





# 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) 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) were instrumental. They wrote our scattered code into functions and notebooks and help editing the resource in [Overleaf](#). They also tested the resource.

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.

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 geosciences areas.

You can download or subscribe to changes in the resource using our 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.

## References

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- Allmendinger, R.W. 2019. Modern Structural Practice: A structural geology laboratory manual for the 21st century. Available at [this site](#).
- 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. The website will recognize your operating system and present you with two possible installers, one for Python 3 and another for Python 2. We recommend you install the Python 3 version. Download the installer. Windows and macOS users just need to run the installer and follow the steps to install Anaconda. Linux users need to type a set of commands in a terminal window. Further instructions can be found in the online [Anaconda documentation](#), installation section.

## 1.4 A first introduction to Python

In this section, we use our first Jupyter notebook to learn the basics of Python. Download the notebook ch1.ipynb from 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 notebook ch1.ipynb and open it. 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 many different notebooks. This is basically 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 as your notebook. 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. The third line makes sure the plots are rendered in the notebook:

```
1 import numpy as np
2 import matplotlib.pyplot as plt
3 %matplotlib inline
```

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:  
428 ms  $\pm$  3.02 ms per loop (mean  $\pm$  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  $\approx 500$  milliseconds, while NumPy *dot* function uses  $\approx 200$  microseconds. The NumPy *dot* function is a staggering 2500 times faster!

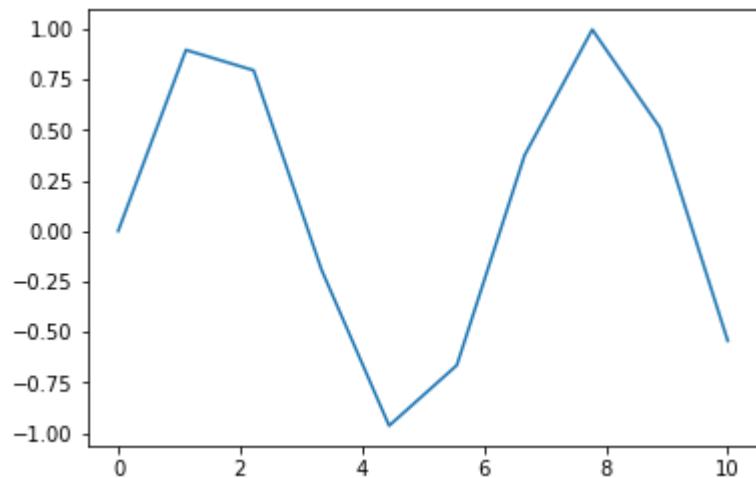
### 1.4.6 Plotting

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. 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:



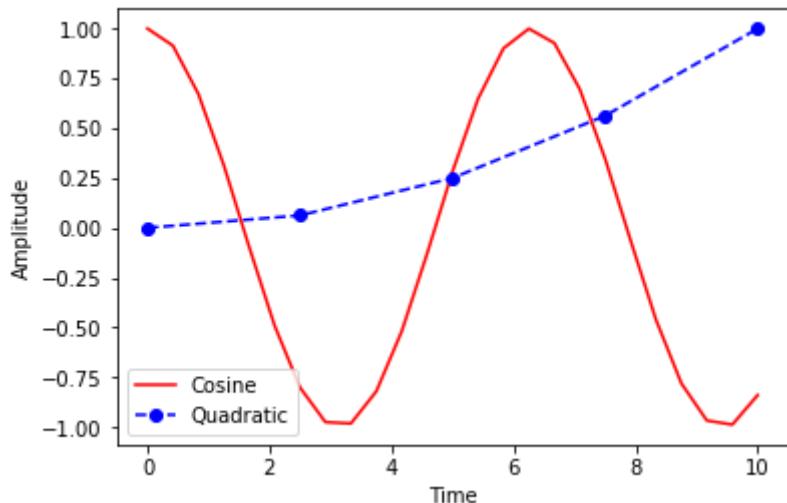
We end with a slightly more advanced plot, showing how to change line style and markers, and add axes labels and a legend. The NumPy *cos* function takes the cosine of the array, and *xlabel*, *ylabel* and *legend* are all Matplotlib commands to add labels to the axes and a legend to the graph.

```

1 n = 25
2 x = np.linspace(0, 10, 25)
3 y = np.cos(x)
4 plt.plot(x, y, 'r')
5 x = np.linspace(0, 10, 5)
6 y = 0.01*x**2
7 plt.plot(x, y, 'bo--')
8 plt.xlabel('Time')
9 plt.ylabel('Amplitude')
10 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.
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).

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:
- the sum of the matrices ( $\mathbf{A} + \mathbf{B}$ ),
  - The difference of the matrices ( $\mathbf{A} - \mathbf{B}$ ),
  - The product of the matrices ( $\mathbf{AB}$ ),
  - The square root of matrix  $\mathbf{A}$ ,
  - The sum of all elements of matrix  $\mathbf{B}$ ,
  - The column sum of matrix  $\mathbf{A}$ ,
  - The row sum of matrix  $\mathbf{A}$ ,
  - The transpose of matrix  $\mathbf{A}$  ( $\mathbf{A}^T$ ),
  - 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.

- Make a function to compute the apparent dip  $\alpha$  from the true dip  $\delta$  and structural bearing  $\beta$ .
- Use this function in a notebook 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 the figure below:

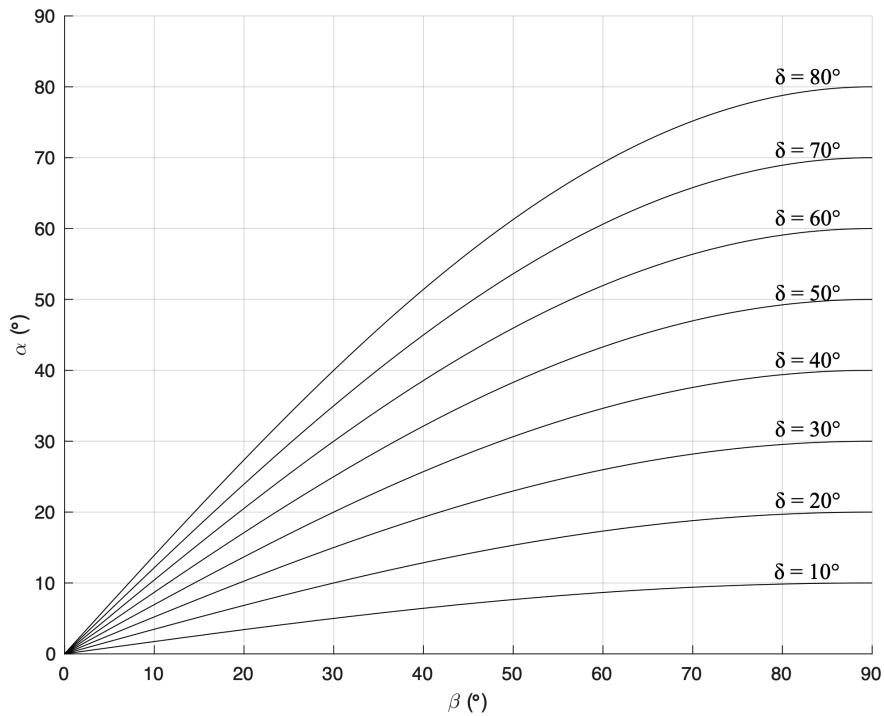


Figure 1.1: Apparent dip  $\alpha$  as function of section bearing  $\beta$  and true dip  $\delta$

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# **Chapter 2**

## **Understanding location**

**2.1 Locations**

**2.2 Geodesy basics**

**2.3 Projections**

**2.4 Reference systems and datums**

**2.5 Coordinate conversion and transformation**

**2.6 Exercises**



# 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).

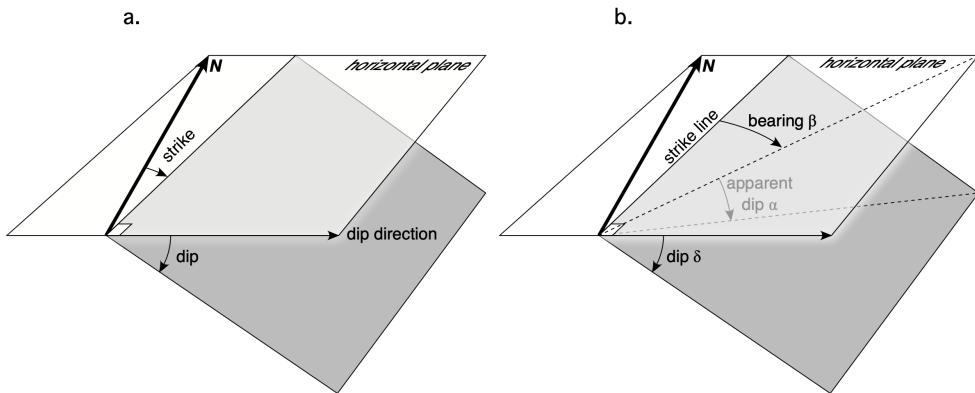


Figure 3.1: **a.** Strike and dip of a plane, **b.** Apparent dip of a plane. Modified from Allmendinger et al. (2012)

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  $180^\circ$ .

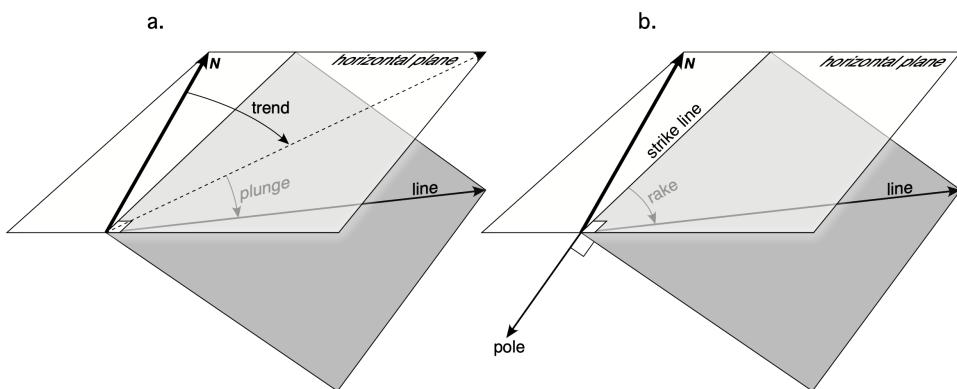


Figure 3.2: **a.** Trend and plunge of a line, **b.** Rake of a line and pole to a plane. Modified from Allmendinger et al. (2012).

### 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 Python function *Pole* below 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:

