If plunge is negative

```

```

73     if rot[2] < 0:
74         rot[1] = ZeroTwoPi(rot[1]+np.pi)
75         rot[2] = -rot[2]
76         rot[0] = -rot[0]
77
78     return eps,ome,pstrain,rotc,rot

```

### 8.3.1 Mohr Circle for infinitesimal strain

As discussed in section 6.4.1, the rotation of the infinitesimal strain tensor about one principal axis can be represented by a Mohr Circle. We start with the infinitesimal strain tensor in principal coordinates:

$$\varepsilon_{ij} = \begin{bmatrix} \varepsilon_1 & 0 & 0 \\ 0 & \varepsilon_2 & 0 \\ 0 & 0 & \varepsilon_3 \end{bmatrix}$$

and perform a rotation  $\theta$  about  $\mathbf{X}_2$  (Fig. 8.3a), which is described by the transformation matrix:

$$a_{ij} = \begin{pmatrix} \cos \theta & 0 & \sin \theta \\ 0 & 1 & 0 \\ -\sin \theta & 0 & \cos \theta \end{pmatrix}$$

The tensor transformation equation is:

$$\varepsilon'_{ij} = a_{ik}a_{jl}\varepsilon_{kl} \quad (8.18)$$

which results in the new form of the strain tensor:

$$\varepsilon'_{ij} = \begin{bmatrix} \varepsilon_1 \cos^2 \theta + \varepsilon_3 \sin^2 \theta & 0 & -(\varepsilon_1 - \varepsilon_3) \sin \theta \cos \theta \\ 0 & \varepsilon_2 & 0 \\ -(\varepsilon_1 - \varepsilon_3) \sin \theta \cos \theta & 0 & \varepsilon_1 \sin^2 \theta + \varepsilon_3 \cos^2 \theta \end{bmatrix} \quad (8.19)$$

Upon rearranging, we get:

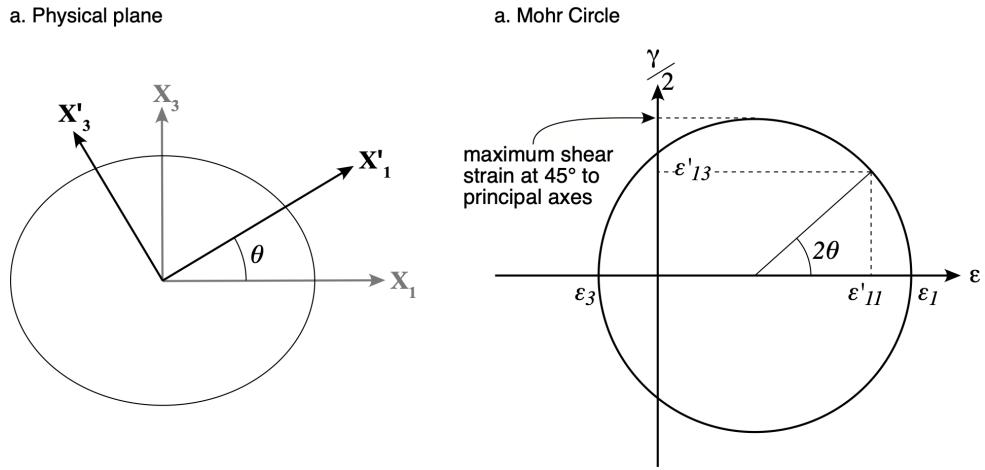


Figure 8.3: Rotation of the infinitesimal strain tensor about principal axis  $\mathbf{X}_2$ . **a.** Physical plane representation, **b.** Mohr Circle representation. Modified from Allmendinger et al. (2012).

$$\begin{aligned}\varepsilon'_{11} &= \frac{\varepsilon_1 + \varepsilon_3}{2} + \frac{\varepsilon_1 - \varepsilon_3}{2} \cos 2\theta \\ \varepsilon'_{33} &= \frac{\varepsilon_1 + \varepsilon_3}{2} - \frac{\varepsilon_1 - \varepsilon_3}{2} \cos 2\theta \\ \varepsilon'_{13} &= \varepsilon'_{31} = \frac{\gamma}{2} = -\frac{\varepsilon_1 - \varepsilon_3}{2} \sin 2\theta\end{aligned}\quad (8.20)$$

which are the equations of the Mohr Circle for infinitesimal strain (Fig. 8.3b). This Mohr Circle is not very useful, but perhaps the most important thing illustrated by it is that the two directions of maximum shear strain are at  $\pm 45^\circ$  to the principal axes,  $\varepsilon_1$  and  $\varepsilon_3$  (Fig. 8.3b). Turning this around for the infinitesimal strain in a shear zone, the infinitesimal shortening and extension directions are always at  $45^\circ$  to the shear zone boundary. For example, gash fractures, foliation at the edge of a shear zone, and P and T axes of earthquakes (section 8.3.2) are all oriented  $45^\circ$  to the shear (fault) zone (Fig. 8.4).

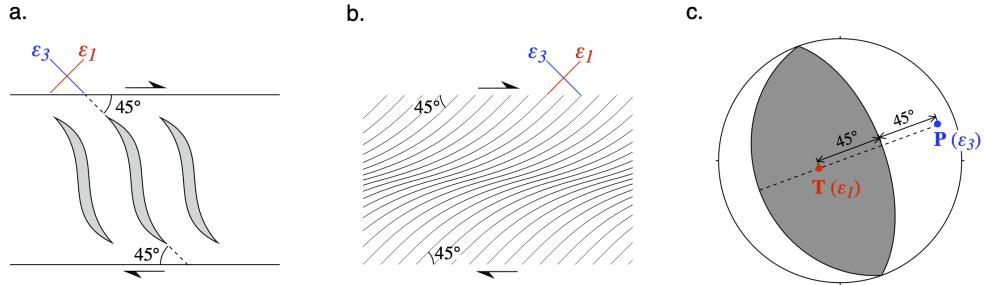


Figure 8.4: The infinitesimal extension and shortening directions are always at 45° to the shear zone boundaries. **a.** Sigmoidal veins, **b.** Foliation in shear zone, and **c.** P and T axes of earthquakes. Modified from Allmendinger et al. (2012).

### 8.3.2 Applications of Infinitesimal Strain

#### P and T axes

Our first application is based on the observation we just made regarding the orientation of the principal axes of infinitesimal strain with respect to a shear zone (Fig. 8.4). In a fault, the infinitesimal shortening  $P$  and extension  $T$  axes are at 45° to the slip vector (e.g. fault striae), and they lie on the plane defined by the fault striae and the fault pole. This plane is known as the movement plane  $M$  (Fig. 8.5).

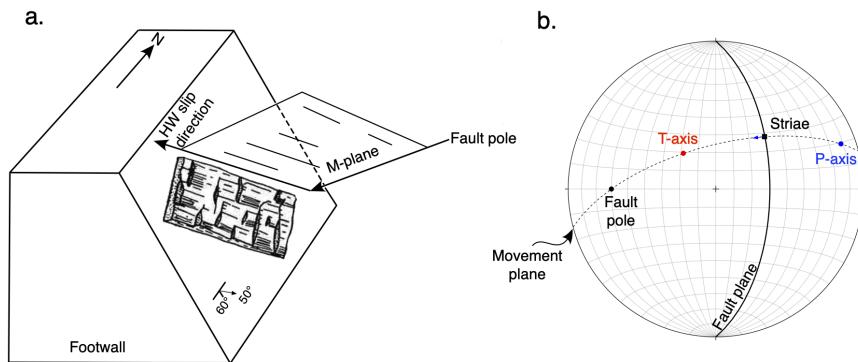


Figure 8.5: **a.** Reverse fault, striae and movement plane  $M$ . **b.** Representation of **a** on a lower hemisphere equal area stereonet. Modified from Marshak and Mitra (1988).

The displacement gradient tensor,  $e_{ij}$  of a population of  $n$  small faults with poles vectors,  $n_i$ , and slip vectors,  $u_i$ , is given by (Allmendinger et al., 2012):

$$e_{ij} = \frac{\sum_{i=1}^n (M_g u_i n_j)}{V} \quad (8.21)$$

where  $M_g$  is the geometric moment and  $V$  is the volume of the region being deformed. As discussed in section 8.3, we can decompose this equation to yield the infinitesimal strain and rotation tensors:

$$e_{ij} = \varepsilon_{ij} + \omega_{ij} = \frac{M_g (u_i n_j + u_j n_i)}{2V} + \frac{M_g (u_i n_j - u_j n_i)}{2V} \quad (8.22)$$

Because  $M_g/2V$  is a scalar, the orientations of the principal axes of infinitesimal strain are identical to the principal axes of the symmetric tensor  $(u_i n_j + u_j n_i)$ , which are just a function of the fault planes and striae orientations. The  $P$  and  $T$  axes are therefore a simple, direct representation of fault geometry and the orientation and sense of slip (Allmendinger et al., 1989).

The function `PTAxes` computes and plots the P and T axes from the orientation of several faults and their slip vectors:

```

1 import numpy as np
2 import matplotlib.pyplot as plt
3
4 from CartToSph import CartToSph as CartToSph
5 from ZeroTwoPi import ZeroTwoPi as ZeroTwoPi
6 from SphToCart import SphToCart as SphToCart
7 from Stereonet import Stereonet as Stereonet
8 from GreatCircle import GreatCircle as GreatCircle
9 from StCoordLine import StCoordLine as StCoordLine
10
11 def PTAxes(fault,slip,sense, fpsv):
12     """
13         PTAxes computes the P and T axes from the orientation
14         of several fault planes and their slip vectors. Results
15         are plotted in an equal area stereonet
16
17     USE: P,T,senseC = PTAxes(fault,slip,sense)
18
19     fault = nfaults x 2 vector with strikes and dips of
20         faults

```

```

21 slip = nfaults x 2 vector with trend and plunge of
22   slip vectors
23 sense = nfaults x 1 vector with sense of faults
24 fpsv = A flag to tell whether the fault plane and
25   slip vector are plotted (1) or not
26 P = nfaults x 2 vector with trend and plunge of P axes
27 T = nfaults x 2 vector with trend and plunge of T axes
28 senseC = nfaults x 1 vector with corrected sense of slip
29
30 NOTE: Input/Output angles are in radians
31
32 PTAxes uses functions SphToCart, ZeroTwoPi, CartToSph,
33 Stereonet, GreatCircle and StCoordLine
34
35 Python function based on the Matlab function
36 PTAxes in Allmendinger et al. (2012)
37 '''
38 pi = np.pi
39 # Initialize some vectors
40 n = np.zeros(3)
41 u = np.zeros(3)
42 eps = np.zeros((3,3))
43 P = np.zeros((np.size(fault,0),2))
44 T = np.zeros((np.size(fault,0),2))
45 senseC = sense
46
47 # For all faults
48 for i in range(np.size(fault,0)):
49   # Direction cosines of pole to fault and slip vector
50   n[0],n[1],n[2] = SphToCart(fault[i,0],fault[i,1],1)
51   u[0],u[1],u[2] = SphToCart(slip[i,0],slip[i,1],0)
52   # Compute u(i)*n(j) + u(j)*n(i)
53   for j in range(3):
54     for k in range(3):
55       eps[j,k]=u[j]*n[k]+u[k]*n[j]
56   # Compute orientations of principal axes of strain
57   # Here we use the function eigh
58   _,V = np.linalg.eigh(eps)
59   # P orientation
60   P[i,0],P[i,1] = CartToSph(V[0,2],V[1,2],V[2,2])
61   if P[i,1] < 0:
62     P[i,0] = ZeroTwoPi(P[i,0]+pi)
63     P[i,1] = P[i,1]*-1.0
64   # T orientation
65   T[i,0],T[i,1] = CartToSph(V[0,0],V[1,0],V[2,0])
66   if T[i,1] < 0.0:
67     T[i,0] = ZeroTwoPi(T[i,0]+pi)
68     T[i,1] = T[i,1]*-1.0
69   # Determine 3rd component of pole cross product slip

```