```

```

28         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).

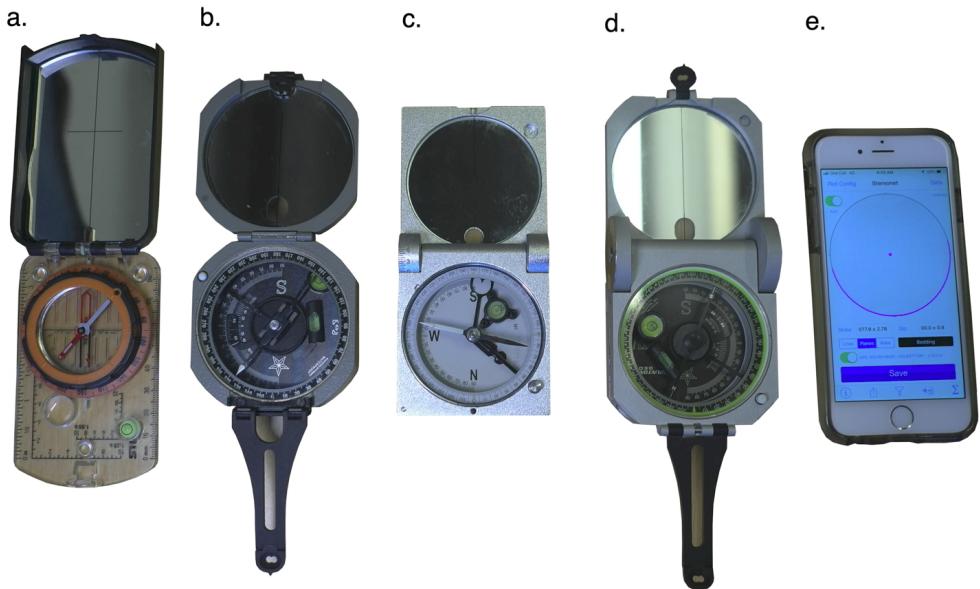


Figure 3.3: **a.** Silva, **b.** Brunton, **c.** Krantz, **d.** Brunton Geo, and **e.** Smartphone with Stereonet Mobile.

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

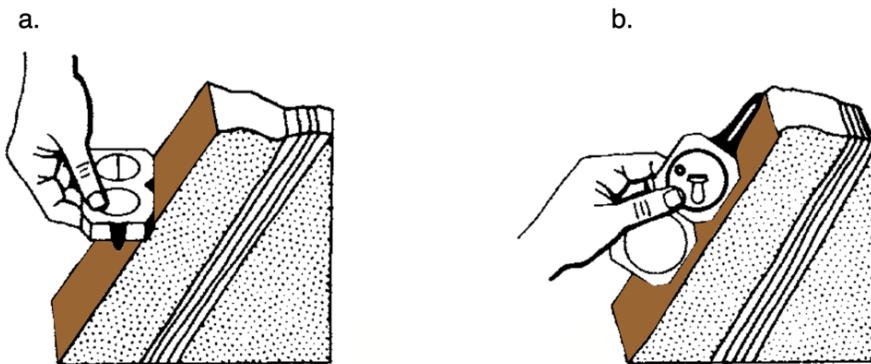


Figure 3.4: Measuring the **a.** strike and **b.** dip of a plane. Modified from Compton (1985).

plane or along the line. Thus, one can capture a large number of measurements 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):

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

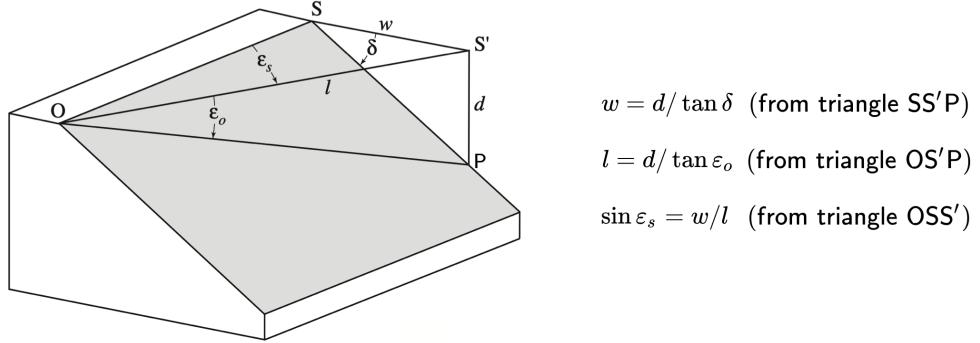


Figure 3.5: Geometrical relations for estimating the strike error  $\varepsilon_s$  from the operator error (or departure of the compass from the horizontal)  $\varepsilon_o$ . Modified from Ragan (2009).

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, it 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):

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

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

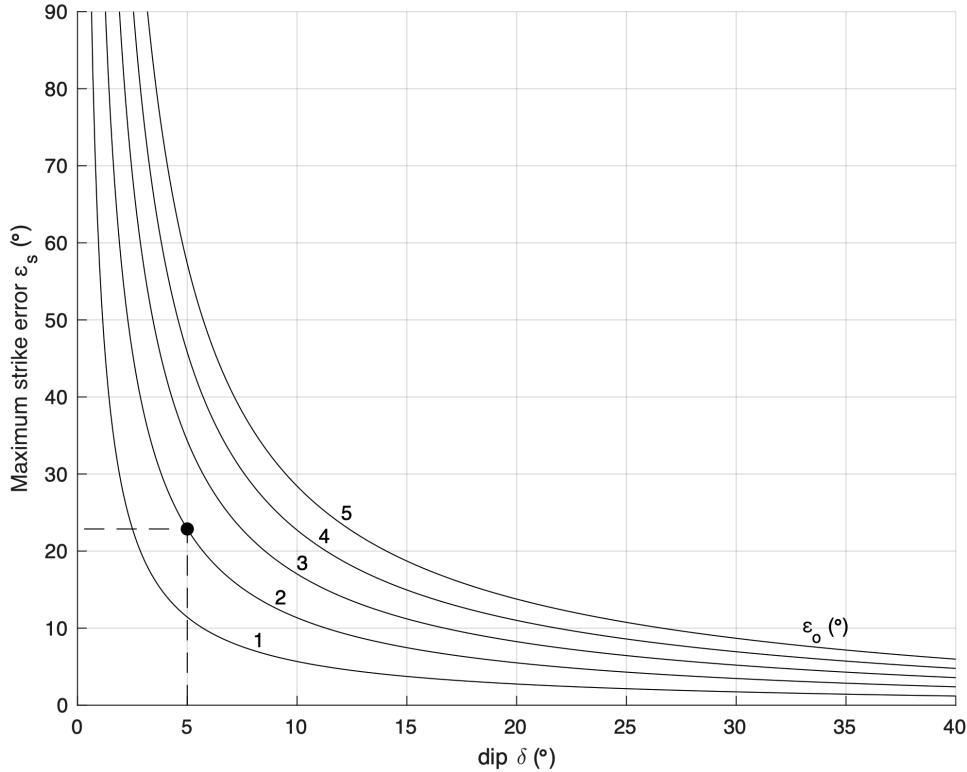


Figure 3.6: Strike error  $\varepsilon_s$  as a function of dip  $\delta$  for values of operator error  $\varepsilon_o$  of 1-5°. The notebook that produced this graph is available from the resource git repository.

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.

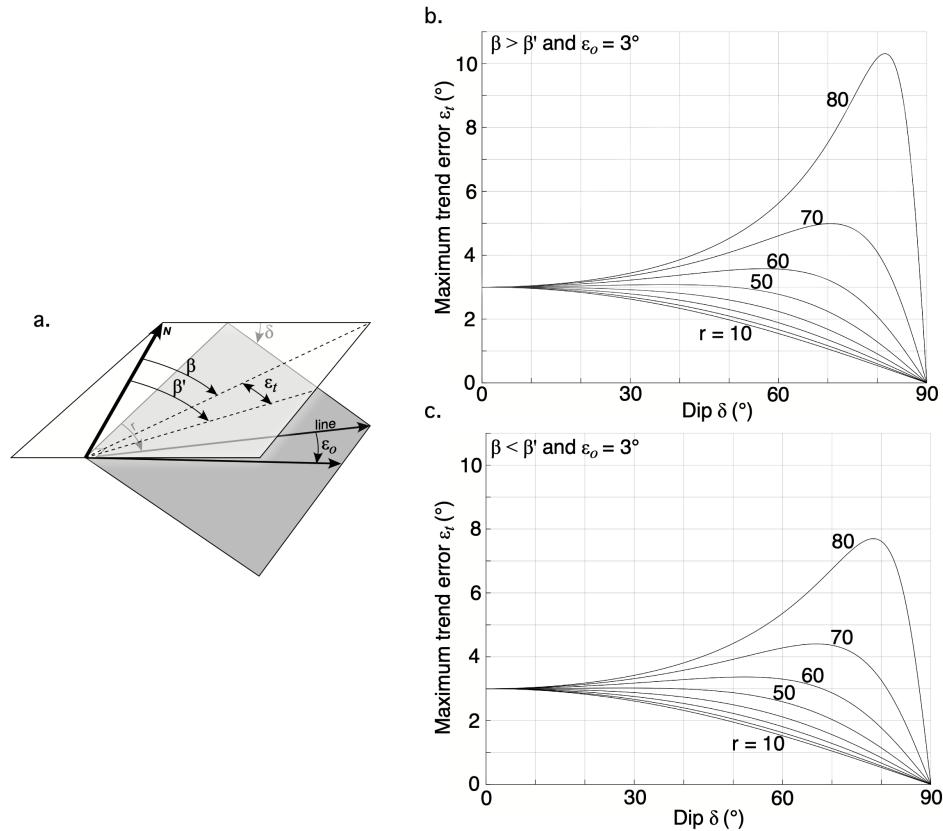


Figure 3.7: **a.** Geometrical relations for estimating the trend error  $\varepsilon_t$  from the rake  $r$  of the line, the dip  $\delta$  of the plane, and the angle on the plane  $\varepsilon_o$  between the measured and the true lines. Trend error as function of dip for **b.** a measured line on 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:

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

For a topographic map, this relation becomes:

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

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).

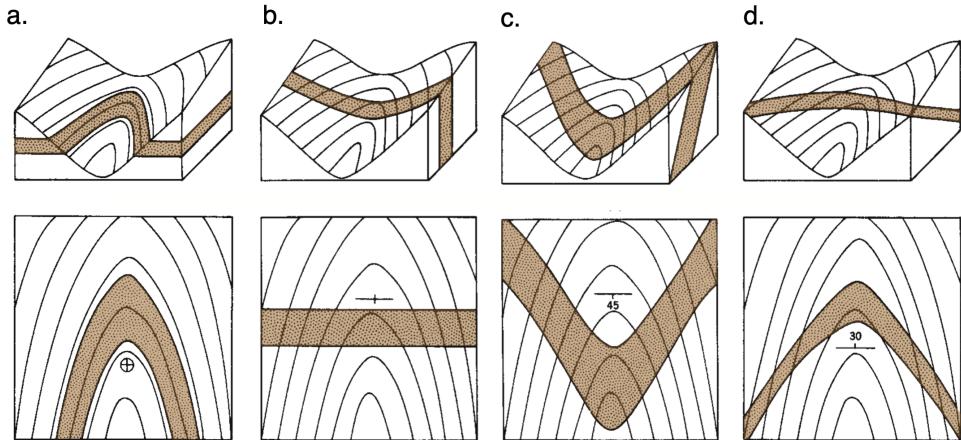


Figure 3.8: Outcrop pattern across a valley of **a.** Horizontal bed, **b.** Vertical bed, **c.** Bed dipping downstream, and **d.** Bed dipping upstream. Modified from Ragan (2009).

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 have the plane's orientation and

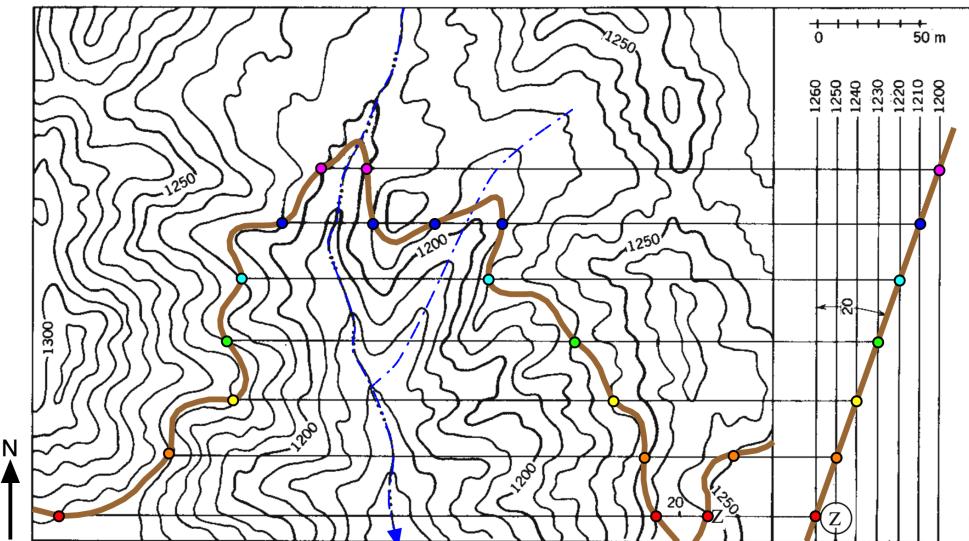


Figure 3.9: Outcrop trace of a plane dipping  $20^{\circ}\text{N}$ . The left figure is the map, and the right figure is a N-S cross section. Color points are the locations where the plane’s structure contours have the same elevation than the topographic contours. The line joining these points is the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

one outcrop location, it is possible to project the plane throughout the 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,

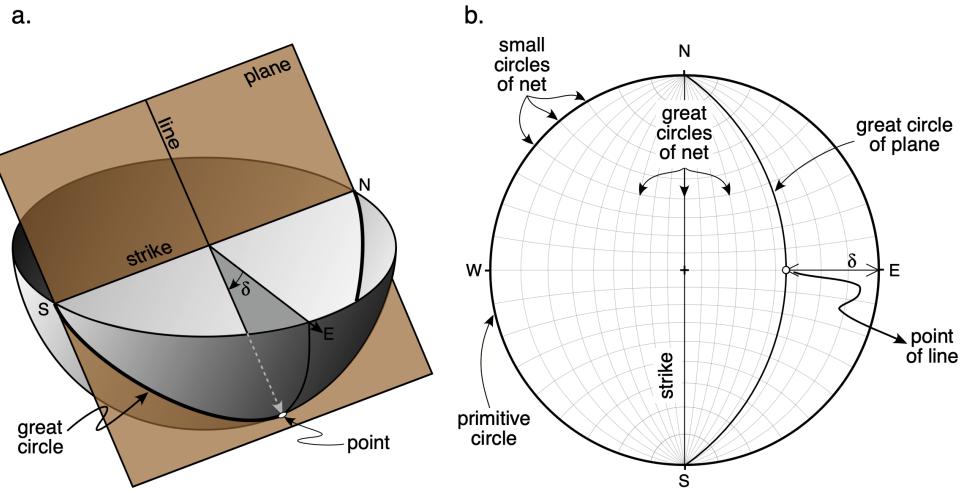


Figure 3.10: **a.** Plane and line intersecting the lower half of a sphere. The rake of the line is  $90^\circ$  and therefore its plunge is equal to the plane's dip  $\delta$ . **b.** Lower hemisphere stereographic projection of plane and line. Modified from Allmendinger et al. (2012) and Allmendinger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

and the projection plane passes through the center of the sphere. In a stereonet, 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:

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

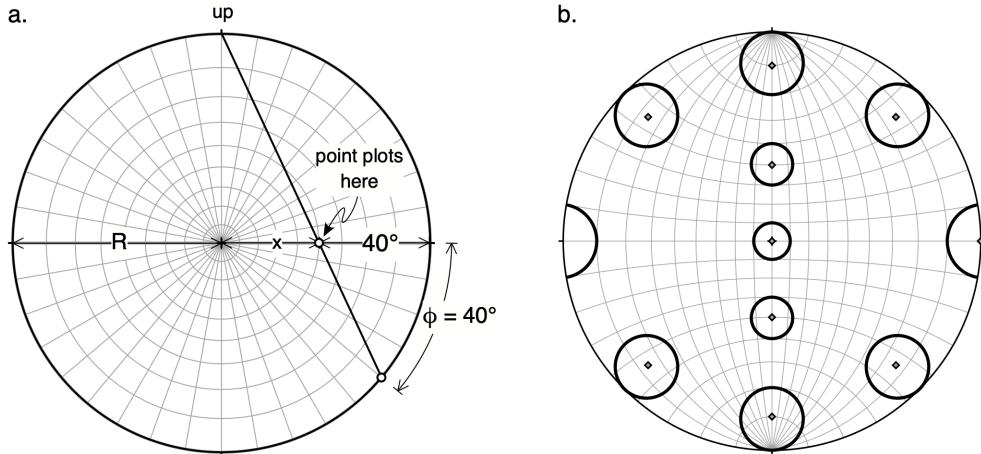


Figure 3.11: **a.** The equal angle stereonet illustrated on a vertical plane passing through the center of the sphere. **b.** Lower hemisphere equal angle projection of small circles of  $10^\circ$  radius but different axis orientations. Modified from Allmendinger et al. (2012).

where  $x$  is the distance of the point from the center of the net,  $R$  is 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  $10^\circ$  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:

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

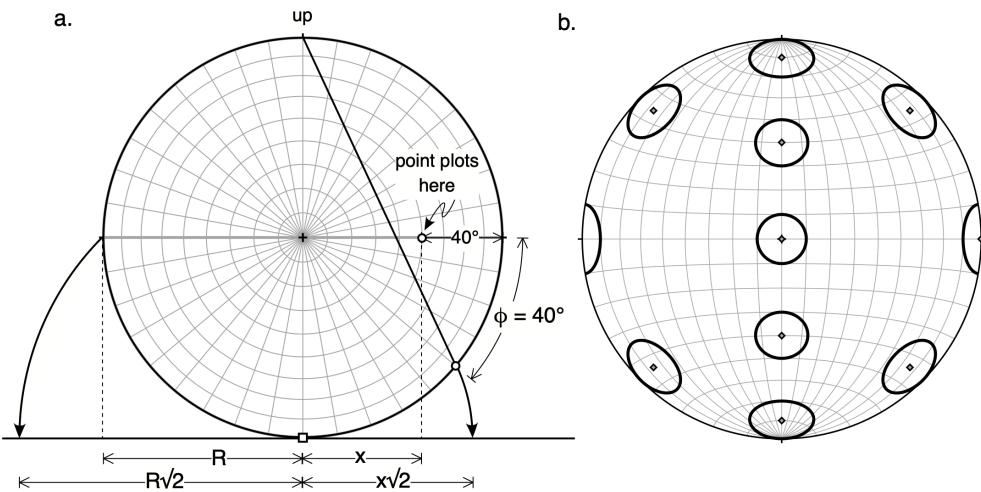


Figure 3.12: **a.** The equal area stereonet illustrated on a vertical plane passing through the center of the sphere. **b.** Lower hemisphere equal area projection of small circles of  $10^\circ$  radius but different axis orientations. Modified from Allmendinger et al. (2012).

The tradeoff is that angles are no longer preserved, and small circles are no 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 Python function *StCoordLine* below 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
16     StCoordLine uses function ZeroTwoPi
17
18     Python function translated from the Matlab function
19     StCoordLine in Allmendinger et al. (2012)
20     ...
21
22     # Take care of negative plunges
23     if plg < 0:
24         trd = ZeroTwoPi(trd+math.pi)
25         plg = -plg
26
27     # Some constants
28     piS4 = math.pi/4
29     s2 = math.sqrt(2)
30     plgS2 = plg/2
31
32     # Equal angle stereonet, Eq. 3.6
33     if ststype == 0:
34         xp = math.tan(piS4 - plgS2)*math.sin(trd)
35         yp = math.tan(piS4 - plgS2)*math.cos(trd)
36     # Equal area stereonet, Eq. 3.7
37     elif ststype == 1:
38         xp = s2*math.sin(piS4 - plgS2)*math.sin(trd)
39         yp = s2*math.sin(piS4 - plgS2)*math.cos(trd)
40
41     return xp, yp

```

### 3.3.3 Plotting lines and poles in a stereonet

The notebook ch3.ipynb below 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.

```

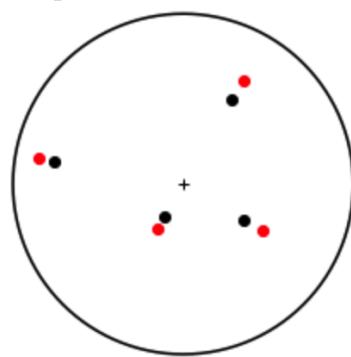
1 import numpy as np
2 import matplotlib.pyplot as plt
3 %matplotlib inline
4
5 from Pole import Pole as Pole
6 from StCoordLine import StCoordLine as StCoordLine
7
8 # Plot the following four lines (trend and plunge)
9 # on an equal angle or equal area stereonet

```

```

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

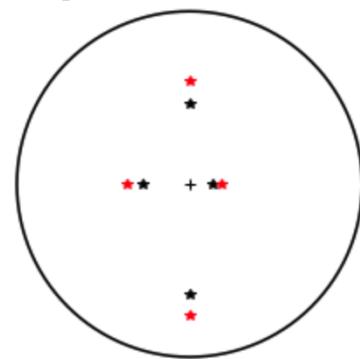
Output:



```

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('scaled')
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 these planes as poles 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.