```

70     cross = n[0] * u[1] - n[1] * u[0]
71     # Use cross and first character in sense to
72     # determine if kinematic axes should be switched
73     s2 = 'N'
74     if sense[i][0] == 'T' or sense[i][0] == 't':
75         s2 = 'Y'
76     if (sense[i][0]=='R' or sense[i][0]=='r') and cross>0.0:
77         s2 = 'Y'
78     if (sense[i][0]=='L' or sense[i][0]=='l') and cross<0.0:
79         s2 = 'Y'
80     if s2 == 'Y':
81         temp1 = P[i,0]
82         temp2 = P[i,1]
83         P[i,0] = T[i,0]
84         P[i,1] = T[i,1]
85         T[i,0] = temp1
86         T[i,1] = temp2
87     if cross < 0.0:
88         senseC[i] = 'TL'
89     if cross > 0.0:
90         senseC[i] = 'TR'
91     else:
92         if cross < 0.0:
93             senseC[i] = 'NR'
94         if cross > 0.0:
95             senseC[i] = 'NL'

96
97     # Plot in equal area stereonet
98     Stereonet(0,90*pi/180,10*pi/180,1)
99     # Plot P and T axes
100    for i in range(np.size(fault,0)):
101        if fpsv == 1:
102            # Plot fault
103            path = GreatCircle(fault[i,0],fault[i,1],1)
104            plt.plot(path[:,0],path[:,1], 'k')
105            # Plot slip vector (black circle)
106            xp,yp = StCoordLine(slip[i,0],slip[i,1],1)
107            plt.plot(xp,yp, 'ko', 'MarkerFaceColor', 'k')
108            # Plot P axis (blue circle)
109            xp,yp = StCoordLine(P[i,0],P[i,1],1)
110            plt.plot(xp,yp, 'bo', 'MarkerFaceColor', 'b')
111            # Plot T axis (red circle)
112            xp,yp = StCoordLine(T[i,0],T[i,1],1)
113            plt.plot(xp,yp, 'ro', 'MarkerFaceColor', 'r')

114
115    # Show plot
116    plt.show()

117
118    return P,T,senseC

```

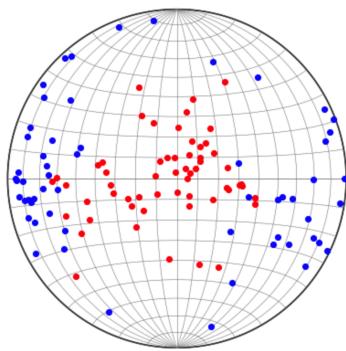
Let's use this function to plot the  $P$  and  $T$  axes for a group of faults from the Central Andes in Northern Argentina. The file [jujuy.txt](#) contains the orientation (strike and dip) of the faults, and the orientation (trend and plunge) and sense of movement of the slip vectors (striae)<sup>3</sup>. The notebook [ch8-1](#) shows how to do this:

```

1 # Import libraries
2 import numpy as np
3 pi = np.pi
4
5 # Import function PTAxes
6 import sys, os
7 sys.path.append(os.path.abspath('../functions'))
8 from PTAxes import PTAxes as PTAxes
9
10 # Read the faults
11 jujuy = np.loadtxt(os.path.abspath('../data/ch8-1/jujuy.txt'),
12 , usecols = [0,1,2,3])
13 fault = np.zeros((np.size(jujuy,0),2))
14 fault[:,0] = jujuy[:,0] * pi/180
15 fault[:,1] = jujuy[:,1] * pi/180
16 slip = np.zeros((np.size(jujuy,0),2))
17 slip[:,0] = jujuy[:,2] * pi/180
18 slip[:,1] = jujuy[:,3] * pi/180
19 sense = np.loadtxt(os.path.abspath('../data/ch8-1/jujuy.txt'),
20 , usecols = 4, dtype = 'str')
21
22 # Compute P and T axes and plot them
23 # Don't plot the faults and slip vectors
24 P,T,senseC= PTAxes(fault,slip,sense,0)

```

Output:



<sup>3</sup>This is the same file included in the program [FaultKin](#) by Richard Allmendinger

Here, the overall shortening direction given by the  $P$  axes (blue dots) is about E-W. From the  $P$  and  $T$  axes, it is possible to calculate a moment tensor summation and the kinematic axes, which define two nodal planes separating the regions of extension ( $T$  axes) and shortening ( $P$  axes). The regions of extension are typically shaded, and so the diagram looks like a beach ball (Fig. 8.4c). These "beach ball" diagrams are also used to display the focal mechanisms of earthquakes, where P-waves first arrivals pushing the ground up are marked as  $T$  axes, and those pushing the ground down are marked as  $P$  axes. We leave the moment tensor summation for the Exercises section.

## 2D strain from GPS data

The global positioning system (GPS) has revolutionized earth sciences in the last 30 years by providing geoscientists with real time monitoring of active deformation. Continuous GPS measurements provide mm resolution of the displacement of stations. Because the changes in distance between stations is very small (10s of mm) relative to the distance between stations (10s of km), the strains measured by GPS networks are infinitesimal. Figure 8.6 shows this problem in two dimensions:

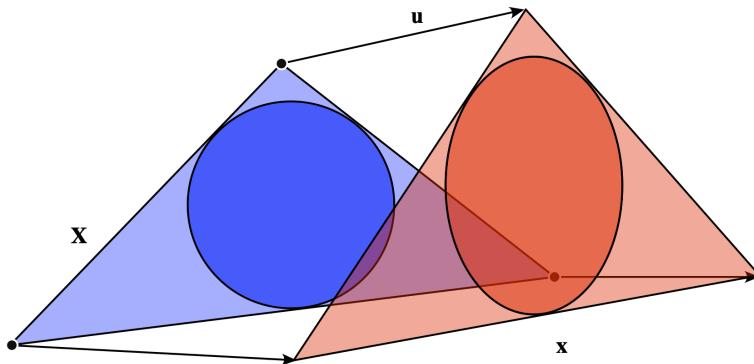


Figure 8.6: Three points in an initial configuration  $\mathbf{X}$  move along non-parallel vectors  $\mathbf{u}$  to a final configuration  $\mathbf{x}$ , resulting in strain. Modified from Allmendinger et al. (2012).

If the strain is homogeneous, the displacement of the stations is expressed by the following equation:

$$u_i = t_i + e_{ij}X_j \quad (8.23)$$

where  $t_i$  is the translation vector and  $e_{ij}$  is the displacement gradient tensor. In matrix form, this equation can be written as:

$$\begin{bmatrix} {}^1u_1 \\ {}^1u_2 \\ {}^2u_1 \\ {}^2u_2 \\ \dots \\ \dots \\ {}^nu_1 \\ {}^nu_2 \end{bmatrix} = \begin{bmatrix} 1 & 0 & {}^1X_1 & {}^1X_2 & 0 & 0 \\ 0 & 1 & 0 & 0 & {}^1X_1 & {}^1X_2 \\ 1 & 0 & {}^2X_1 & {}^2X_2 & 0 & 0 \\ 0 & 1 & 0 & 0 & {}^2X_1 & {}^2X_2 \\ \dots & \dots & \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots & \dots \\ 1 & 0 & {}^nX_1 & {}^nX_2 & 0 & 0 \\ 0 & 1 & 0 & 0 & {}^nX_1 & {}^nX_2 \end{bmatrix} \begin{bmatrix} t_1 \\ t_2 \\ e_{11} \\ e_{12} \\ e_{21} \\ e_{22} \end{bmatrix} \quad (8.24)$$

where the superscripts 1 to  $n$  refer to the stations. The column vector to the right of Eq. 8.24 contains the unknowns, which are the two components of the translation vector ( $t_1$  and  $t_2$ ) and the four components of the displacement gradient tensor ( $e_{11}$ ,  $e_{12}$ ,  $e_{21}$  and  $e_{22}$ ). Therefore, in 2D there are 6 unknowns, and since each station delivers 2 equations, we need a minimum of 3 non-collinear stations to determine the strain ellipse<sup>4</sup>.

Notice that Eq. 8.24 is written not just for 3 stations but for  $n$  stations. If there are more than 3 stations in 2D (or 4 stations in 3D), the system is overdetermined (more equations than unknowns), and we can use the extra information to assess the uncertainties of the model parameters.

The solution to Eq. 8.24 is a classical application of inverse theory, specifically the solution of the linear least-squares problem (Press et al., 1986). This problem has the form:

$$\mathbf{y} = \mathbf{M}\mathbf{x} \quad (8.25)$$

where  $\mathbf{y}$  is the vector with known displacements,  $\mathbf{M}$  is the matrix with the location of the stations (this matrix is known as the design matrix), and  $\mathbf{x}$  is the vector with the unknowns. To solve for  $\mathbf{x}$ ,  $\mathbf{y}$  is multiplied by the inverse of  $\mathbf{M}$ :

$$\mathbf{x} = \mathbf{M}^{-1}\mathbf{y} \quad (8.26)$$

---

<sup>4</sup>In 3D there are 12 unknowns and each station delivers 3 equations. Therefore, we need a minimum of 4 non-collinear stations to determine the strain ellipsoid.

In Matlab or Python, there are routines specifically designed to solve this problem. We use the function *lscov* by Paul Müller to solve this problem.

There are three main strategies to compute the strain from a network of stations: i. To calculate the strain on triangular cells whose vertices are defined by the stations (Delaunay triangulation), ii. To calculate the strain on a regular grid of cells, using the stations within a radius,  $r$ , from the center of each cell (nearest neighbor method), or iii. To calculate the strain on a regular grid of cells, using all the stations weighted by their distance to the center of each cell (distance weighted method; Cardozo and Allmendinger; 2009). In this last case, the weighting factor is given by:

$$W = \exp\left[\frac{-d^2}{2\alpha^2}\right] \quad (8.27)$$

where  $d$  is the distance of the station from the center of the cell, and  $\alpha$  is a constant that specifies how the impact of a station decays with distance. A larger value of  $\alpha$  smooths out local variations.

The function *GridStrain* computes and plots the infinitesimal strain of a network of GPS stations<sup>5</sup>. Notice that after computing the displacement gradient for each cell, we use the function *InfStrain* to compute the strain:

```

1 import numpy as np
2 import matplotlib.pyplot as plt
3 import matplotlib.colors as mcolors
4 from matplotlib.patches import Polygon
5 from matplotlib.collections import PatchCollection
6 from scipy.spatial import Delaunay
7
8 from lscov import lscov as lscov
9 from InfStrain import InfStrain as InfStrain
10
11 def GridStrain(pos, disp, k, par, plotpar, plotst):
12     '''
13     GridStrain computes the infinitesimal strain of a network
14     of stations with displacements in x (east) and y (north).
15     Strain in z is assumed to be zero (plane strain)
16
17     USE: cent, eps, ome, pstrain, rotc = GridStrain(pos, disp, k, par,
18             plotpar, plotst)

```

---

<sup>5</sup>This is a long but handy function. In the function we use the character \ to break long lines.

```

18 pos = nstations x 2 matrix with x (east) and y (north)
19   positions of stations in meters
20 disp = nstations x 2 matrix with x (east) and y (north)
21   displacements of stations in meters
22 k = Type of computation: Delaunay (k = 0), nearest
23   neighbor (k = 1), or distance weighted (k = 2)
24 par = Parameters for nearest neighbor or distance
25   weighted computation. If Delaunay (k = 0), enter
26   a scalar corresponding to the minimum internal
27   angle of a triangle valid for computation.
28   If nearest neighbor (k = 1), input a 1 x 3 vector
29   with grid spacing, number of nearest neighbors,
30   and maximum distance to neighbors. If distance
31   weighted (k = 2), input a 1 x 2 vector with grid
32   spacing and distance weighting factor alpha
33 plotpar = Parameter to color the cells: Max elongation
34   (plotpar = 0), minimum elongation
35   (plotpar = 1), rotation (plotpar = 2),
36   or dilatation (plotpar = 3)
37 plotst = A flag to plot the stations (1) or not (0)
38 cent = ncells x 2 matrix with x and y positions of cells
39   centroids
40 eps = 3 x 3 x ncells array with strain tensors of
41   the cells
42 ome = 3 x 3 x ncells array with rotation tensors of
43   the cells
44 pstrain = 3 x 3 x ncells array with magnitude and
45   orientation of principal strains of
46   the cells
47 rotc = ncells x 3 matrix with rotation components
48   of cells
49
50
51 NOTE: Input/Output angles are in radians. Output
52   azimuths are given with respect to North
53   pos, disp, grid spacing, max. distance to
54   neighbors, and alpha should be in meters
55
56 GridStrain uses functions lscov and InfStrain
57
58 Python function translated from the Matlab function
59 GridStrain in Allmendinger et al. (2012)
60   ''
61 pi = np.pi
62 # If Delaunay
63 if k == 0:
64   # Indexes of triangles vertices
65   # Use function Delaunay
66   tri = Delaunay(pos)

```

```

67     inds = tri.simplices
68     # Number of cells
69     ncells = np.size(inds,0)
70     # Number of stations per cell = 3
71     nstat = 3
72     # Centers of cells
73     cent = np.zeros((ncells,2))
74     for i in range(ncells):
75         # Triangle vertices
76         v1x=pos[inds[i,0],0]
77         v2x=pos[inds[i,1],0]
78         v3x=pos[inds[i,2],0]
79         v1y=pos[inds[i,0],1]
80         v2y=pos[inds[i,1],1]
81         v3y=pos[inds[i,2],1]
82         # Center of cell
83         cent[i,0]=(v1x + v2x + v3x)/3.0
84         cent[i,1]=(v1y + v2y + v3y)/3.0
85         # Triangle internal angles
86         s1 = np.sqrt((v3x-v2x)**2 + (v3y-v2y)**2)
87         s2 = np.sqrt((v1x-v3x)**2 + (v1y-v3y)**2)
88         s3 = np.sqrt((v2x-v1x)**2 + (v2y-v1y)**2)
89         a1 = np.arccos((v2x-v1x)*(v3x-v1x)/(s3*s2)+\
90                         (v2y-v1y)*(v3y-v1y)/(s3*s2))
91         a2 = np.arccos((v3x-v2x)*(v1x-v2x)/(s1*s3)+\
92                         (v3y-v2y)*(v1y-v2y)/(s1*s3))
93         a3 = np.arccos((v2x-v3x)*(v1x-v3x)/(s1*s2)+\
94                         (v2y-v3y)*(v1y-v3y)/(s1*s2))
95         # If any of the internal angles is less than
96         # specified minimum, invalidate triangle
97         if a1 < par or a2 < par or a3 < par:
98             inds[i,:] = np.zeros(3)
99         # If nearest neighbor or distance weighted
100     else:
101         # Construct grid
102         xmin = min(pos[:,0]); xmax = max(pos[:,0])
103         ymin = min(pos[:,1]); ymax = max(pos[:,1])
104         cellsx = int(np.ceil((xmax-xmin)/par[0]))
105         cellsy = int(np.ceil((ymax-ymin)/par[0]))
106         xgrid = np.arange(xmin,(xmin+(cellsx+1)*par[0]),par[0])
107         ygrid = np.arange(ymin,(ymin+(cellsy+1)*par[0]),par[0])
108         XX,YY = np.meshgrid(xgrid,ygrid)
109         # Number of cells
110         ncells = cellsx * cellsy
111         # Number of stations per cell (nstat) and
112         # other parameters
113         # If nearest neighbor
114         if k == 1:
115             nstat = par[1] # max neighbors

```

```

116     sqmd = par[2]**2 # max squared distance
117 # If distance weighted
118 elif k == 2:
119     nstat = np.size(pos,0) # all stations
120     dalpha = 2.0*par[1]*par[1] # 2*alpha*alpha
121 # Cells' centers
122 cent = np.zeros((ncells,2))
123 count = 0
124 for i in range(cellsy):
125     for j in range(cellsx):
126         cent[count,0] = (XX[i,j]+XX[i,j+1])/2.0
127         cent[count,1] = (YY[i,j]+YY[i+1,j])/2.0
128         count += 1
129 # Initialize stations indexes for cells to -1
130 inds = np.ones((ncells,nstat), dtype=int)*-1
131 # Initialize weight matrix for distance weighted
132 wv = np.zeros((ncells,nstat*2))
133 # For all cells set stations indexes
134 for i in range(ncells):
135     # Initialize sq distances to -1.0
136     sds = np.ones(nstat)*-1.0
137     # For all stations
138     for j in range(np.size(pos,0)):
139         # Sq distance from cell center to station
140         dx = cent[i,0] - pos[j,0]
141         dy = cent[i,1] - pos[j,1]
142         sd = dx**2 + dy**2
143         # If nearest neighbor
144         if k == 1:
145             # If within the max sq distance
146             if sd <= sqmd:
147                 minsd = min(sds)
148                 mini = np.argmin(sds)
149                 # If less than max neighbors
150                 if minsd == -1.0:
151                     sds[mini] = sd
152                     inds[i,mini] = j
153                 # If max neighbors
154                 else:
155                     # If sq distance is less
156                     # than neighbors max sq distance
157                     maxsd = max(sds)
158                     maxi = np.argmax(sds)
159                     if sd < maxsd:
160                         sds[maxi] = sd
161                         inds[i,maxi] = j
162 # If distance weighted
163 elif k == 2:
164     # All stations indexes

```

```

165         inds[i,:] = np.arange(nstat)
166         # Eq. 8.27: Weight factor
167         weight = np.exp(-sd/dalpha)
168         wv[i,j*2] = weight
169         wv[i,j*2+1] = weight
170
171     # Initialize arrays
172     y = np.zeros(nstat*2)
173     M = np.zeros((nstat*2,6))
174     e = np.zeros((3,3))
175     eps = np.zeros((3,3,ncells))
176     ome = np.zeros((3,3,ncells))
177     pstrain = np.zeros((3,3,ncells))
178     rotc = np.zeros((ncells,3))
179
180     # For each cell
181     for i in range(ncells):
182         # If required minimum number of stations
183         if min(inds[i,:]) >= 0:
184             # Eq. 8.24: Displacements column vector y
185             # and design matrix M. X1 = North, X2 = East
186             for j in range(nstat):
187                 ic = inds[i,j]
188                 y[j*2] = disp[ic,1]
189                 y[j*2+1] = disp[ic,0]
190                 M[j*2,:] = [1.,0.,pos[ic,1],pos[ic,0],0.,0.]
191                 M[j*2+1,:] = [0.,1.,0.,0.,pos[ic,1],pos[ic,0]]
192             # Eqs. 8.25-8.26: Find x using function lscov
193             # If Delaunay or nearest neighbor
194             if k == 0 or k == 1:
195                 x = lscov(M,y)
196             # If distance weighted
197             elif k == 2:
198                 x = lscov(M,y,wv[i,:])
199             # Displacement gradient tensor
200             for j in range(2):
201                 e[j,0] = x[j*2+2]
202                 e[j,1] = x[j*2+3]
203             # Compute strain
204             eps[:, :, i], ome[:, :, i], pstrain[:, :, i], \
205                 rotc[i, :, :] = InfStrain(e)
206
207             # Variable to plot
208             # If maximum principal strain
209             if plotpar == 0:
210                 vp = pstrain[0,0,:]
211                 lcb = "emax"
212             # If minimum principal strain
213             elif plotpar == 1:

```

```

214     vp = pstrain[2,0,:]
215     lcb = "emin"
216 # If rotation:
217 # For plane strain, rotation = rotc(3)
218 elif plotpar == 2:
219     vp = rotc[:,2]*180/pi
220     lcb = "Rotation (deg)"
221 # If dilatation
222 elif plotpar == 3:
223     vp = pstrain[0,0,:]+pstrain[1,0,:]+pstrain[2,0,:]
224     lcb = "dilatation"
225
226 # Make a figure
227 fig, ax = plt.subplots()
228 fig.set_size_inches(15.0, 7.5)
229
230 # Patches and colors for cells
231 patches = []
232 colors = []
233
234 # Fill cells patches and colors
235 # If Delaunay
236 if k == 0:
237     for i in range(ncells):
238         # If minimum number of stations
239         if min(ind[i,:]) >= 0:
240             xpyp = [[pos[ind[i,0],0],pos[ind[i,0],1]],\
241                     [pos[ind[i,1],0],pos[ind[i,1],1]],\
242                     [pos[ind[i,2],0],pos[ind[i,2],1]]]
243         # length in km
244         xpyp = np.divide(xpyp,1e3)
245         polygon = Polygon(xpyp, True)
246         patches.append(polygon)
247         colors.append(vp[i])
248 # If nearest neighbor or distance weighted
249 if k == 1 or k == 2:
250     count = 0
251     for i in range(cellsy):
252         for j in range(cellsx):
253             # If minimum number of stations
254             if min(ind[count,:]) >= 0:
255                 xpyp = [[XX[i,j],YY[i,j]],[XX[i,j+1],YY[i,j+1]],\
256                         [XX[i+1,j+1],YY[i+1,j+1]],[XX[i+1,j],YY[i+1,j]]]
257             # length in km
258             xpyp = np.divide(xpyp,1e3)
259             polygon = Polygon(xpyp, True)
260             patches.append(polygon)
261             colors.append(vp[count])
262             count += 1

```

```

263
264 # Collect cells patches
265 pcoll = PatchCollection(patches)
266 # Cells colors
267 pcoll.set_array(np.array(colors))
268 # Color map is blue to red
269 pcoll.set_cmap('bwr')
270 # Positive values are red, negative are
271 # blue and zero is white
272 vmin = min(vp)
273 vmax = max(vp)
274 norm=mcOLORS.TwoSlopeNorm(vmin=vmin,vcenter=0.0,vmax=vmax)
275 pcoll.set_norm(norm)
276
277 # Draw cells
278 ax.add_collection(pcoll)
279
280 # Plot stations
281 if plotst == 1:
282     plt.plot(pos[:,0]*1e-3,pos[:,1]*1e-3,'k.',markersize=2)
283
284 # Axes
285 plt.axis('equal')
286 plt.xlabel('x (km)')
287 plt.ylabel('y (km)')
288
289 # Color bar with nice ticks
290 intv = (vmax-vmin)*0.25
291 ticks=[vmin,vmin+intv,vmin+2*intv,vmin+3*intv,vmax]
292 lticks = ['{:2e}'.format(ticks[0]),\
293           '{:2e}'.format(ticks[1]),'{:2e}'.format(ticks[2]),\
294           '{:2e}'.format(ticks[3]),'{:2e}'.format(ticks[4])]
295 cbar = fig.colorbar(pcoll, label=lcb, ticks=ticks)
296 cbar.ax.set_yticklabels(lticks)
297
298 # Show plot
299 plt.show()
300
301 return cent,eps,ome,pstrain,rotc

```

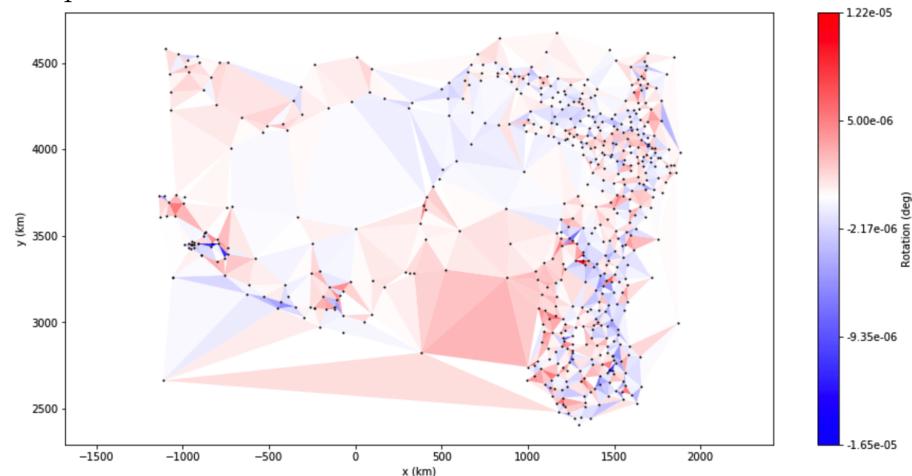
Let's use this function to compute the infinitesimal rotation in Tibet and the Himalaya. The file *tibet.txt* contains the UTM, east and west, coordinates of GPS stations in this region and their displacements in meters (from Zhang et al., 2004). The notebook [ch8-2](#) shows the solution to this problem using the Delaunay, nearest neighbor, and distance weighted methods.