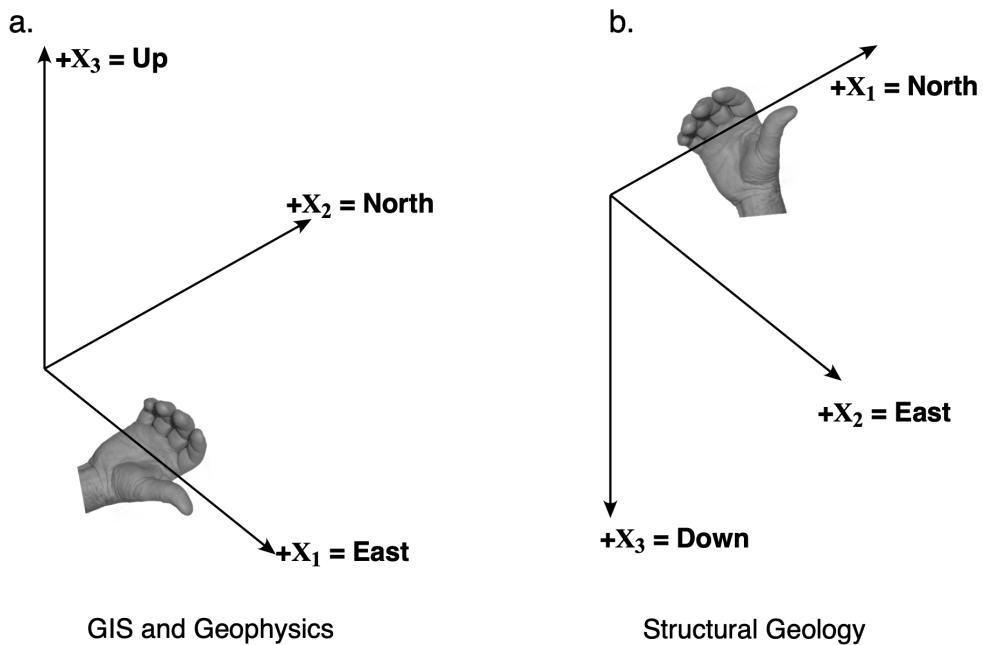


Figure 4.1: Right-handed Cartesian coordinate systems. **a.** The **ENU** coordinate system used when dealing with topography, and **b.** The **NED** coordinate system used in Structural Geology. Modified from Allmendinger et al. (2012).

## 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).

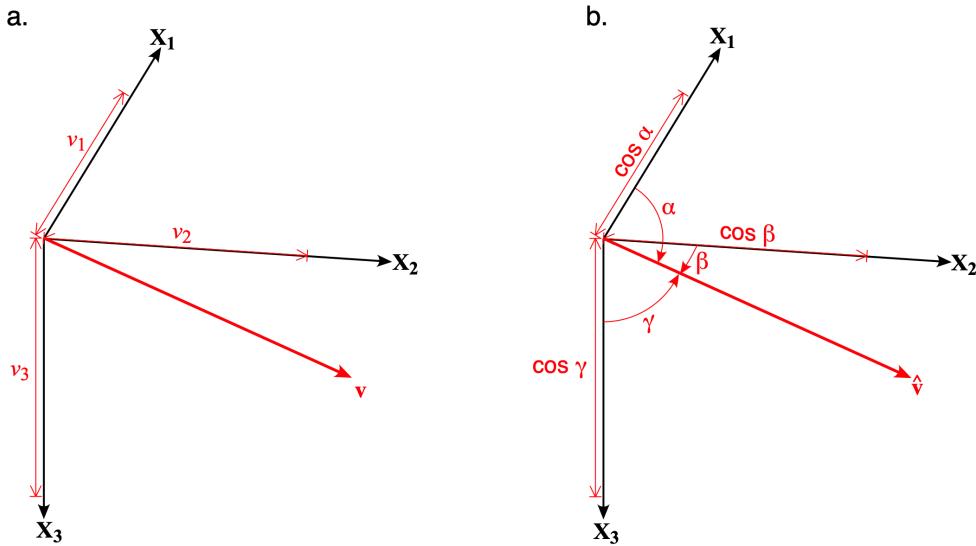


Figure 4.2: **a.** Components of a vector. **b.** Direction cosines of a unit vector. Modified from Allmendinger et al. (2012)

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.ipynb:

```

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).

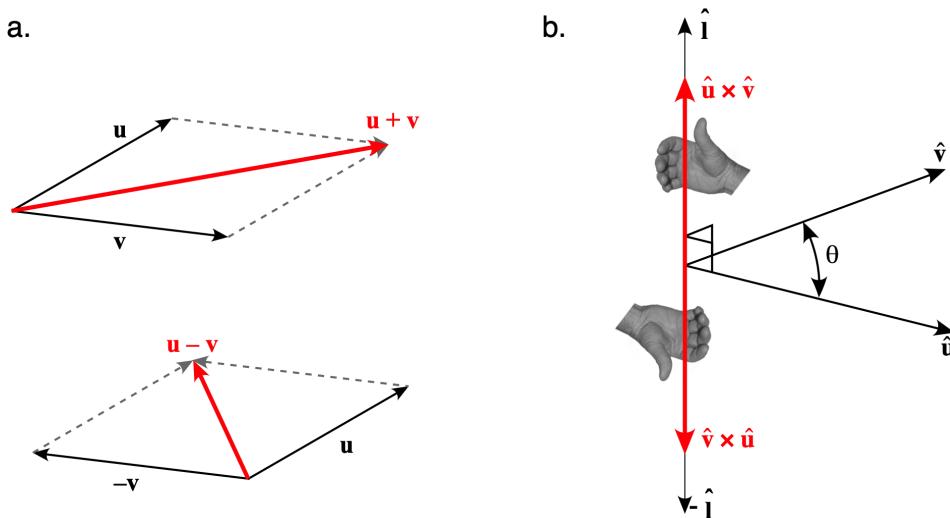


Figure 4.3: a. Vector addition and subtraction. b. Cross product of two unit vectors. Modified from Allmendinger et al. (2012).

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.ipynb:

```

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

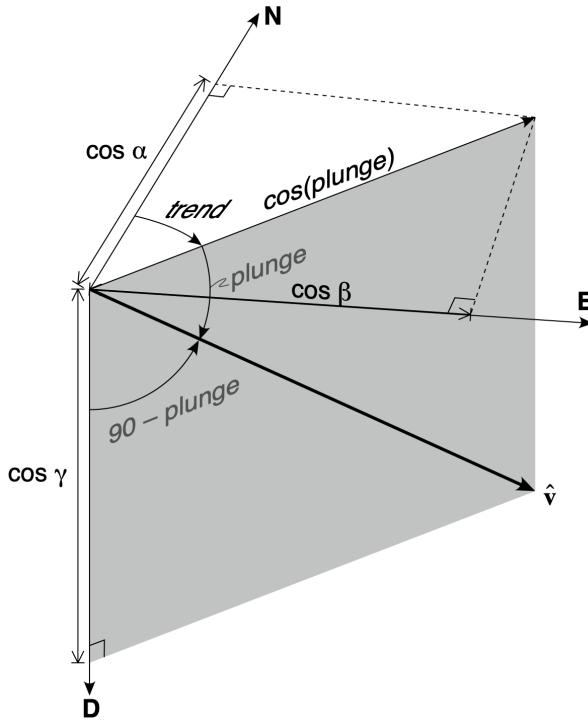


Figure 4.4: Diagram showing the relations between the trend and plunge and the direction cosines in the **NED** coordinate system. Gray plane is the vertical plane in which the plunge is measured. Modified from Allmendinger et al. (2012).

(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:

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

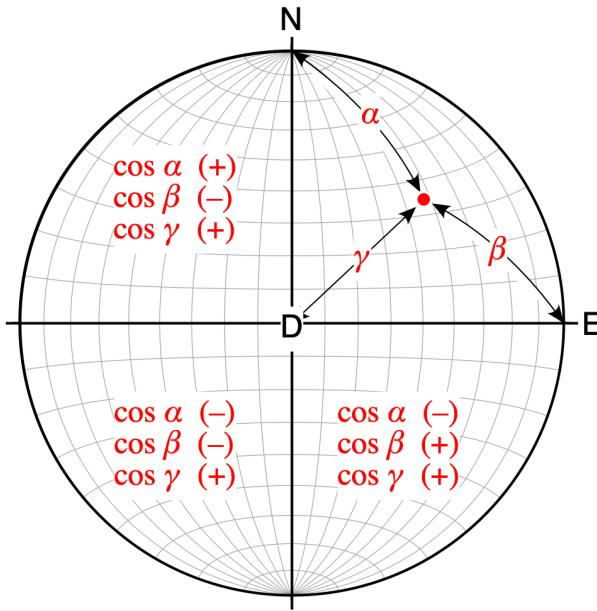


Figure 4.5: Lower hemisphere stereonet showing the sign of the direction cosines in each quadrant. In the NE quadrant, all three direction cosines are positive. Modified from Allmendinger et al. (2012).

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

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

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 Python 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
6         Cartesian coordinates
7
8         SphToCart(trd,plg,k) returns the north (cn),
9         east (ce), and down (cd) direction cosines of a line.
10
11        k: integer to tell whether the trend and plunge of a line
12        (k = 0) or strike and dip of a plane in right hand rule
13        (k = 1) are being sent in the trd and plg slots. In this
14        last case, the direction cosines of the pole to the plane
15        are returned
16
17        NOTE: Angles should be entered in radians
18
19        Python function translated from the Matlab function
20        SphTpCart in Allmendinger et al. (2012)
21        """
22
23        # If line  (see Table 4.1)
24        if k == 0:
25            cn = math.cos(trd) * math.cos(plg)
26            ce = math.sin(trd) * math.cos(plg)
27            cd = math.sin(plg)
28
29        # Else pole to plane (see Table 4.1)
30        elif k == 1:
31            cn = math.sin(trd) * math.sin(plg)
32            ce = -math.cos(trd) * math.sin(plg)
33            cd = math.cos(plg)
34
35        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:

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

or:

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

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:

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

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

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

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

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

The following Python 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
7     coordinates
8
9     CartToSph(cn,ce,cd) returns the trend (trd)
10    and plunge (plg) of a line for input north (cn),
11    east (ce), and down (cd) direction cosines
12
13    NOTE: Trend and plunge are returned in radians
14
15    CartToSph uses function ZeroTwoPi
16
17    Python function translated from the Matlab function
18    CartToSph in Allmendinger et al. (2012)
19    ...
20
21    pi = math.pi
22    # Plunge
23    plg = math.asin(cd) # Eq. 4.13a
24
25    #Trend
26    #If north direction cosine is zero, trend is east or west
27    #Choose which one by the sign of the east direction
28    #cosine
29    if cn == 0.0:
30        if ce < 0.0:
31            trd = 3.0/2.0*pi # Eq. 4.14d, trend is west
32        else:
33            trd = pi/2.0 # Eq. 4.14c, trend is east
34    # Else
35    else:
36        trd = math.atan(ce/cn) # Eq. 4.14a
37        if cn < 0.0:
38            #Add pi
39            trd = trd+pi # Eq. 4.14b
40        # Make sure trd is between 0 and 2*pi
41        trd = ZeroTwoPi(trd)
42
43    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 Python function *CalcMV* below 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
24    # Number of lines
25    nlines = len(T)
26
27    # Initialize the 3 direction cosines which contain the
28    # sums of the individual vectors
29    CNsum = 0.0
30    CEsum = 0.0
31    CDsum = 0.0
32
33    #Now add up all the individual vectors. Eq. 4.15a
34    for i in range(nlines):
35        cn,ce,cd = SphToCart(T[i],P[i],0)
36        CNsum += cn
37        CEsum += ce
38        CDsum += cd
39
40    # R is the length of the resultant vector and
41    # Rave is the mean resultant length. Eqs. 4.15b and d
42    R = math.sqrt(CNsum*CNsum + CEsum*CEsum + CDsum*CDsum)
43    Rave = R/nlines
44    # If Rave is lower than 0.1, the mean vector is
45    # insignificant, return error
46    if Rave < 0.1:
47        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
73                     -1.0))
74                 afact = 1.0/0.05
75                 d95 = math.acos(1.0-((nlines-R)/R)*(afact**bfact
76                     -1.0))