```

1 import numpy as np
2 pi = np.pi
3
4 # Import function GridStrain
5 import sys, os
6 sys.path.append(os.path.abspath('../functions'))
7 from GridStrain import GridStrain as GridStrain
8
9 # Load Zhang et al. GPS data from the Tibetan plateau
10 # load x, y coordinates and displacements
11 tibet = np.loadtxt(os.path.abspath('../data/ch8-2/tibet.txt'))
12 pos = np.zeros((np.size(tibet,0),2))
13 pos[:,0] = tibet[:,0]
14 pos[:,1] = tibet[:,1]
15 disp = np.zeros((np.size(tibet,0),2))
16 disp[:,0] = tibet[:,2]
17 disp[:,1] = tibet[:,3]
18
19 # Rotation from Delaunay triangulation, plot stations
20 par = 10 * pi/180 #Minimum internal angle of triangles
21 cent,eps,ome,pstrain,rotc = GridStrain(pos,disp,0,par,2,1)

```

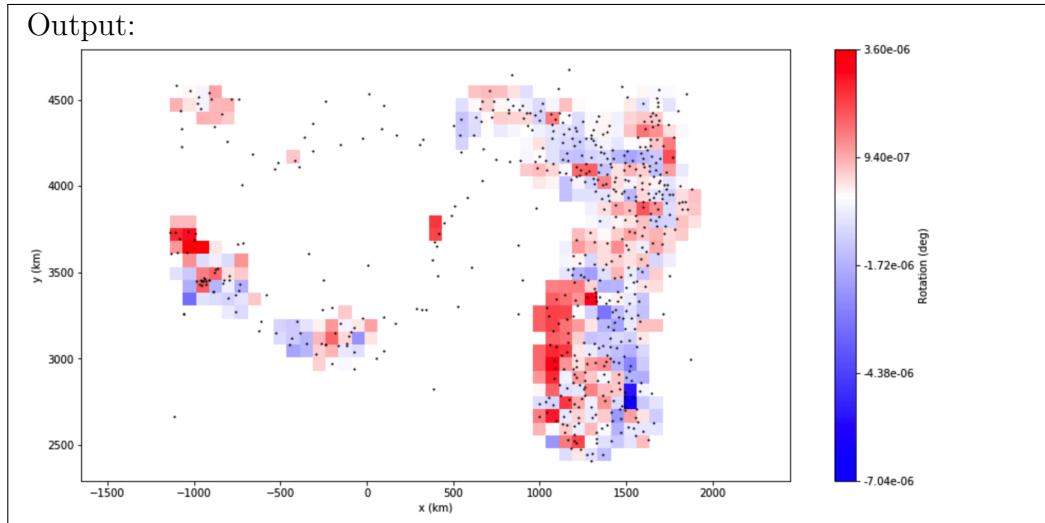
Output:



```

1 # Rotation from nearest neighbor
2 # Grid spacing = 75 km, neighbors 6,
3 # max. distance = 150 km, plot stations
4 par=[75e3,6,150e3]
5 cent,eps,ome,pstrain,rotc = GridStrain(pos,disp,1,par,2,1)

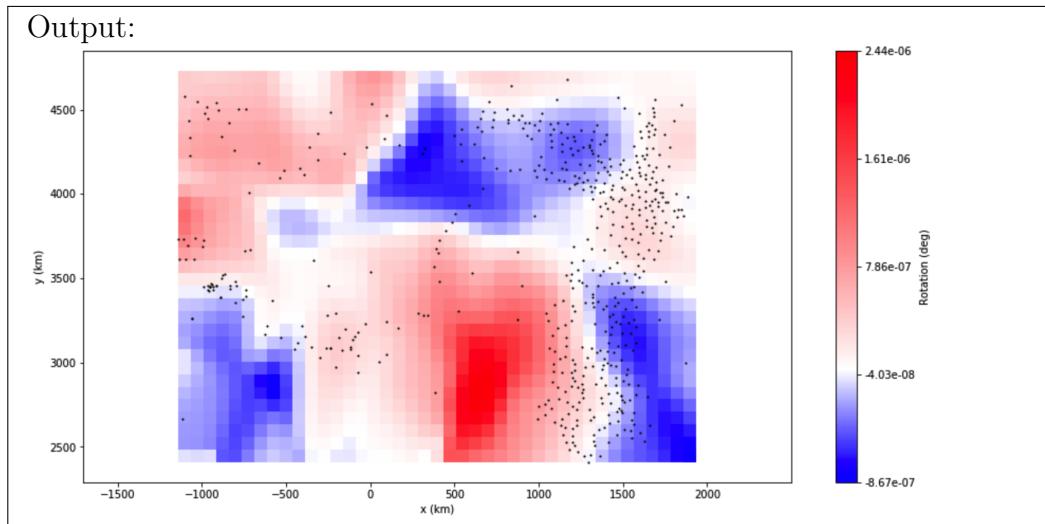
```



```

1 # Rotation from distance Weighted
2 # Grid spacing = 75 km, alpha = 150 km, plot stations
3 par=[75e3,150e3]
4 cent,eps,ome,pstrain,rotc = GridStrain(pos,disp,2,par,2,1)

```



Given the uneven distribution of the stations, the distance weighted method is perhaps the best representation of the infinitesimal strain. The rotation is about a downward vertical axis. The GPS-based rotation shows large coherent domains of clockwise (positive) and counterclockwise (negative) rotation. Interestingly enough, these domains are consistent with the permanent, long-term deformation of this region (Allmendinger et al., 2007).

## 8.4 Finite strain

When deformations are large, the initial and final states are not anymore identical:

$$dX_i \neq dx_i \quad \text{and} \quad \frac{\partial u_i}{\partial X_i} \neq \frac{\partial u_i}{\partial x_i} \quad (8.28)$$

and therefore, we need to use all the tensors in Table 8.1.

The mathematics of finite strain is quite lengthy (e.g. Means, 1976; Allmendinger et al., 2012) and we will not cover it in detail here. Rather, we will focus on the main tensors required to compute finite strain. We start with the finite strain tensor in the undeformed configuration:

$$E_{ij} = \frac{1}{2} \left[ \frac{\partial u_i}{\partial X_j} + \frac{\partial u_j}{\partial X_i} + \frac{\partial u_k}{\partial X_i} \frac{\partial u_k}{\partial X_j} \right] = \frac{1}{2} [e_{ij} + e_{ji} + e_{ki}e_{kj}] \quad (8.29)$$

where  $E_{ij}$  is known as the *Lagrangian finite strain tensor*. Similarly, we can compute the finite strain tensor in the deformed configuration:

$$\bar{E}_{ij} = \frac{1}{2} \left[ \frac{\partial u_i}{\partial x_j} + \frac{\partial u_j}{\partial x_i} - \frac{\partial u_k}{\partial x_i} \frac{\partial u_k}{\partial x_j} \right] = \frac{1}{2} [\bar{e}_{ij} + \bar{e}_{ji} - \bar{e}_{ki}\bar{e}_{kj}] \quad (8.30)$$

where  $\bar{E}_{ij}$  is known as the *Eulerian finite strain tensor*<sup>6</sup>. Notice that Eqs. 8.29 and 8.30 are similar to Eq. 8.14 for the infinitesimal strain tensor, but with an extra term ( $e_{ki}e_{kj}$  or  $\bar{e}_{ki}\bar{e}_{kj}$ ).

From the deformation gradient  $\mathbf{F}$ , we can also compute deformation tensors. In the undeformed configuration:

$$C_{ij} = \frac{\partial x_k}{\partial X_i} \frac{\partial x_k}{\partial X_j} = F_{ki}F_{kj} \quad (8.31)$$

where  $C_{ij}$  is known as the *Green deformation tensor*, and in the deformed configuration:

---

<sup>6</sup>We use an upper bar to denote tensors in the deformed configuration, e.g.  $\bar{e}_{ij}$  and  $\bar{E}_{ij}$

$$\bar{C}_{ij} = \frac{\partial X_k}{\partial x_i} \frac{\partial X_k}{\partial x_j} = \bar{F}_{ki} \bar{F}_{kj} \quad (8.32)$$

where  $\bar{C}_{ij}$  is known as the *Cauchy deformation tensor*.

The finite strain and deformation tensors are related. In the undeformed configuration:

$$E_{ij} = \frac{1}{2} (C_{ij} - \delta_{ij}) \quad \text{and} \quad C_{ij} = \delta_{ij} + 2E_{ij} \quad (8.33)$$

and in the deformed configuration:

$$\bar{E}_{ij} = \frac{1}{2} (\delta_{ij} - \bar{C}_{ij}) \quad \text{and} \quad \bar{C}_{ij} = \delta_{ij} - 2\bar{E}_{ij} \quad (8.34)$$

where  $\delta_{ij}$  is the Kronecker delta, a function that returns 1 if  $i = j$ , or 0 otherwise.

Thus, the finite strain tensors do not contain any more information than the deformation tensors, and viceversa. They are all symmetric tensors that have principal axes and can be represented by Mohr Circles (see next section). From Eqs. 8.33 and 8.34, it is clear that  $E_{ij}$  and  $C_{ij}$ , and  $\bar{E}_{ij}$  and  $\bar{C}_{ij}$ , have the same principal axes orientations. Also, these tensors are easily related to the quadratic elongation,  $\lambda_i$ , along the coordinate axes:

$$\lambda_i = C_{ii} = 1 + 2E_{ii} \quad (8.35)$$

and:

$$\frac{1}{\lambda_i} = \bar{C}_{ii} = 1 - 2\bar{E}_{ii} \quad (8.36)$$

Table 8.2 shows the finite strain and deformation tensors for the deformation in Fig. 8.2.

You can see that the diagonal components of the Green deformation tensor,  $C_{ij}$ , are the quadratic elongations,  $\lambda_i$ , along the coordinate axes, and the

---

Undeformed	$E_{ij} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & -0.375 & 0 \\ 0 & 0 & 1.5 \end{bmatrix}$	$C_{ij} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0.25 & 0 \\ 0 & 0 & 4 \end{bmatrix}$
Deformed	$\bar{E}_{ij} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & -1.5 & 0 \\ 0 & 0 & 0.375 \end{bmatrix}$	$\bar{C}_{ij} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 4 & 0 \\ 0 & 0 & 0.25 \end{bmatrix}$

---

Table 8.2: Finite strain and deformation tensors for the deformation in Fig. 8.2

diagonal components of the Cauchy deformation tensor,  $\bar{C}_{ij}$ , are the inverse of the quadratic elongations,  $1/\lambda_i$ . The diagonal components of the Lagrangian and Eulerian finite strain tensors,  $E_{ij}$  and  $\bar{E}_{ij}$ , can be found from Eqs. 8.35 and 8.36.

The function *FinStrain* computes the finite strain from the displacement gradient tensor, in the undeformed (*frame* = 0) or deformed (*frame* = 1) configuration. Notice that the function computes the magnitude and orientation of the maximum shear strain for the case of plane strain (Ramsay, 1967; his Eqs. 3.45 and 3.46).