76     return trd, plg, Rave, conc, d99, d95

```

The notebook ch4-3.ipynb below 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 numpy as np
2 import matplotlib.pyplot as plt
3 %matplotlib inline
4
5 from StCoordLine import StCoordLine as StCoordLine
6 from CalcMV import CalcMV as CalcMV
7
8 # Arrays T and P contain the trend (T)
9 # and plunge (P) of the 10 poles

```

```

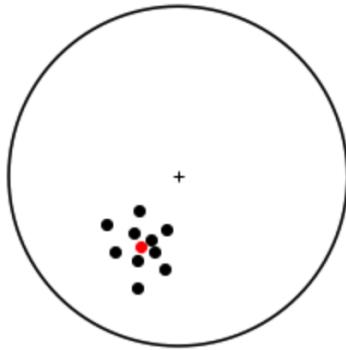
10 T = np.array([206, 220, 204, 198, 200, 188, 192, 228, 236,
11     218])
12 P = np.array([32, 30, 46, 40, 20, 32, 54, 56, 36, 44])
13 # Convert T and P from degrees to radians
14 pi = np.pi
15 TR = T * pi/180
16 PR = P * pi/180
17
18 # Compute the mean vector and print orientation
19 # and mean resultant length
20 trd, plg, Rave, conc, d99, d95 = CalcMV(TR,PR)
21 print('Mean vector trend = {:.1f}, plunge {:.1f}'.format(trd
22     *180/pi,plg*180/pi))
22 print('Mean resultant length = {:.3f}'.format(Rave))
23
24 # Plot the primitive of the stereonet
25 r = 1; # unit radius
26 TH = np.arange(0,360,1)*pi/180
27 x = r * np.cos(TH)
28 y = r * np.sin(TH)
29 plt.plot(x,y,'k')
30 # Plot center of circle
31 plt.plot(0,0,'k+')
32 # Make axes equal and remove them
33 plt.axis('scaled')
34 plt.axis('off')
35
36 # Plot the poles as black points
37 # on an equal angle stereonet
38 npoles = len(T)
39 eqAngle = np.zeros((npoles, 2))
40 for i in range(npoles):
41     # Equal angle coordinates
42     eqAngle[i,0], eqAngle[i,1] = StCoordLine(TR[i],PR[i],0)
43 plt.plot(eqAngle[:,0],eqAngle[:,1],'ko')
44
45 # Plot the mean vector as a red point
46 mvx, mvy = StCoordLine(trd,plg,0)
47 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 0.963, 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 Python function *Angles* below 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
39    # If planes have been entered
40    if ans0 == 'i' or ans0 == 'p':
41        k = 1
42    # Else if lines have been entered
43    elif ans0 == 'a' or ans0 == 'l':
44        k = 0

```

```

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.ipynb below illustrates the use of the function *Angles* to solve several interesting 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 from Angles import Angles as Angles
5
6 # Strike and dip of the limbs in radians
7 str1 = 120 * pi/180 # SW dipping limb
8 dip1 = 40 * pi/180
9 str2 = 250 * pi/180 # NE dipping limb
10 dip2 = 60 * pi/180
11
12 # (a) Chevron folds have planar limbs. The hinge
13 # of the fold is the intersection of the limbs
14 htrd, hplg = Angles(str1,dip1,str2,dip2,'i')
15 print('Hinge trend = {:.1f}, plunge {:.1f}'.format(htrd*180/
    pi,hplg*180/pi))
16
17 # The rake of the hinge on either limb is the angle
18 # between the hinge and the strike line on the limb.
19 # This line is horizontal and has plunge = 0
20 plg = 0
21
22 # (b) For the SW dipping limb
23 ang1, ang2 = Angles(str1,plg,htrd,hplg,'l')
24 print('Rake of hinge in SW dipping limb = {:.1f}'.format(ang1
    *180/pi))
25
26 # (c) And for the NE dipping limb
27 ang1, ang2 = Angles(str2,plg,htrd,hplg,'l')
28 print('Rake of hinge in NE dipping limb = {:.1f}'.format(ang1
    *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° and the other 135°. The apparent dip of bedding on the faces are 40°N and 30°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
    *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° 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*180/pi,lplg*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*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 derives from 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.

There is however 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 Python 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    # make vectors v (p1 - p3) and u (p2 - p3)
24    v = p1 - p2
25    u = p2 - p3

```

```

26
27     # take the cross product of v and u
28     vcu = np.cross(v,u)
29
30     # make this vector a unit vector
31     mvcu = la.norm(vcu) # magnitude of the vector
32     uvcu = vcu/mvcu # unit vector
33
34     # make the pole vector in NED coordinates
35     p = [uvcu[1], uvcu[0], -uvcu[2]]
36
37     # Make pole point downwards
38     if p[2] < 0:
39         p = [-elem for elem in p]
40
41     # 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 Python notebook ch4-5.ipynb below shows the solution to this problem:

```

1 import math
2 pi = math.pi
3 from ThreePoint import ThreePoint as ThreePoint
4
5 # ENU coordinates of the three points
6 p1 = np.array([509, 2041, 400])
7 p2 = np.array([1323, 2362, 500])
8 p3 = np.array([2003, 2913, 700])

```

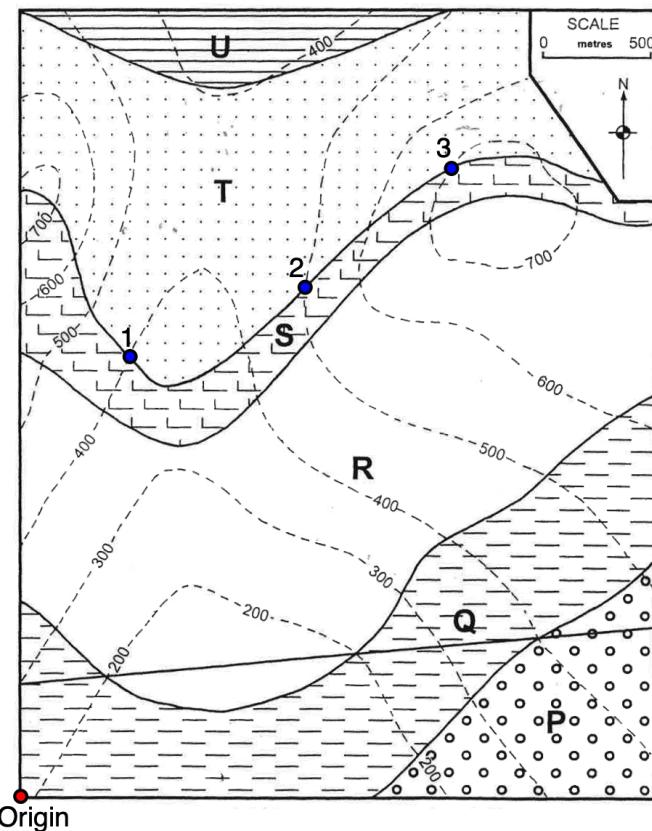


Figure 4.6: Geologic map of sedimentary units dipping south (Bennison et al., 2011). Points 1 to 3 on the base of unit S are used to estimate the orientation of bedding. Notice that the origin is at the lower left corner of the map.

```

9
10 # Compute the orientation of the plane
11 strike, dip = ThreePoint(p1,p2,p3)
12 print('Plane strike = {:.1f}, dip = {:.1f}'.format(strike
           *180/pi,dip*180/pi))

```

Output:  
Plane strike = 84.5, dip = 22.5

## 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 Python functions *AnglesU* and *ThreePointU* in our 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.ipynb.

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 numpy as np
2 pi = np.pi
```

```

3 import uncertainties as unc
4 from AnglesU import AnglesU as AnglesU
5
6 # Strike and dip of the limbs in radians
7 str1 = 120 * pi/180 # SW dipping limb
8 dip1 = 40 * pi/180
9 str2 = 250 * pi/180 # NE dipping limb
10 dip2 = 60 * pi/180
11
12 # Errors in radians
13 ustr = 4 * pi/180 # Error in strike
14 udip = 2 * pi/180 # Error in dip
15
16 # Create the input values with uncertainties
17 str1 = unc.ufloat(str1, ustr) # str1 = str1 +/-ustr
18 dip1 = unc.ufloat(dip1, udip) # dip1 = dip1 +/-udip
19 str2 = unc.ufloat(str2, ustr) # str2 = str2 +/-ustr
20 dip2 = unc.ufloat(dip2, udip) # dip2 = dip2 +/-udip
21
22 # (a) Chevron folds have planar limbs. The hinge
23 # of the fold is the intersection of the limbs
24 htrd, hplg = AnglesU(str1,dip1,str2,dip2,'i')
25 print('Hinge trend = {:.1f}, plunge {:.1f}'.format(htrd*180/
    pi,hplg*180/pi))
26
27 # The rake of the hinge on either limb is the angle
28 # between the hinge and the strike line on the limb.
29 # This line is horizontal and has plunge = 0
30 plg = unc.ufloat(0, udip) # plg = 0 +/-udip
31
32 # (b) For the SW dipping limb
33 ang1, ang2 = AnglesU(str1,plg,htrd,hplg,'l')
34 print('Rake of hinge in SW dipping limb = {:.1f}'.format(ang1
    *180/pi))
35
36 # (c) And for the NE dipping limb
37 ang1, ang2 = AnglesU(str2,plg,htrd,hplg,'l')
38 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 from ThreePointU import ThreePointU as ThreePointU
2
3 # ENU coordinates of the three points
4 # with uncertainties in E-N = 10, and U = 5
5 p1 = np.array([unc.ufloat(509, 10), unc.ufloat(2041, 10), unc.
6 .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
12 # Compute the orientation of the plane
13 strike, dip = ThreePointU(p1,p2,p3)
14 print('Plane strike = {:.1f}, dip = {:.1f}'.format(strike
15 *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?

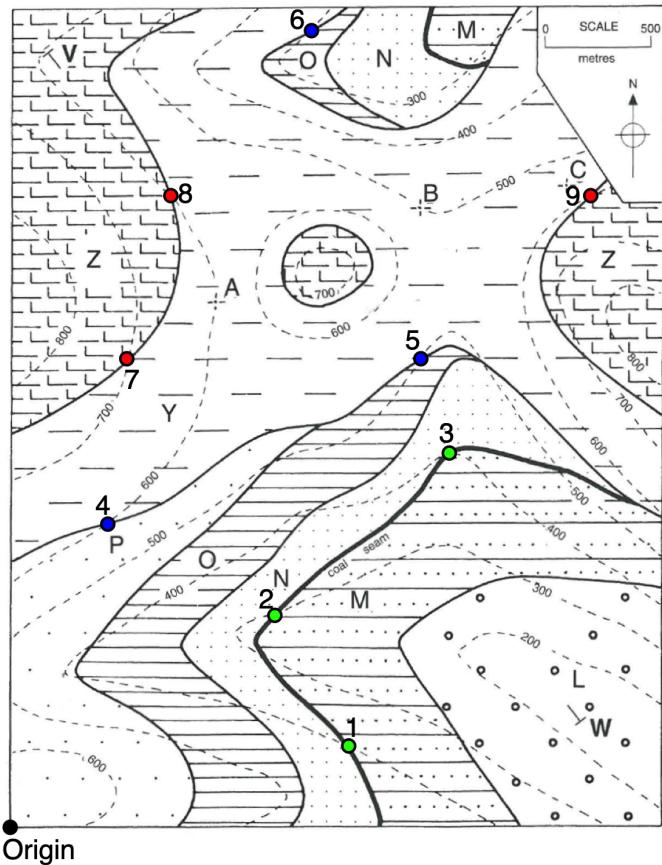


Figure 4.7: Map for exercise 2. This is map 10 of Bennison et al. (2011).

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]
point6 = [1408, 3737, 300]
point7 = [536, 2196, 700]
point8 = [743, 2963, 600]
point9 = [2720, 2963, 600]