```

1 import numpy as np
2
3 from CartToSph import CartToSph as CartToSph
4
5 def FinStrain(e, frame):
6     """
7         FinStrain computes finite strain from an input
8         displacement gradient tensor
9
10    USE: eps, pstrain, dilat, maxsh = FinStrain(e, frame)
11
12    e = 3 x 3 Lagrangian or Eulerian displacement gradient
13        tensor
14    frame = Reference frame. 0 = undeformed (Lagrangian)
15        state, 1 = deformed (Eulerian) state
16    eps = 3 x 3 Lagrangian or Eulerian strain tensor
17    pstrain = 3 x 3 matrix with magnitude (column 1), trend
18        (column 2) and plunge (column 3) of maximum
19        (row 1), intermediate (row 2), and minimum
20        (row 3) elongations
21    dilat = dilatation

```

```

22 maxsh = 1 x 2 vector with max. shear strain and
23 orientation with respect to maximum principal
24 strain direction. Only valid in 2D
25
26 NOTE: Output angles are in radians
27
28 FinStrain uses function CartToSph
29
30 Python function translated from the Matlab function
31 FinStrain in Allmendinger et al. (2012)
32 '''
33 # Initialize variables
34 eps = np.zeros((3,3))
35 pstrain = np.zeros((3,3))
36 maxsh = np.zeros(2)
37
38 # Compute strain tensor
39 for i in range(3):
40     for j in range(3):
41         eps[i,j] = 0.5*(e[i][j]+e[j][i])
42         for k in range(3):
43             # If undeformed reference frame:
44             # Lagrangian strain tensor, Eq. 8.29
45             if frame == 0:
46                 eps[i,j] = eps[i,j] + 0.5*(e[k][i]*e[k][j])
47             # If deformed reference frame:
48             # Eulerian strain tensor, Eq. 8.30
49             elif frame == 1:
50                 eps[i,j] = eps[i,j] - 0.5*(e[k][i]*e[k][j])
51
52 # Compute principal elongations and orientations
53 D, V = np.linalg.eigh(eps)
54
55 # Principal elongations
56 for i in range(3):
57     ind = 2-i
58     # Magnitude
59     # If undeformed reference frame:
60     # Lagrangian strain tensor, Eq. 8.33
61     if frame == 0:
62         pstrain[i,0] = np.sqrt(1.0+2.0*D[ind])-1.0
63     # If deformed reference frame:
64     # Eulerian strain tensor, Eq. 8.34
65     elif frame == 1:
66         pstrain[i,0] = np.sqrt(1.0/(1.0-2.0*D[ind]))-1.0
67     # Orientations
68     pstrain[i,1],pstrain[i,2] = CartToSph(V[0,ind],V[1,ind],V
69 [2,ind])

```

```

70 # Dilatation
71 dilat = (1.0+pstrain[0,0])*(1.0+pstrain[1,0])*(1.0+pstrain
72   [2,0]) - 1.0
73
74 # Maximum shear strain: This only works if plane strain
75 lmax = (1.0+pstrain[0,0])**2 # Maximum quad. elongation
76 lmin = (1.0+pstrain[2,0])**2 # Minimum quad. elongation
77 # Maximum shear strain: Ramsay (1967) Eq. 3.46
78 maxsh[0] = (lmax-lmin)/(2.0*np.sqrt(lmax*lmin))
79 # Angle of maximum shear strain with respect to maximum
80 # principal strain. Ramsay (1967) Eq. 3.45
81 # If undeformed reference frame
82 if frame == 0:
83   maxsh[1] = np.pi/4.0
84 # If deformed reference frame
85 elif frame == 1:
86   maxsh[1] = np.arctan(np.sqrt(lmin/lmax))
87
88 return eps, pstrain, dilat, maxsh

```

### 8.4.1 Mohr Circle for finite strain

As we said before, the finite strain and deformation tensors are symmetric tensors. Therefore, a rotation about one of the principal axis of the tensor can be represented by a Mohr Circle. As you may suspect, there are Mohr Circles for finite strain in the undeformed and deformed configuration (Ramsay, 1967). For geoscientists, however, the Mohr Circle for finite strain in the deformed configuration is much more important, since in nature we do observe deformed rocks.

To derive this Mohr Circle, we can start with the Cauchy deformation tensor in a principal axes coordinate system:

$$\bar{C}_{ij} = \begin{bmatrix} \bar{C}_1 & 0 & 0 \\ 0 & \bar{C}_2 & 0 \\ 0 & 0 & \bar{C}_3 \end{bmatrix}$$

and perform a rotation  $\theta$  about  $\mathbf{X}_2$ , which is described by the transformation matrix:

$$a_{ij} = \begin{pmatrix} \cos \theta & 0 & \sin \theta \\ 0 & 1 & 0 \\ -\sin \theta & 0 & \cos \theta \end{pmatrix}$$

The tensor transformation equation is:

$$\bar{C}'_{ij} = a_{ik}a_{jl}\bar{C}_{kl} \quad (8.37)$$

which results in the new form of the tensor:

$$\bar{C}'_{ij} = \begin{bmatrix} \bar{C}_1 \cos^2 \theta + \bar{C}_3 \sin^2 \theta & 0 & -(\bar{C}_1 - \bar{C}_3) \sin \theta \cos \theta \\ 0 & \bar{C}_2 & 0 \\ -(\bar{C}_1 - \bar{C}_3) \sin \theta \cos \theta & 0 & \bar{C}_1 \sin^2 \theta + \bar{C}_3 \cos^2 \theta \end{bmatrix} \quad (8.38)$$

Upon rearranging, we get:

$$\begin{aligned} \bar{C}'_{11} &= \frac{\bar{C}_1 + \bar{C}_3}{2} + \frac{\bar{C}_1 - \bar{C}_3}{2} \cos 2\theta \\ \bar{C}'_{33} &= \frac{\bar{C}_1 + \bar{C}_3}{2} - \frac{\bar{C}_1 - \bar{C}_3}{2} \cos 2\theta \\ \bar{C}'_{13} &= \bar{C}'_{31} = -\frac{\bar{C}_1 - \bar{C}_3}{2} \sin 2\theta \end{aligned} \quad (8.39)$$

As stated in Eq. 8.36,  $\bar{C}_{ii} = 1/\lambda_i$ . Also  $\bar{C}_{ij}$  for  $i \neq j$  is equal to  $\gamma/\lambda$ . Using  $\lambda' = 1/\lambda$  and  $\gamma' = \gamma/\lambda$ , we get the equations for the Mohr Circle for finite strain in the deformed configuration:

$$\begin{aligned} \lambda' &= \frac{(\lambda'_1 + \lambda'_3)}{2} + \frac{(\lambda'_1 - \lambda'_3)}{2} \cos 2\theta \\ \gamma' &= -\frac{(\lambda'_1 - \lambda'_3)}{2} \sin 2\theta \end{aligned} \quad (8.40)$$

As an example, Figure 8.7a shows a deformed circle and an inscribed triangle after 30°clockwise shear. Figure 8.7b shows the Mohr Circle for this

deformation. In the Mohr Circle, the horizontal axis is  $\lambda'$ , and the vertical axis is  $\gamma'$ . We follow the convention of Ragan (2009): Positive angular shear,  $\psi$ , corresponds to anticlockwise rotation of the original line's normal (Fig. 8.7a), and the  $\gamma'$  axis in the Mohr Circle increases downwards (Fig. 8.7b). Notice that the angle between the horizontal axis and a line from the origin to any point in the Mohr circle is equal to  $\psi$ . Therefore, a line from the origin and tangent to the Mohr Circle indicates  $\psi_{\max}$  (Fig. 8.7b).

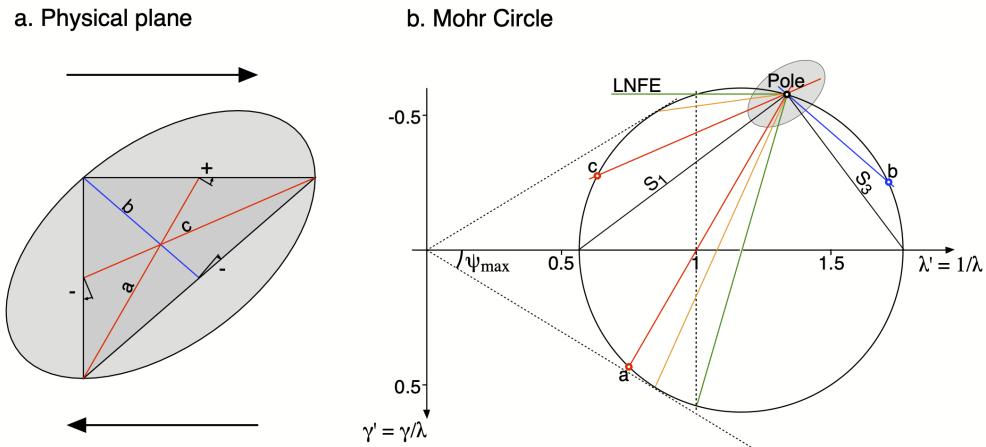


Figure 8.7: **a.** Physical plane, and **b.** Mohr Circle for 30°clockwise shear of a circle and a triangle. The pole, the triangle bisectors a, b and c (red), the principal strain axes  $S_1$  and  $S_3$ , the LNFE (green), and the lines of maximum shear strain (orange) are drawn in the Mohr Circle.

From points in the Mohr Circle, one can trace the corresponding lines with the same orientation than in the physical plane (Fig. 8.7b, triangle bisectors a, b and c). These lines will intersect at a point called the *pole* to the Mohr Circle (Fig. 8.7b). From the pole, one can trace lines of any orientation; they will intersect the circle at points that represent the strain of lines with the same orientation in the physical plane. Thus, you can imagine the pole to be the center of the strain ellipse, and from it, it is easy to trace the principal axes of strain ( $S_1$  and  $S_3$ ), the lines of no finite elongation (LNFE,  $\lambda' = 1$ ), and the lines of maximum shear strain (Fig. 8.7b).

### 8.4.2 2D finite strain from displacement data

If we have a group of points or stations with displacement data, we can determine the finite strain following a strategy similar to the one we used for infinitesimal strain. The function *GridFinStrain* computes and plots the finite strain for a group of points with displacement data. This function is very similar to our previous function *GridStrain*, and therefore we are only including its header here. Notice that after computing the displacement gradient in the undeformed (*frame* = 0) or deformed (*frame* = 1) configuration, we use our function *FinStrain* to compute the finite strain in each cell.