```

- (a) Compute the strike and dip of the coal seam (points 1-3).
- (b) 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?
- (c) 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?
- (d) 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:

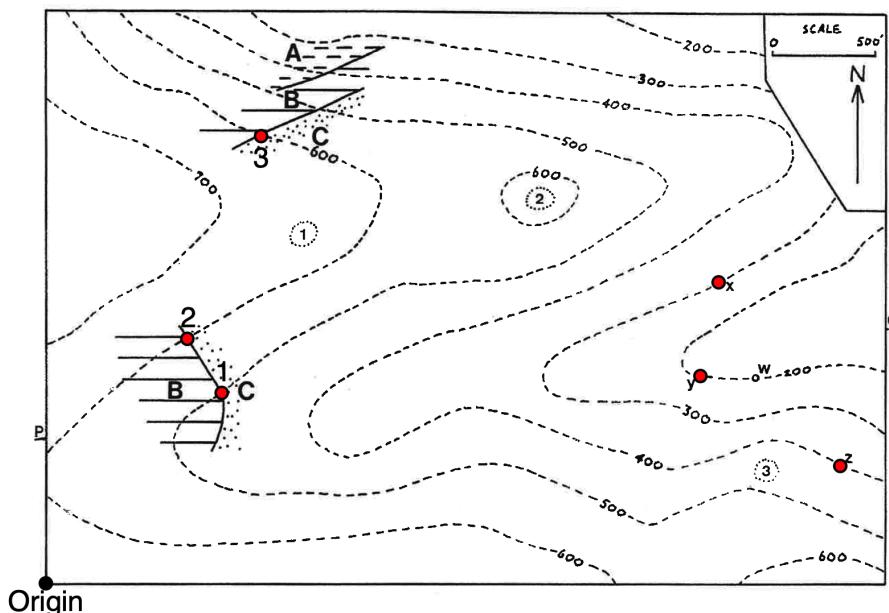


Figure 4.8: Map for exercise 3

```
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

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# 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

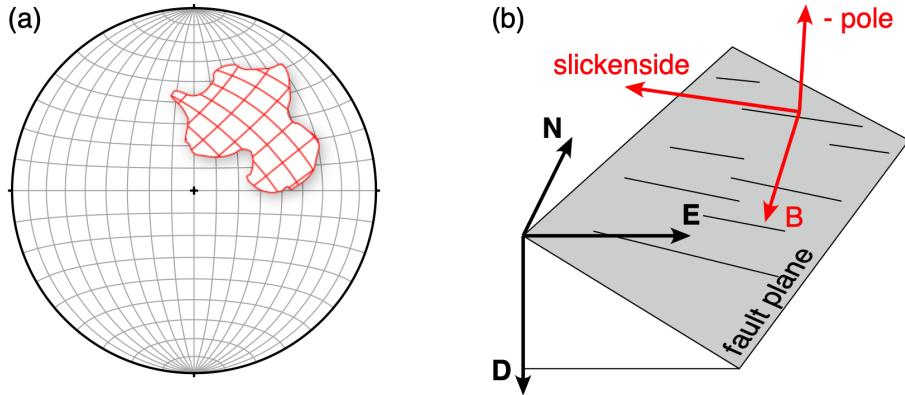


Figure 5.1: Examples of coordinate transformations in geology. **a.** Continental drift, **b.** A fault plane. Red is the coordinate system for analysis, and gray is the geographic coordinate system. Modified from Allmendinger et al. (2012).

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).

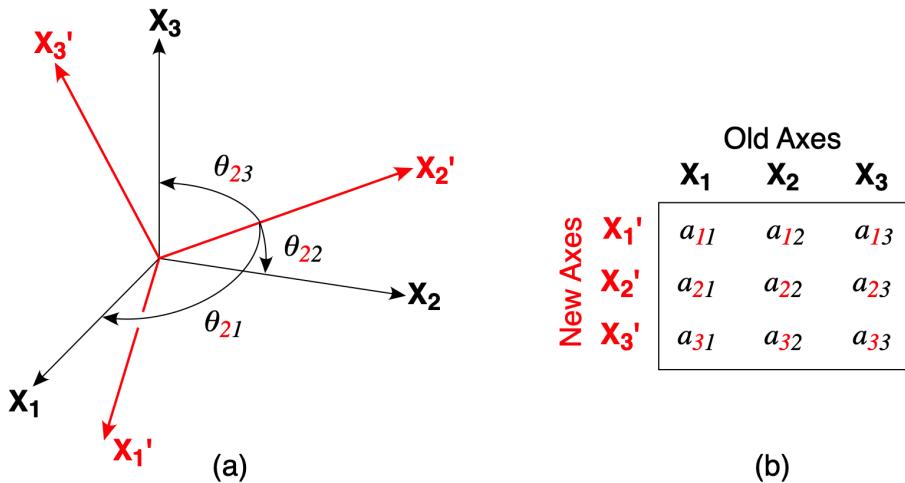


Figure 5.2: **a.** Rotation of a Cartesian coordinate system. The old axes are black, the new axes are primed and red. Only three of the nine possible angles are shown. **b.** Graphic device for remembering how the subscript of the direction cosines relate to the new and the old axes. Modified from Allmendinger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

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:

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

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 indexes of  $i$ ), each one with three terms (the three indexes 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 very 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:

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

which simplifies to:

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

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 a point on the top of the unit and the **P** coordinate of any point on the base.

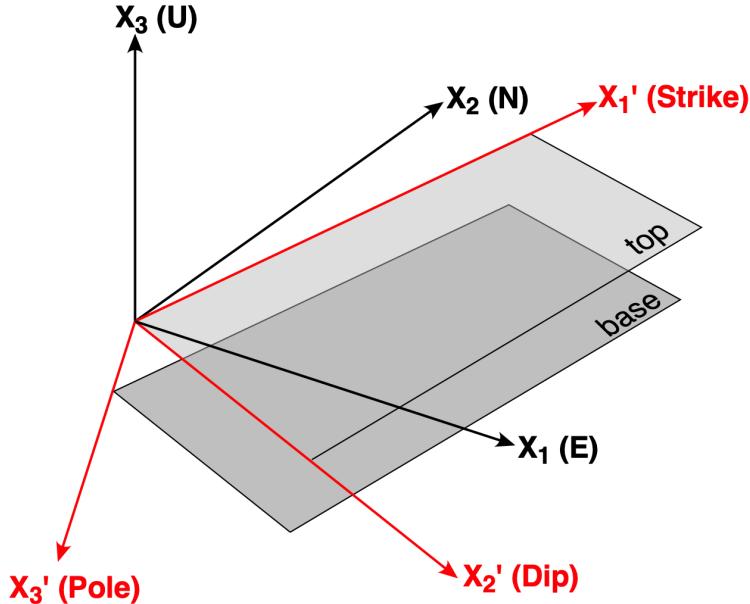


Figure 5.3: Coordinate transformation from an **ENU** to a Strike-Dip-Pole (**SDP**) coordinate system. The thickness of the unit can be calculated by subtracting the **P** coordinates of any point on the top and any point on the base. Modified from Allmendinger (2019).

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:

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

which is equal to:

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

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  $\mathbf{P}$  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 Python function *TrueThickness* calculates the thickness of a unit given the strike and dip of the unit, and the ENU coordinates of two points at the top and base of the unit:

```

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:

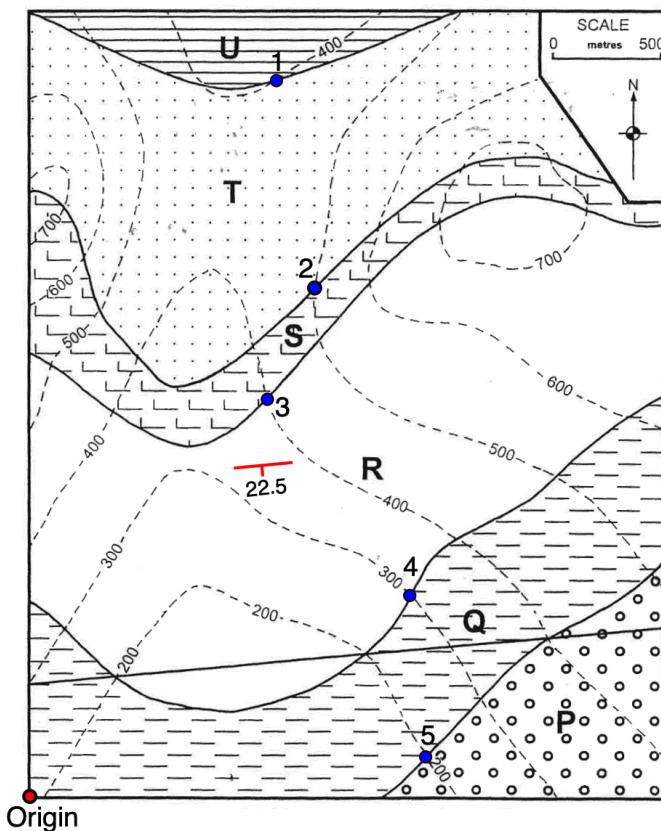


Figure 5.4: Geologic map of sedimentary units with an orientation 84.5/22.5 (RHR) (Bennison et al., 2011). Points at the top and base of units T to Q are used to determine the thickness of the units.

```
point1 = [1147, 3329, 400]
```

```
point2 = [1323, 2362, 500]
```

```
point3 = [1105, 1850, 400]
```

```
point4 = [1768, 940, 300]
```

```
point5 = [1842, 191, 200]
```

The Python notebook ch5-1.ipynb below shows the solution to this problem:

```

1 import numpy as np
2 pi = np.pi
3 from TrueThickness import TrueThickness as TrueThickness
4
5 # Strike and dip of the unit in radians
6 strike = 84.5 * pi/180
7 dip = 22.5 * pi/180
8
9 # ENU coordinates of the points
10 p1 = np.array([1147, 3329, 400])
11 p2 = np.array([1323, 2362, 500])
12 p3 = np.array([1105, 1850, 400])
13 p4 = np.array([1768, 940, 300])
14 p5 = np.array([1842, 191, 200])
15
16 # Compute the thickness of the units
17 thickT = TrueThickness(strike,dip,p2,p1)
18 thickS = TrueThickness(strike,dip,p3,p2)
19 thickR = TrueThickness(strike,dip,p4,p3)
20 thickQ = TrueThickness(strike,dip,p5,p4)
21 print('Thickness of unit T = {:.1f} m'.format(thickT))
22 print('Thickness of unit S = {:.1f} m'.format(thickS))
23 print('Thickness of unit R = {:.1f} m'.format(thickR))
24 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 our git repository handles this case. Suppose that in the problem above, the uncertainties in strike and dip are 4° and 2° respectively, the uncertainty in east and north coordinates is 10 m, and in elevation is 5 m. The Python notebook ch5-2.ipynb below shows the solution to this problem:

```

1 import numpy as np
2 pi = np.pi
3 import uncertainties as unc
4 from TrueThicknessU import TrueThicknessU as TrueThicknessU

```

```

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

```

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

```

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

```

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] +
41 a[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 outcrops at point y and has an orientation 160/22 (RHR). The Python notebook ch5-3.ipynb below draws the outcrop trace of the contact. Notice that the ENU coordinates of the points of the DEM grid are input from text files (*XG.txt*, *YG.txt*, and *ZG.txt*) which are available from our git repository.

```

1 import numpy as np
2 import matplotlib.pyplot as plt
3 from OutcropTrace import OutcropTrace as OutcropTrace
4
5 # Read the DEM grid
6 XG = np.loadtxt('XG.txt')
7 YG = np.loadtxt('YG.txt')
8 ZG = np.loadtxt('ZG.txt')
9
10 # Contour the terrain

```

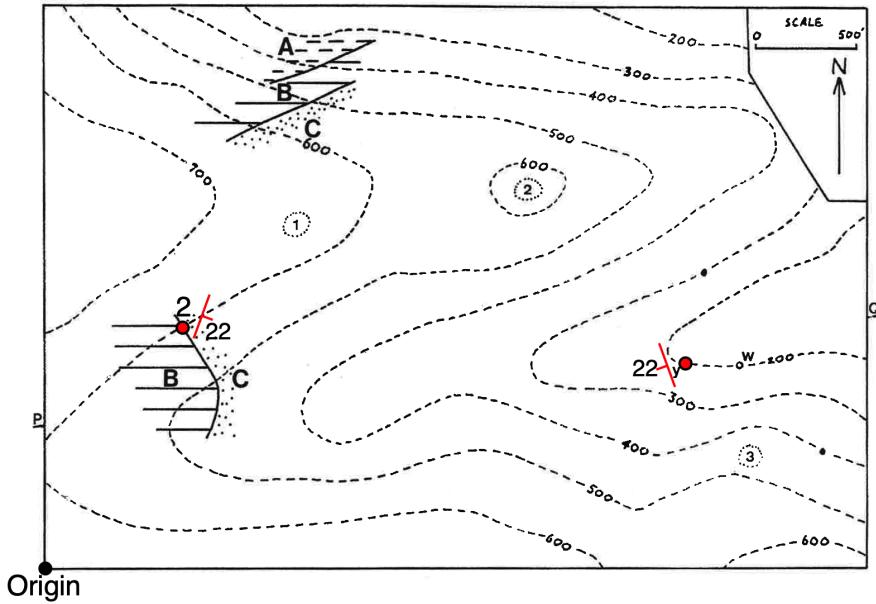
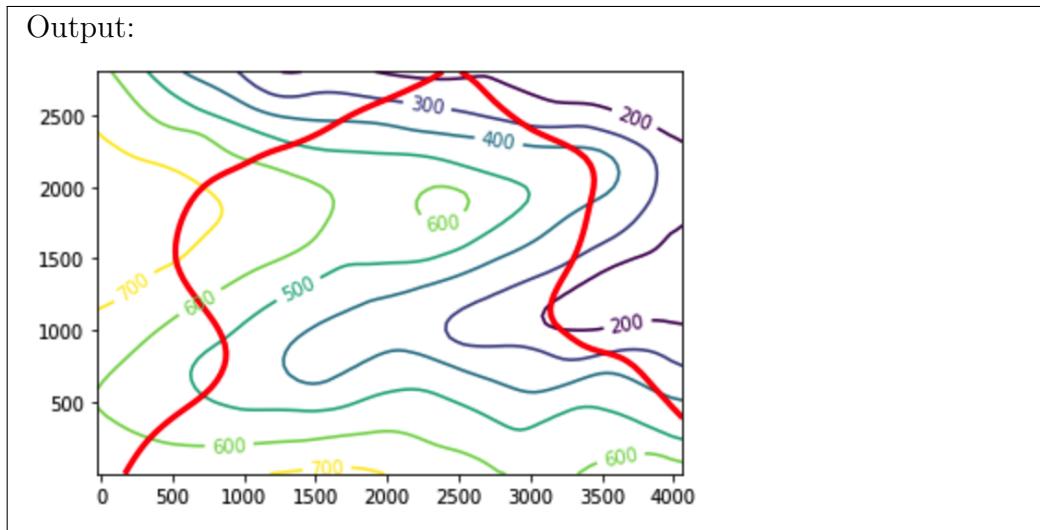


Figure 5.5: The contact between units B and C outcrops at point 2 with orientation 020/22 (RHR), and at point y with orientation 160/22 (RHR). From this information and a DEM of the terrain, we can determine the outcrop trace of the contact.

```

11 cval = np.linspace(200,700,6)
12 cp = plt.contour(XG,YG,ZG,cval)
13 plt.clabel(cp, inline=True, fontsize=10, fmt="%d")
14
15 # Western contact
16 pi = np.pi
17 strike = 20*pi/180
18 dip = 22*pi/180
19 point2 = np.array([692, 1212, 600])
20 DG = OutcropTrace(strike,dip,point2,XG,YG,ZG)
21 cval = 0 # Contour only CG zero value
22 cp = plt.contour(XG,YG,DG,cval,colors='red',linewidths=3)
23
24 # Eastern contact
25 strike = 160*pi/180
26 dip = 22*pi/180
27 pointy = np.array([3203, 1031, 200])
28 DG = OutcropTrace(strike,dip,pointy,XG,YG,ZG)
29 cp = plt.contour(XG,YG,DG,cval,colors='red',linewidths=3)
30
31 # Make axes equal
32 plt.axis('scaled')

```



### 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. 5.7). 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 are given by Table 4.1. If the trend and plunge of the fold axis are  $T$  and  $P$ , these direction cosines are (Fig. 5.6):

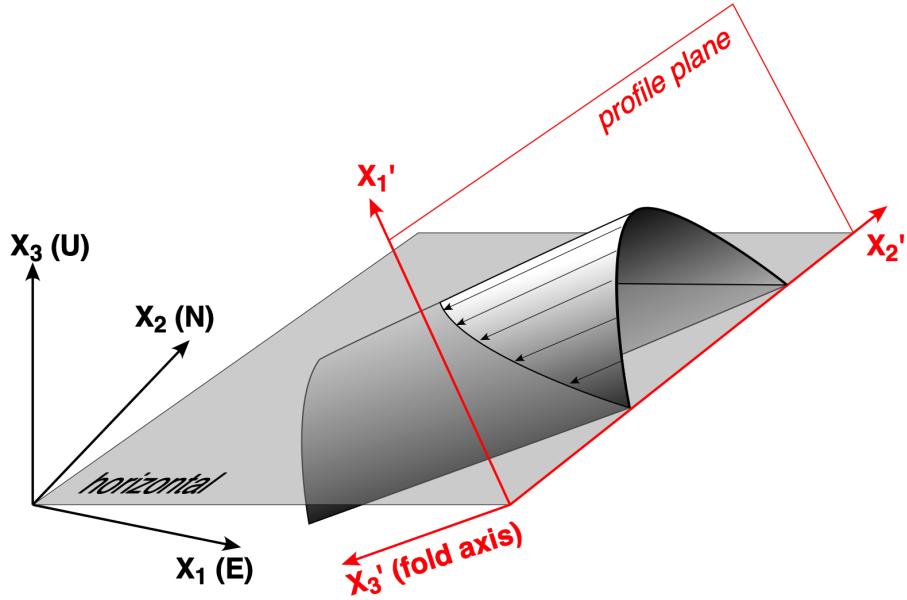


Figure 5.6: The two coordinate systems involved in a Down-Plunge projection of a fold. Modified from Allmendinger et al. (2012).

$$\mathbf{X}_1' = [\cos(T) \cos(P - 90), \sin(T) \cos(P - 90), \sin(P - 90)]$$

$$\mathbf{X}_2' = [\cos(T + 90), \sin(T + 90), 0]$$

$$\mathbf{X}_3' = [\cos(T) \cos(P), \sin(T) \cos(P), \sin(P)]$$

which simplifies to:

$$\mathbf{X}_1' = [\cos(T) \sin(P), \sin(T) \sin(P), -\cos(P)]$$

$$\mathbf{X}_2' = [-\sin(T), \cos(T), 0] \quad (5.14)$$

$$\mathbf{X}_3' = [\cos(T) \cos(P), \sin(T) \cos(P), \sin(P)]$$

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:

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

which is equal to:

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

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:

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

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

The Python function *DownPlunge* below computes the Down-Plunge projection of a bed given the **ENU** coordinates of points on the bed, and the trend and plunge of the fold axis:

```

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         DownPlunge constructs the down plunge projection
8         of a bed
9
10        bedseg is a npoints x 3 array, which holds npoints
11        on the digitized bed, each point defined by
12        3 coordinates: X1 = East, X2 = North, X3 = Up
13
14        trd and plg are the trend and plunge of the fold axis
15
16        NOTE: trd and plg should be entered in radians
17
18        Python function translated from the Matlab function
19        DownPlunge in Allmendinger et al. (2012)
20        """
21
22        # Number of points in bed
23        nvtex = bedseg.shape[0]

```