```

1 import numpy as np
2 import matplotlib.pyplot as plt
3 import matplotlib.colors as mcolors
4 from matplotlib.patches import Polygon
5 from matplotlib.collections import PatchCollection
6 from scipy.spatial import Delaunay
7
8 from lscov import lscov as lscov
9 from FinStrain import FinStrain as FinStrain
10
11 def GridFinStrain(pos,disp,frame,k,par,plotpar,plotst):
12     '''
13     GridFinStrain computes the finite strain of a group
14     of points with displacements in x and y.
15     Strain in z is assumed to be zero (plane strain)
16
17     USE: cent,eps,pstrain,dilat,maxsh = GridFinStrain(pos,disp,
18             frame,k,par,plotpar,plotst)
19
20     pos = npoints x 2 matrix with x and y position
21         of points
22     disp = nstations x 2 matrix with x and y
23         displacements of points
24     frame = Reference frame. 0 = undeformed (Lagrangian)
25         state, 1 = deformed (Eulerian) state
26     k = Type of computation: Delaunay (k = 0), nearest
27         neighbor (k = 1), or distance weighted (k = 2)
28     par = Parameters for nearest neighbor or distance
29         weighted computation. If Delaunay (k = 0), enter
30         a scalar corresponding to the minimum internal
31         angle of a triangle valid for computation.
32         If nearest neighbor (k = 1), input a 1 x 3 vector
33         with grid spacing, number of nearest neighbors,
34         and maximum distance to neighbors. If distance
            weighted (k = 2), input a 1 x 2 vector with grid

```

```

35     spacing and distance weighting factor alpha
36 plotpar = Parameter to color the cells: Max elongation
37     (plotpar = 0), minimum elongation
38     (plotpar = 1), dilatation (plotpar = 2),
39     or max. shear strain (plotpar = 3)
40 plotst = A flag to plot the stations (1) or not (0)
41 cent = ncells x 2 matrix with x and y positions of the
42     cells centroids
43 eps = 3 x 3 x ncells array with strain tensors of
44     the cells
45 pstrain = 3 x 3 x ncells array with magnitude and
46     orientation of principal strains of the cells
47 dilat = ncells x 1 vector with dilatation of the cells
48 maxsh = ncells x 2 matrix with max. shear strain and
49     orientation with respect to maximum principal
50     strain direction, of the cells.
51     Only valid for plane strain
52
53 NOTE: Input/Output angles are in radians. Output
54     azimuths are given with respect to y
55     pos, disp, grid spacing, max. distance to
56     neighbors, and alpha should be in the same
57     length units
58
59 GridFinStrain uses functions lscov and FinStrain
60 '''
61 # Please check the rest of the function in our git
62 # repository

```

Let's use this function to compute the maximum shear strain of a discrete element model<sup>7</sup> of a normal fault. The file [demfault.txt](#) contains the deformed  $x$  and  $y$  coordinates of the elements and their displacements in meters. The notebook [ch8-3](#) shows the solution to this problem using the nearest neighbor method:

```

1 import numpy as np
2
3 # Import function GridFinStrain
4 import sys, os
5 sys.path.append(os.path.abspath('../functions'))
6 from GridFinStrain import GridFinStrain as GridFinStrain
7
8 # load x, y DEFORMED coordinates and displacements

```

---

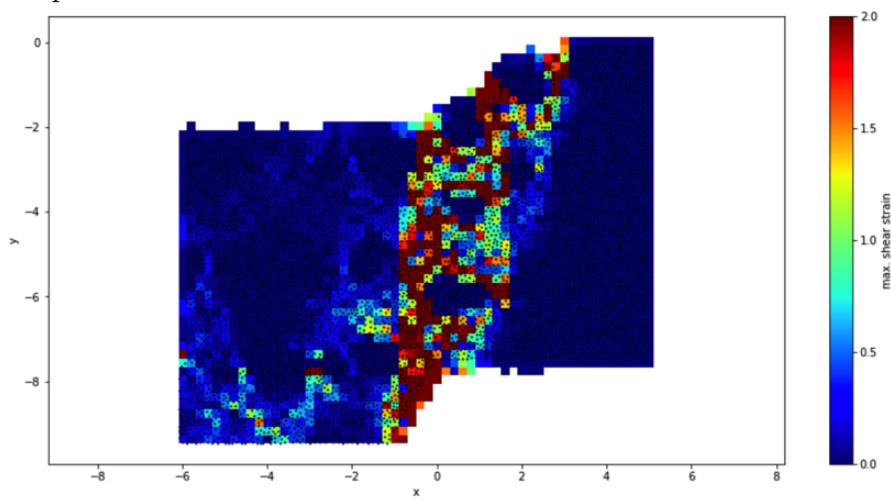
<sup>7</sup>The discrete element method is a mechanical method that simulates the rocks as an assembly of elements. For an example, check the program [cdem](#) by Cardozo and Hardy.

```

9 demfault = np.loadtxt(os.path.abspath('../data/ch8-3/demfault
10 .txt'))
11 pos = np.zeros((np.size(demfault,0),2))
12 pos[:,0] = demfault[:,0]
13 pos[:,1] = demfault[:,1]
14 disp = np.zeros((np.size(demfault,0),2))
15 disp[:,0] = demfault[:,2]
15 disp[:,1] = demfault[:,3]
16
17 # Max. shear strain from nearest neighbor, Def. config.
18 # Grid spacing = 0.2 m, neighbors 6,
19 # max. distance = 0.4 m, plot stations
20 par = [0.2,6,0.4]
21 cent,eps,pstrain,dilat,maxsh = GridFinStrain(pos,disp,1,1,par
,3,1)

```

Output:



The maximum shear strain delineates well the internal structure of the fault. You can find more information about computing strain from displacement or velocity data in Cardozo and Allmendinger (2009).

## 8.5 Progressive strain

In our discussion of finite strain, we focused on the undeformed (initial) and deformed (final) states. However, finite strain is actually the cumulative result of a series of strain increments:

$$\begin{aligned}
{}^1x_i &= {}^1F_{ij}{}^1X_j \\
{}^2X_i &= {}^1x_i \\
{}^2x_i &= {}^2F_{ij}{}^2X_j \\
{}^3X_i &= {}^2x_i \\
{}^3x_i &= {}^3F_{ij}{}^3X_j \\
&\dots \\
{}^nx_i &= {}^nF_{ij}{}^nX_j
\end{aligned} \tag{8.41}$$

where  $F_{ij}$  is the Green deformation gradient, and 1 to  $n$  are the strain increments. This can also be written as:

$$x_i = {}^nF_{ij} \dots {}^3F_{ij}{}^2F_{ij}{}^1F_{ij}{}^1X_j \tag{8.42}$$

Notice that since  ${}^2\mathbf{F}{}^1\mathbf{F} \neq {}^1\mathbf{F}{}^2\mathbf{F}$ , for finite strain we must know the order of deformation. For example, if we want to determine the finite strain produced by a group of faults in a region, we must know the order at which these faults formed. This is often very difficult, if not impossible, to determine.

Let's look at some simple (yet complicated enough) deformations, which are characterized by the same incremental deformation gradient through time. For simplicity, we will assume that there is no strain along the  $\mathbf{X}_2$  axis, and all strain is in the  $\mathbf{X}_1\mathbf{X}_3$  plane. Thus, we will be dealing with plane strain.

### 8.5.1 Pure shear

For pure shear, the principal stretches are along the coordinate axes (e.g. Fig. 8.2). Let's assume the maximum principal stretch,  $S_1$  is along  $\mathbf{X}_1$ , and the minimum principal stretch,  $S_3$  is along  $\mathbf{X}_3$  (Fig. 8.8a).  $S_2 = 1$  (plane strain) and is parallel to  $\mathbf{X}_2$ . The Green deformation gradient for this case is:

$${}^{PS}F_{ij} = \begin{bmatrix} S_1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & S_3 \end{bmatrix} \tag{8.43}$$

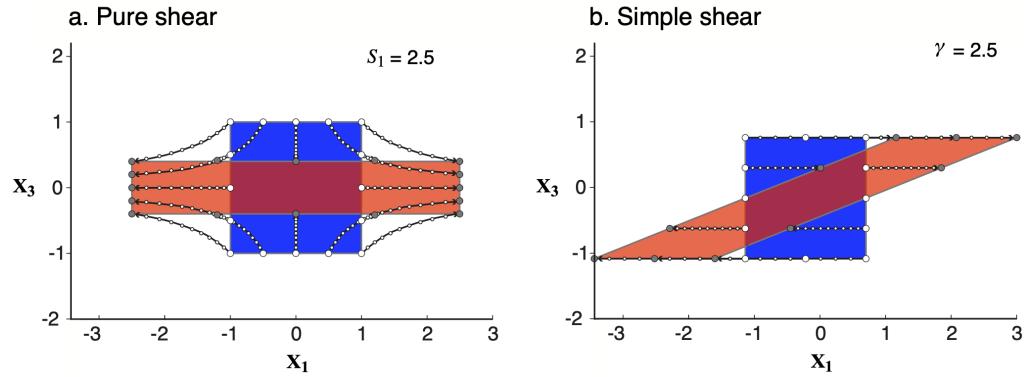


Figure 8.8: **a.** Pure shear, and **b.** Simple shear. Blue is undeformed, and red is deformed geometry. White and gray large circles are initial and final positions, respectively. The displacement paths of the points are divided in 10 increments. Modified from Allmendinger et al. (2012).

The function *PureShear* deforms a collection of points using pure shear, a value of  $S_1$  (*st1*), and assuming plane strain and area conservation ( $S_1 S_3 = 1$ ). The function displays the points' displacement paths for a number of increments (*ninc*), and the progressive strain history as the value of  $S_1$  versus the angle  $S_1$  makes with the  $\mathbf{X}_1$  axis ( $\Theta$ ). Notice that we compute these last two parameters from the eigenvalues and eigenvectors of the Green deformation tensor:

```

1 import numpy as np
2 import matplotlib.pyplot as plt
3
4 def PureShear(pts,st1,ninc):
5     '''
6     PureShear computes and plots displacement paths and
7     progressive finite strain history for pure shear with
8     maximum stretching parallel to the X1 axis
9
10    USE: paths,pfs = PureShear(pts,st1,ninc)
11
12    pts: npoints x 2 matrix with X1 and X3 coord. of points
13    st1 = Maximum principal stretch
14    ninc = number of strain increments
15    paths = displacement paths of points
16    pfs = progressive finite strain history. column 1 =
17        orientation of maximum stretch with respect to X1
18        in degrees, column 2 = maximum stretch magnitude

```

```

19 NOTE: Intermediate principal stretch is 1.0 (Plane
20      strain). Output orientations are in radians
21
22 Python function based on the Matlab function
23 PureShear in Allmendinger et al. (2012)
24 '''
25 # Compute minimum principal stretch and incr. stretches
26 st1inc=st1**(1.0/ninc)
27 st3=1.0/st1
28 st3inc=st3**(1.0/ninc)
29
30 # Initialize displacement paths
31 npts = np.size(pts,0) # Number of points
32 paths = np.zeros((ninc+1,npts,2))
33 paths[0,:,:] = pts # Initial points of paths
34
35 # Calculate incremental deformation gradient tensor
36 F = np.array([[st1inc, 0.0], [0.0, st3inc]])
37
38 # Initialize figure
39 fig = plt.figure(figsize=(15,5)) # Define the size
40 ax1 = fig.add_subplot(1, 2, 1)
41 ax2 = fig.add_subplot(1, 2, 2)
42
43 # Compute displacement paths
44 for i in range(npts): # for all points
45     for j in range(ninc+1): # for all strain increments
46         for k in range(2):
47             for L in range(2):
48                 paths[j,i,k] = F[k,L]*paths[j-1,i,L] + paths[j,i,k]
49 # Plot displacement path of point
50 xx = paths[:,i,0]
51 yy = paths[:,i,1]
52 ax1.plot(xx,yy,'k.-')
53
54 # Plot initial and final polygons
55 inpol = np.zeros((npts+1,2))
56 inpol[0:npts,:] = paths[0,0:npts,:]
57 inpol[npts,:] = inpol[0,:]
58 ax1.plot(inpol[:,0],inpol[:,1], 'b-')
59 finpol = np.zeros((npts+1,2))
60 finpol[0:npts,:] = paths[ninc,0:npts,:]
61 finpol[npts,:] = finpol[0,:]
62 ax1.plot(finpol[:,0],finpol[:,1], 'r-')
63
64 # Release plot and set axes
65 ax1.set_xlabel('X1')
66 ax1.set_ylabel('X3')
67 ax1.grid()

```

```

68     ax1.axis('equal')
69
70     # Initialize progressive finite strain history
71     pfs = np.zeros((ninc+1,2))
72     pfs[0,:] = [0, 1] #Initial state
73
74     # Calculate progressive finite strain history
75     for i in range(1,ninc+1):
76         # Determine the finite deformation gradient tensor
77         finF = np.linalg.matrix_power(F, i)
78         # Determine Green deformation tensor
79         G = np.dot(finF,finF.conj().transpose())
80         # Stretch magnitude and orientation: Maximum
81         # eigenvalue and their corresponding eigenvectors
82         # of Green deformation tensor
83         D, V = np.linalg.eigh(G)
84         pfs[i,0] = np.arctan(V[1,1]/V[0,1])
85         pfs[i,1] = np.sqrt(D[1])
86
87     # Plot progressive finite strain history
88     ax2.plot(pfs[:,0]*180/np.pi,pfs[:,1], 'k.-')
89     ax2.set_xlabel('Θ deg')
90     ax2.set_ylabel('Maximum finite stretch')
91     ax2.set_xlim(-90,90)
92     ax2.set_ylim(1,max(pfs[:,1])+0.5)
93     ax2.grid()
94
95     # show plot
96     plt.show()
97
98     return paths,pfs

```

Let's use this function to reproduce the deformation shown in Fig. 8.8a. The notebook [ch8-4](#) shows how to do this:

```

1 # Import libraries
2 import numpy as np
3
4 # Import function PureShear
5 import sys, os
6 sys.path.append(os.path.abspath('../functions'))
7 from PureShear import PureShear as PureShear
8
9 # Initial points coordinates
10 pts = np.zeros((16,2))
11 pts[:,0]=[-1,-1,-1,-1,-1,-0.5,0,0.5,1,1,1,1,0.5,0,-0.5]

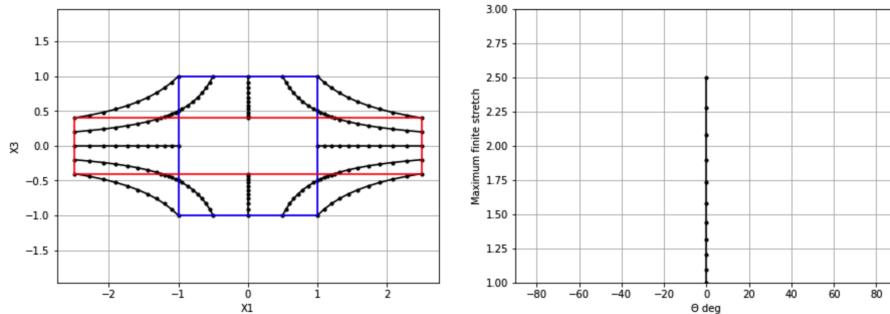
```

```

12 pts[:,1]=[-1,-0.5,0,0.5,1,1,1,1,1,0.5,0,-0.5,-1,-1,-1,-1]
13 st1 = 2.5
14 ninc = 10
15
16 paths,psf = PureShear(pts,st1,ninc)

```

Output:



As you can see the finite strain axes, ( $S_1$  and  $S_3$ ), do not rotate throughout the deformation ( $\Theta$  is 0 throughout the deformation). Pure shear is an *irrotational* deformation.

### 8.5.2 Simple shear

For plane strain and simple shear along the  $\mathbf{X}_1$  axis (Fig. 8.8b), the Green deformation gradient is given by:

$${}^{SS}F_{ij} = \begin{bmatrix} 1 & 0 & \gamma \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad (8.44)$$

where  $\gamma$  is the shear strain.

The function `SimpleShear` deforms a collection of points using simple shear and a value of shear strain (*gamma*). The function displays the points' displacement paths for a number of increments (*ninc*), and the progressive strain history as the value of  $S_1$  versus  $\Theta$ :

```

1 import numpy as np
2 import matplotlib.pyplot as plt

```

```

3
4 def SimpleShear(pts, gamma, ninc):
5     '''
6         SimpleShear computes and plots displacement paths and
7         progressive finite strain history for simple shear
8         parallel to the X1 axis
9
10    USE: paths,pfs = SimpleShear(pts,gamma,ninc)
11
12    pts: npoints x 2 matrix with X1 and X3 coord. of points
13    gamma = Engineering shear strain
14    ninc = number of strain increments
15    paths = displacement paths of points
16    pfs = progressive finite strain history. column 1 =
17        orientation of maximum stretch with respect to X1
18        in degrees, column 2 = maximum stretch magnitude
19
20    NOTE: Intermediate principal stretch is 1.0 (Plane
21        strain). Output orientations are in radians
22
23    Python function based on the Matlab function
24    SimpleShear in Allmendinger et al. (2012)
25    '''
26
27    # Incremental engineering shear strain
28    gammainc = gamma/ninc
29
30    # Initialize displacement paths
31    npts = np.size(pts,0) # Number of points
32    paths = np.zeros((ninc+1,npts,2))
33    paths[0,:,:] = pts # Initial points of paths
34
35    # Calculate incremental deformation gradient tensor
36    F = np.array([[1.0, gammainc],[0.0, 1.0]])
37
38    # Initialize figure
39    fig = plt.figure(figsize=(15,5)) # Define the size
40    ax1 = fig.add_subplot(1, 2, 1)
41    ax2 = fig.add_subplot(1, 2, 2)
42
43    # Compute displacement paths
44    for i in range(npts): # for all points
45        for j in range(ninc+1): # for all strain increments
46            for k in range(2):
47                for L in range(2):
48                    paths[j,i,k] = F[k,L]*paths[j-1,i,L] + paths[j,i,k]
49    # Plot displacement path of point.
50    xx = paths[:,i,0]
51    yy = paths[:,i,1]
52    plt.figure(1)

```

```

52     ax1.plot(xx,yy,'k.-')
53
54 # Plot initial and final polygons
55 inpol = np.zeros((npts+1,2))
56 inpol[0:npts,:] = paths[0,0:npts,:]
57 inpol[npts,:] = inpol[0,:]
58 ax1.plot(inpol[:,0],inpol[:,1], 'b-')
59 finpol = np.zeros((npts+1,2))
60 finpol[0:npts,:] = paths[ninc,0:npts,:]
61 finpol[npts,:] = finpol[0,:]
62 ax1.plot(finpol[:,0],finpol[:,1], 'r-')
63
64 # Release plot and set axes
65 ax1.set_xlabel('X1')
66 ax1.set_ylabel('X3')
67 ax1.grid()
68 ax1.axis('equal')
69
70 # Initialize progressive finite strain history
71 pfs = np.zeros((ninc+1,2))
72 # In. state: Max. extension is at 45 deg from shear zone
73 pfs[0,:] = [np.pi/4.0, 1.0]
74
75 # Calculate progressive finite strain history
76 for i in range(1,ninc+1):
77     # Determine the finite deformation gradient tensor
78     finF = np.linalg.matrix_power(F, i)
79     # Determine Green deformation tensor
80     G = np.dot(finF,finF.conj().transpose())
81     # Stretch magnitude and orientation: Maximum
82     # eigenvalue and their corresponding eigenvectors
83     # of Green deformation tensor
84     D, V = np.linalg.eigh(G)
85     pfs[i,0] = np.arctan(V[1,1]/V[0,1])
86     pfs[i,1] = np.sqrt(D[1])
87
88 # Plot progressive finite strain history
89 ax2.plot(pfs[:,0]*180/np.pi,pfs[:,1], 'k.-')
90 ax2.set_xlabel('θ deg')
91 ax2.set_ylabel('Maximum finite stretch')
92 ax2.set_xlim(-90,90)
93 ax2.set_ylim(1,max(pfs[:,1])+0.5)
94 ax2.grid()
95
96 # Show plot
97 plt.show()
98
99 return paths,pfs

```

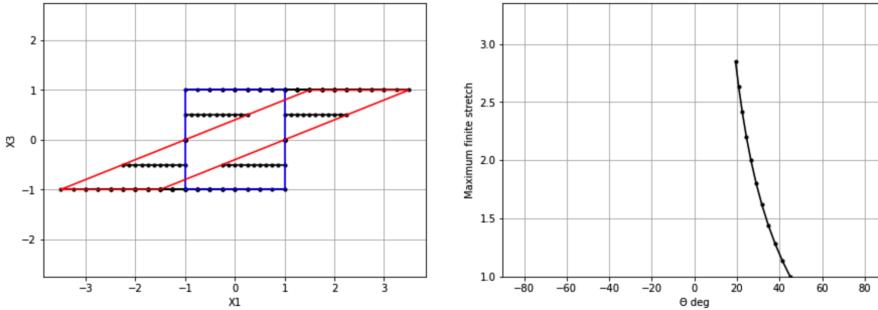
Let's use this function to reproduce the deformation shown in Fig. 8.8b. The notebook [ch8-5](#) shows how to do this:

```

1 # Import libraries
2 import numpy as np
3
4 # Import function SimpleShear
5 import sys, os
6 sys.path.append(os.path.abspath('../functions'))
7 from SimpleShear import SimpleShear as SimpleShear
8
9 # Initial points coordinates
10 pts = np.zeros((16,2))
11 pts[:,0]=[-1,-1,-1,-1,-1,-0.5,0,0.5,1,1,1,1,1,0.5,0,-0.5]
12 pts[:,1]=[-1,-0.5,0,0.5,1,1,1,1,1,0.5,0,-0.5,-1,-1,-1,-1]
13 gamma = 2.5
14 ninc = 10
15 paths,psf = SimpleShear(pts, gamma, ninc)

```

Output:



In this case, the finite strain axes, ( $S_1$  and  $S_3$ ), rotate throughout the deformation.  $\Theta$  is initially  $45^\circ$ (as predicted by the theory of infinitesimal strain, Fig. 8.4), and it progressively decreases to a value of  $20^\circ$ by the end of the deformation. Simple shear is a *rotational* deformation.

### 8.5.3 General shear

Sub-simple shear (De Paor, 1983) or general shear is a combination of pure shear and simple shear. If the shear direction and  $S_1$  are parallel to  $\mathbf{X}_1$ ,  $S_2 = 1$  (plane strain) and area is constant, the Green deformation gradient for general shear is (Allmendinger et al., 2012):

$${}^{GS}F_{ij} = \begin{bmatrix} S_1 & 0 & \frac{\gamma(S_1-S_3)}{2\ln S_1} \\ 0 & 1 & 0 \\ 0 & 0 & S_3 \end{bmatrix} \quad (8.45)$$

If on the other hand the shear direction is parallel to  $\mathbf{X}_1$ , but  $S_1$  is parallel to  $\mathbf{X}_3$ , the Green deformation gradient is (Allmendinger et al., 2012):

$${}^{GS}F_{ij} = \begin{bmatrix} S_3 & 0 & \frac{\gamma(S_3-S_1)}{2\ln S_3} \\ 0 & 1 & 0 \\ 0 & 0 & S_1 \end{bmatrix} \quad (8.46)$$

A simple dimensionless measure of the ratio of simple to pure shear is the cosine of the acute angle between the eigenvectors of the Green deformation gradient  $\mathbf{F}$ . This measure is known as the *kinematic vorticity number*,  $W_k$  (Truesdell, 1953). General shear is characterized by a  $W_k$  between 0 (pure shear) and 1 (simple shear).

The function *GeneralShear* deforms a collection of points using general shear and values of  $S_1$  (*st1*) and  $\gamma$  (*gamma*), for a shear direction parallel to  $\mathbf{X}_1$ , and  $S_1$  parallel (*kk* = 0) or perpendicular to the shear direction (*kk* = 1). Similar to the two previous functions, *GeneralShear* displays the points' displacement paths for a number of increments (*ninc*), and  $S_1$  versus  $\Theta$ :