```

24 # Allocate some arrays
25 a=np.zeros((3,3))
26 dpbedseg = np.zeros((np.shape(bedseg)))
27
28 # Calculate the transformation matrix a(i,j) Eq. 5.15
29 a[0,0] = np.sin(trd)*np.sin(plg)
30 a[0,1] = np.cos(trd)*np.sin(plg)
31 a[0,2] = np.cos(plg)
32 a[1,0] = np.cos(trd)
33 a[1,1] = -np.sin(trd)
34 a[2,0] = np.sin(trd)*np.cos(plg)
35 a[2,1] = np.cos(trd)*np.cos(plg)
36 a[2,2] = -np.sin(plg)
37
38 # Perform transformation
39 for nv in range(0,nvtex,1):
40     for i in range(0,3,1):
41         dpbedseg[nv,i] = 0.0
42         for j in range(0,3,1):
43             dpbedseg[nv,i] = a[i,j]*bedseg[nv,j] +
44             dpbedseg[nv,i]
45
46 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 in our git repository 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.ipynb shows the solution to this problem:

```

1 import numpy as np
2 import matplotlib.pyplot as plt
3 from DownPlunge import DownPlunge as DownPlunge
4
5 # Trend and plunge of the fold axis in radians
6 trend = 125 * np.pi/180;
7 plunge = 26 * np.pi/180;
8
9 # Read the tops from the text files
10 jtc = np.loadtxt('jtc.txt');
11 js = np.loadtxt('js.txt');
12 kp = np.loadtxt('kp.txt');
13

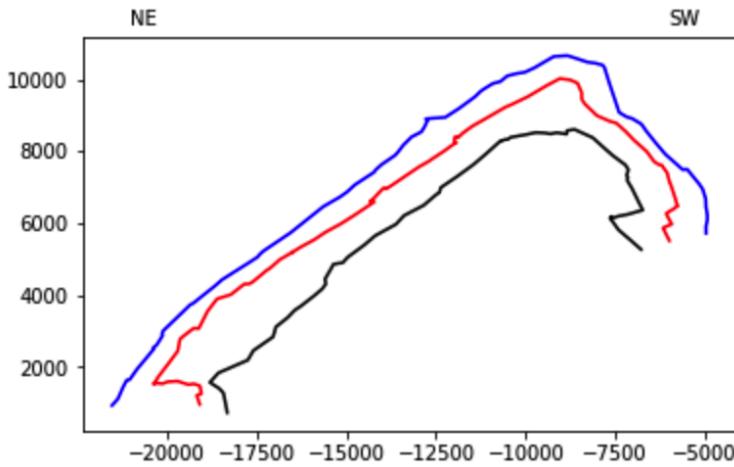
```

```

14 # Transform the points
15 jtcdp = DownPlunge(jtc,trend,plunge);
16 jsdp = DownPlunge (js,trend,plunge);
17 kpdp = DownPlunge(kp,trend,plunge);
18
19 # Plot the Down-plunge section
20 plt.plot(jtcdp[:,1],jtcdp[:,0], 'k-');
21 plt.plot(jsdp[:,1],jsdp[:,0], 'r-');
22 plt.plot(kpdp[:,1],kpdp[:,0], 'b-');
23
24 # Display the section's orientation
25 # Notice that the fold axis plunges SE
26 # Therefore the left side of the section is NE
27 # and the right side is SW
28 plt.text(-2.1e4,11.5e3,'NE')
29 plt.text(-0.6e4,11.5e3,'SW')
30
31 # Make axes equal
32 plt.axis('scaled')

```

Output:



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?

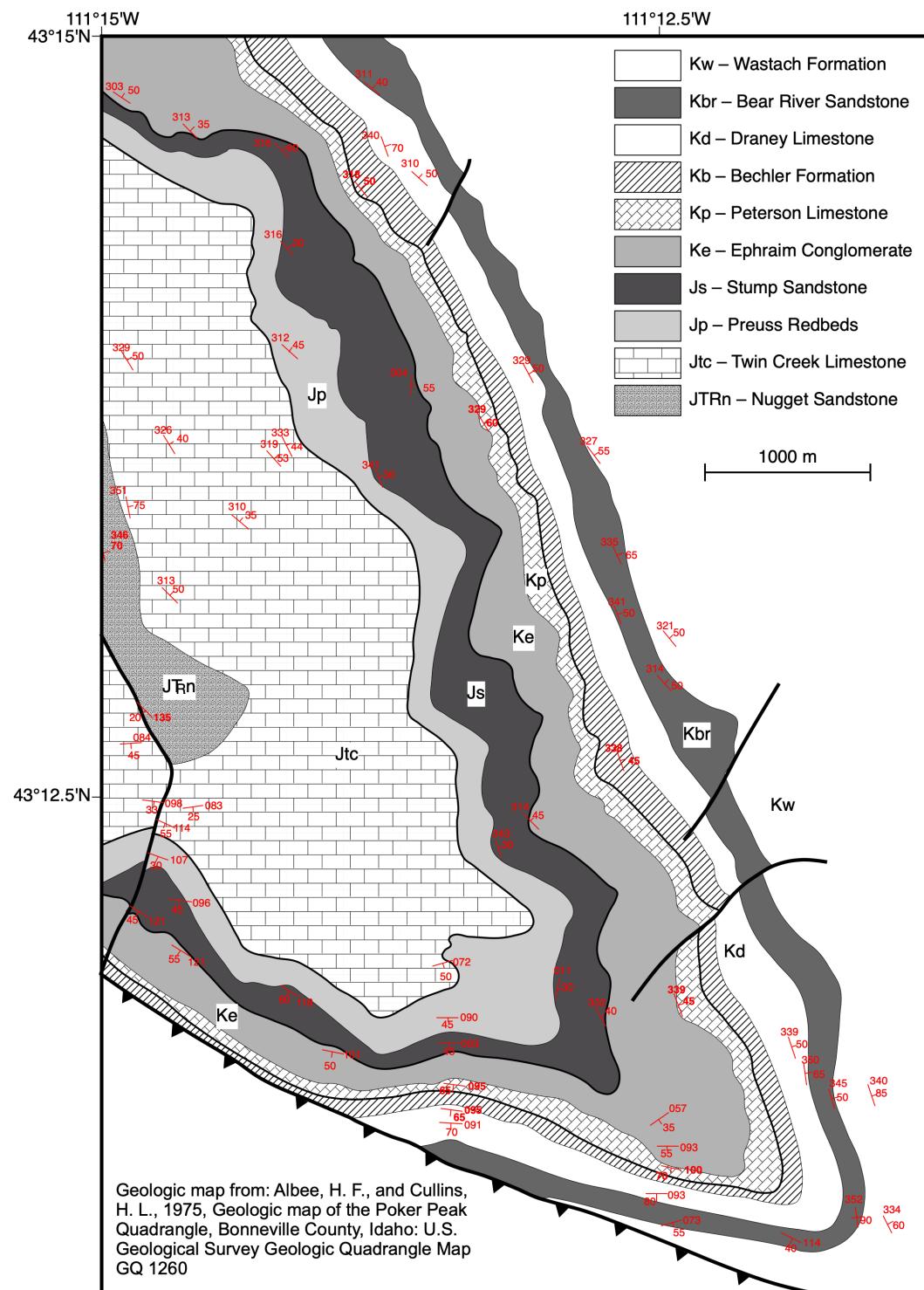


Figure 5.7: Simplified geologic map of the Big Elk anticline in southeastern Idaho. Modified from Allmendinger et al. (2012).

### 5.2.4 Rotations

Rotations are essential in geology. For example, when we take the orientation of current lineations on tilted beds, and we want to figure out the orientation of the paleo-current 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 it 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 Python function *Rotate* below 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
18    is an axis (ans0 = 'a') or a vector (ans0 = 'v')
19
20    NOTE: All angles are in radians
21
22    Rotate uses functions SphToCart and CartToSph
23
24    Python function translated from the Matlab function
25    Rotate in Allmendinger et al. (2012)
26    '''
27
28    # Allocate some arrays
29    a = np.zeros((3,3)) #'Transformation matrix
30    pole = np.zeros(3) #'Direction cosines of rotation axis
31    plotr = np.zeros(3) #'Direction cosines of rotated vector
32    temp = np.zeros(3) #'Direction cosines of unrotated
33    vector
34
35
36    # Convert rotation axis to direction cosines. Note that
37    # the
38    # convention here is X1 = North, X2 = East, X3 = Down
39    pole[1] , pole[2] , pole[3] = SphToCart(rtrd,rplg,0)
40
41
42    # Calculate the transformation matrix a for the rotation
43    # Eq. 5.17
44    x = 1.0 - np.cos(rot)
45    sinRot = np.sin(rot)
46    cosRot = np.cos(rot)
47    a[1,1] = cosRot + pole[1]*pole[1]*x
48    a[1,2] = -pole[3]*sinRot + pole[1]*pole[2]*x
49    a[1,3] = pole[2]*sinRot + pole[1]*pole[3]*x
50    a[2,1] = pole[3]*sinRot + pole[2]*pole[1]*x
51    a[2,2] = cosRot + pole[2]*pole[2]*x

```

```

46     a[2,3] = -pole[1]*sinRot + pole[2]*pole[3]*x
47     a[3,1] = -pole[2]*sinRot + pole[3]*pole[1]*x
48     a[3,2] = pole[1]*sinRot + pole[3]*pole[2]*x
49     a[3,3] = cosRot + pole[3]*pole[3]*x
50
51
52 # Convert trend and plunge of vector to be rotated into
53 # direction cosines
54 temp[1], temp[2], temp[3] = SphToCart(trd, plg, 0)
55
56 # Perform the coordinate transformation
57 for i in range(0,3,1):
58     plotr[i] = 0.0
59     for j in range(0,3,1):
60         plotr[i] = a[i,j]*temp[j] + plotr[i]
61
62 # Convert to lower hemisphere projection if data are
63 # axes (ans0 = 'a')
64 if plotr[3] < 0.0 and ans0 == 'a' :
65     plotr[1] = -plotr[1]
66     plotr[2] = -plotr[2]
67     plotr[3] = -plotr[3]
68
69 # Convert from direction cosines back to trend and plunge
70 rtrd, rplg = CartToSph(plotr[1], plotr[2], plotr[3])
71
72 return rtrd, rplg

```

The notebook ch4-5.ipynb below 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 from Pole import Pole as Pole
5 from Rotate import Rotate as Rotate
6 from ZeroTwoPi import ZeroTwoPi as ZeroTwoPi
7

```

```

8 # Strike and dip of bed in radians
9 strike = 305*pi/180
10 dip = 60*pi/180
11
12 # Pole of bed
13 rtrd, rplg = Pole(strike, dip, 1)
14
15 # To find the orientation of the lineations
16 # rotate the strike line clockwise about the
17 # pole an amount equal to the pitch
18
19 # strike line
20 trd = strike
21 plg = 0
22
23 # rotation = pitch in radians
24 rot = 60 * pi/180
25
26 # orientation of lineations
27 trdr, plgr = Rotate(rtrd,rplg,rot,trd,plg,'a')
28
29 # Now we need to rotate the lineations about
30 # the strike line to their pre-tilted orientation
31
32 # The bed is overturned, so it has been rotated
33 # pass the vertical. The amount of rotation
34 # required to restore the bed to its pre-tilted
35 # orientation is 180- 60 = 120 deg, and it
36 # should be clockwise
37 rot = 120 * pi/180 # rotation in radians
38
39 # rotate lineations to their pre-tilted orientation
40 trdl, plgl = Rotate(trd,plg,rot,trdr,plgr,'a')
41
42 # The current flows up the plunge,
43 # so the trend of the paleocurrents is:
44 trdl = ZeroTwoPi(trdl + pi)
45 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 on stereonets

## 5.3 Exercises

### References