```

1 import numpy as np
2 import matplotlib.pyplot as plt
3
4 def GeneralShear(pts,st1,gamma,kk,ninc):
5     """
6         GeneralShear computes displacement paths, kinematic
7         vorticity numbers and progressive finite strain
8         history, for general shear with a pure shear stretch,
9         no area change, and a single shear strain
10
11 USE: paths,wk,pfs = GeneralShear(pts,st1,gamma,kk,ninc)
12
13 pts = npoints x 2 matrix with X1 and X3 coord. of points
14 st1 = Pure shear stretch parallel to shear zone
15 gamma = Engineering shear strain
16 kk = An integer that indicates whether the maximum
17     finite stretch is parallel (kk = 0), or
18     perpendicular (kk=1) to the shear direction
19 ninc = number of strain increments

```

```

20 paths = displacement paths of points
21 wk = Kinematic vorticity number
22 pfs = progressive finite strain history. column 1 =
23     orientation of maximum stretch with respect to
24     X1, column 2 = maximum stretch magnitude
25
26 NOTE: Intermediate principal stretch is 1.0 (Plane
27     strain). Output orientations are in radians
28
29 Python function translated from the Matlab function
30 GeneralShear in Allmendinger et al. (2012)
31 '''
32 # Compute minimum principal stretch and incr. stretches
33 st1inc =st1** (1.0/ninc)
34 st3 =1.0/st1
35 st3inc =st3** (1.0/ninc)
36
37 # Incremental engineering shear strain
38 gammainc = gamma/ninc
39
40 # Initialize displacement paths
41 npts = np.size(pts,0) # Number of points
42 paths = np.zeros((ninc+1,npts,2))
43 paths[0,:,:] = pts # Initial points of paths
44
45 # Initialize figure
46 fig = plt.figure(figsize=(15,5)) # Define the size
47 ax1 = fig.add_subplot(1, 2, 1)
48 ax2 = fig.add_subplot(1, 2, 2)
49
50 # Calculate incremental deformation gradient tensor
51 # If max. finite stretch parallel to shear direction
52 if kk == 0:
53     F=np.zeros((2,2))
54     F[0,]=[st1inc, (gammainc*(st1inc-st3inc))/(2.0*np.log(
55         st1inc))]
56     F[1,]=[0.0, st3inc]
57 # If max. finite stretch perpendicular to shear direction
58 elif kk == 1:
59     F=np.zeros((2,2))
60     F[0,]= [st3inc, (gammainc*(st3inc-st1inc))/(2.0*np.log(
61         st3inc))]
62     F[1,]= [0.0, st1inc]
63
64 # Compute displacement paths
65 for i in range(npts): # for all points
66     for j in range(ninc+1): # for all strain increments
67         for k in range(2):
68             for L in range(2):

```

```

67     paths[j,i,k] = F[k,L]*paths[j-1,i,L] + paths[j,i,k]
68 # Plot displacement path of point
69 xx = paths[:,i,0]
70 yy = paths[:,i,1]
71 ax1.plot(xx,yy,'k.-')

72 # Plot initial and final polygons
73 inpol = np.zeros((npts+1,2))
74 inpol[0:npts,:] = paths[0,0:npts,:]
75 inpol[npts,:] = inpol[0,:]
76 ax1.plot(inpol[:,0],inpol[:,1], 'b-')
77 finpol = np.zeros((npts+1,2))
78 finpol[0:npts,:] = paths[ninc,0:npts,:]
79 finpol[npts,:] = finpol[0,:]
80 ax1.plot(finpol[:,0],finpol[:,1], 'r-')

81 # Set axes
82 ax1.set_xlabel('X1')
83 ax1.set_ylabel('X3')
84 ax1.grid()
85 ax1.axis('equal')

86 # Determine the eigenvectors of the flow (apophyses)
87 # Since F is not symmetrical, use function eig
88 _,V = np.linalg.eig(F)
89 theta2 = np.arctan(V[1,1]/V[0,1])
90 wk = np.cos(theta2)

91 # Initialize progressive finite strain history.
92 # We are not including the initial state
93 pfs = np.zeros((ninc,ninc))

94 # Calculate progressive finite strain history
95 for i in range(1,ninc+1):
96     # Determine the finite deformation gradient tensor
97     finF = np.linalg.matrix_power(F, i)
98     # Determine Green deformation tensor
99     G = np.dot(finF,finF.conj().transpose())
100    # Stretch magnitude and orientation: Maximum
101    # eigenvalue and their corresponding eigenvectors
102    # of Green deformation tensor
103    D, V = np.linalg.eigh(G)
104    pfs[i-1,0] = np.arctan(V[1,1]/V[0,1])
105    pfs[i-1,1] = np.sqrt(D[1])

106 # Plot progressive finite strain history
107 ax2.plot(pfs[:,0]*180/np.pi,pfs[:,1], 'k.-')
108 ax2.set_xlabel('θ deg')
109 ax2.set_ylabel('Maximum finite stretch')
110
111
112
113
114
115

```

```

116     ax2.set_xlim(-90,90)
117     ax2.set_ylim(1,max(pfs[:,1])+0.5)
118     ax2.grid()
119
120     # Show plot
121     plt.show()
122
123     return paths,wk,pfs

```

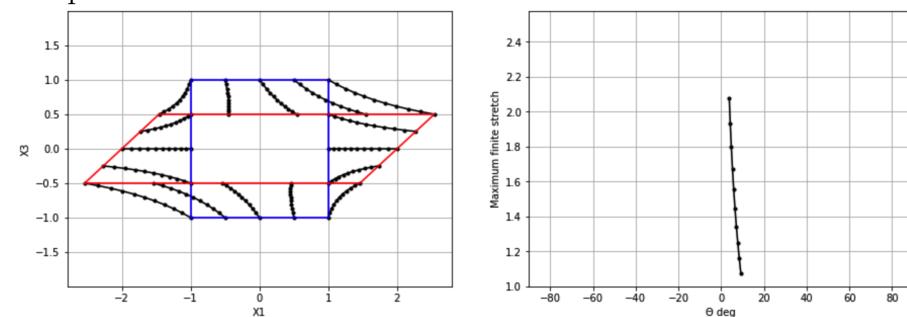
Let's use this function to reproduce the deformation produced by  $S_1 = 2.0$  and  $\gamma = 0.5$ , for a shear direction parallel to  $\mathbf{X}_1$ , and  $S_1$  parallel or perpendicular to it. The notebook ch8-6 shows the solution to this problem:

```

1 # Import libraries
2 import numpy as np
3
4 # Import function GeneralShear
5 import sys, os
6 sys.path.append(os.path.abspath('../functions'))
7 from GeneralShear import GeneralShear as GeneralShear
8
9 # Initial points coordinates
10 pts = np.zeros((16,2))
11 pts[:,0]=[-1,-1,-1,-1,-1,-0.5,0,0.5,1,1,1,1,1,0.5,0,-0.5]
12 pts[:,1]=[-1,-0.5,0,0.5,1,1,1,1,1,0.5,0,-0.5,-1,-1,-1,-1]
13 st1 = 2.0
14 gamma = 0.5
15 ninc = 10
16
17 # Max. finite stretch parallel to shear direction
18 kk = 0
19 paths1,wk1,psf1= GeneralShear(pts,st1,gamma,kk,ninc)
20 print('Wk = {:.4f}'.format(wk1))

```

Output:



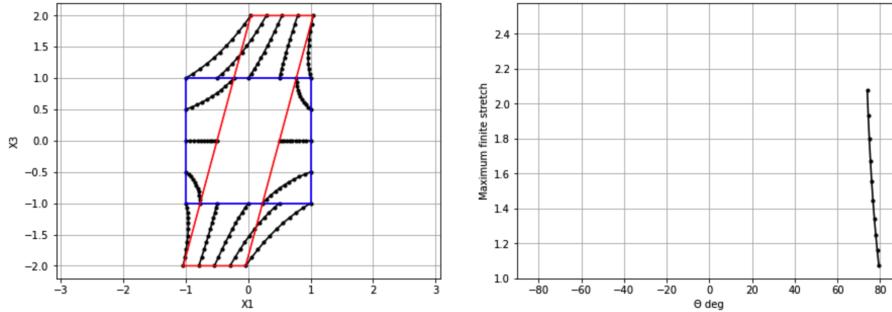
$W_k = 0.3393$

```

1 # Max. finite stretch perpendicular to shear direction
2 kk = 0
3 paths2, wk2, pfs2= GeneralShear(pts, st1, gamma, kk, ninc)
4 print('Wk = {:.4f}'.format(wk2))

```

Output:



Wk = 0.3393

In this case, the contribution of simple shear is about one third that of pure shear ( $W_k = 0.34$ ). Try running the notebook with different values of  $S_1$  and  $\gamma$ , and check  $W_k$  and  $\Theta$  throughout the deformation.

## 8.6 Exercises

1. This exercise is from Rowland and Duebendorfer (1994). The file [basinAndRange.txt](#) contains the strike and dip (RHR), slip direction, and slip sense of faults within the Basin and Range province, specifically southern Nevada and the Lake Mead area. Plot the P and T axes for these data using the function [PTAxes](#). Are these data consistent with the regional E-W extension direction in the Basin and Range province?
2. From the P and T axes, one can compute an unweighted moment tensor summation as follows (Allmendinger et al., 1989):

$$\mathbf{K} = \begin{bmatrix} \sum(P_N)^2 - (T_N)^2 & \sum(P_N)(P_E) - (T_N)(T_E) & \sum(P_N)(P_D) - (T_N)(T_D) \\ \sum(P_E)(P_N) - (T_E)(T_N) & \sum(P_E)^2 - (T_E)^2 & \sum(P_E)(P_D) - (T_E)(T_D) \\ \sum(P_D)(P_N) - (T_D)(T_N) & \sum(P_D)(P_E) - (T_D)(T_E) & \sum(P_D)^2 - (T_D)^2 \end{bmatrix}$$

where the subscripts  $N$ ,  $E$ , and  $D$  refer to the east, north and down direction cosines of the P and T axes. The eigenvalues and eigenvectors of

**K** give the relative magnitudes and orientations of the kinematic axes. These kinematic axes define the orientation of two nodal planes, or possible faults, separating the areas of infinitesimal extension (T axes) from those of infinitesimal shortening (P axes). The faults intersect at the intermediate eigenvector, the minimum and maximum eigenvectors define the movement plane, and the fault slip vectors are on the movement plane at 45° from the minimum and maximum eigenvectors. Modify function *PTAxes* to plot the nodal planes. This is not a simple problem, don't give up.

3. The file *andes.txt* contains GPS data (stations UTM coordinates and displacements in meters) from the Central Andes (Kendrick et al., 2001; Brooks et al., 2003). Compute the infinitesimal rotation in this region using the function *GridStrain*. What does the rotation tell you about the tectonics of this region? Check Allmendinger et al. (2005) to support your answer.
4. The file *antithetic.txt* contains data from a discrete element model of a low angle normal fault (deformed elements' coordinates and displacements). Use the function *GridFinStrain* to compute the shear strain of this model.
5. The file *trilobite.txt* contains the  $x$  and  $y$  coordinates of points delineating a trilobite specimen. Deform the trilobite using pure shear with  $S_1 = 2.0$ , simple shear with  $\gamma = 1.0$ , and general shear with  $S_1 = 1.5$ ,  $\gamma = 1.0$ , and shear direction and  $S_1$  parallel to  $x$ . **Hint:** Use functions *PureShear*, *SimpleShear*, and *GeneralShear*.

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