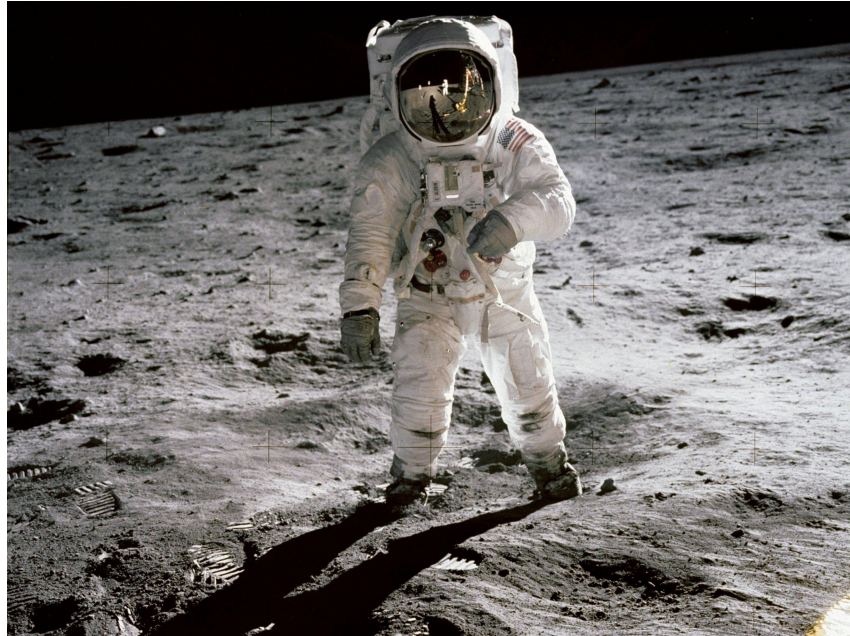


# Labs for Foundations of Applied Mathematics

Volume II: Algorithm Design and Optimization





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# Preface

This lab manual is designed to accompany the textbook *Foundations of Applied Mathematics* by Humpherys and Jarvis.

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**Part I**

**Labs**



## Lab 1

# Data Structures I: Linked Lists

**Lab Objective:** *Analyzing and manipulating data are essential skills in scientific computing. Storing, retrieving, and rearranging data take time. As a dataset grows, so does the amount of time it takes to access and analyze it. To write efficient algorithms involving large data sets, it is therefore essential to be able to design or choose the data structures that are most optimal for a particular problem. In this lab we begin our study of data structures by constructing a generic linked list, then using it to implement a few common data structures.*

## Introduction

*Data structures* are specialized objects for organizing data efficiently. There are many kinds, each with specific strengths and weaknesses, and different applications require different structures for optimal performance. For example, some data structures take a long time to build, but once built their data are quickly accessible. Others are built quickly, but are not as efficiently accessible. These strengths and weaknesses are determined by how the structure is implemented.

Python has several built-in data structure classes, namely `list`, `set`, `dict`, and `tuple`. Being able to use these structures is important, but selecting the correct data structure to begin with is often what makes or breaks a good program. In this lab we create a structure that mimics the built-in list class, but that has a different underlying implementation. Thus our class will be better than a plain Python list for some tasks, but worse for others.

## Nodes

Think of data as several types of objects that need to be stored in a warehouse. A *node* is like a standard size box that can hold all the different types of objects. For example, suppose a particular warehouse stores lamps of various sizes. Rather than trying to carefully stack lamps of different shapes on top of each other, it is preferable to first put them in boxes of standard size. Then adding new boxes and retrieving stored ones becomes much easier. A *data structure* is like the warehouse, which specifies where and how the different boxes are stored.

A node class is usually simple. The data in the node is stored as an attribute. Other attributes may be added (or inherited) specific to a particular data structure.

**Problem 1.** Consider the following generic node class.

```
class Node(object):
    """A basic node class for storing data."""
    def __init__(self, data):
        """Store 'data' in the 'value' attribute."""
        self.value = data
```

Modify the constructor so that it only accepts data of type `int`, `long`, `float`, or `str` (comparable types). If another type of data is given, raise a `TypeError` with an appropriate error message. Modify the constructor docstring to document these restrictions.

#### NOTE

Often the data stored in a node is actually a *key* value. The key might be a memory address, a dictionary key, or the index of an array where the true desired information resides. For simplicity, in this and the following lab we store actual data in node objects, not references to data located elsewhere.

## Linked Lists

A *linked list* is a data structure that chains nodes together. Every linked list needs a reference to the first node in the chain, called the `head`. A reference to the last node in the chain, called the `tail`, is also often included. Each node instance in the list stores a piece of data, plus at least one reference to another node in the list.

The nodes of a *singly linked list* have a single reference to the next node in the list (see Figure 1.1), while the nodes of a *doubly linked list* have two references: one for the previous node, and one for the next node in the list (see Figure 1.2). This allows for a doubly linked list to be traversed in both directions, whereas a singly linked list can only be traversed in one direction.

```
class LinkedListNode(Node):
    """A node class for doubly linked lists. Inherits from the 'Node' class.
    Contains references to the next and previous nodes in the linked list.
    """
    def __init__(self, data):
        """Store 'data' in the 'value' attribute and initialize
        attributes for the next and previous nodes in the list.
        """
        Node.__init__(self, data)      # Use inheritance to set self.value.
        self.next = None
        self.prev = None
```

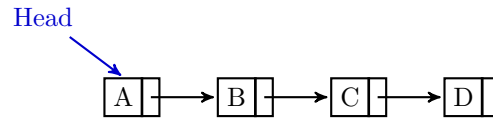


Figure 1.1: A singly linked list. Each node has a reference to the next node in the list. The head attribute is always assigned to the first node.

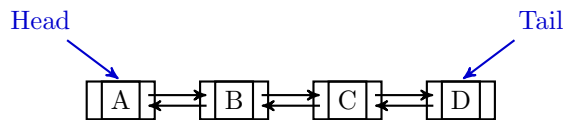


Figure 1.2: A doubly linked list. Each node has a reference to the node before it and a reference to the node after it. In addition to the head attribute, this list has a tail attribute that is always assigned to the last node.

Now we create a new class, `LinkedList`, that will link `LinkedListNode` instances together by modifying each node's `next` and `prev` attributes. The list is empty initially, so we assign the `head` and `tail` attributes the placeholder value `None`.

We also need a method for adding data to the list. The `append()` makes a new node and adds it to the very end of the list. There are two cases to consider: appending to an empty list, and appending to a nonempty list. See Figure 1.3.

```
class LinkedList(object):
    """Doubly linked list data structure class.

    Attributes:
        head (LinkedListNode): the first node in the list.
        tail (LinkedListNode): the last node in the list.
    """
    def __init__(self):
        """Initialize the 'head' and 'tail' attributes by setting
        them to 'None', since the list is empty initially.
        """
        self.head = None
        self.tail = None

    def append(self, data):
        """Append a new node containing 'data' to the end of the list."""
        # Create a new node to store the input data.
        new_node = LinkedListNode(data)
        if self.head is None:
            # If the list is empty, assign the head and tail attributes to
            # new_node, since it becomes the first and last node in the list.
            self.head = new_node
            self.tail = new_node
        else:
            # If the list is not empty, place new_node after the tail.
            self.tail.next = new_node          # tail --> new_node
            new_node.prev = self.tail          # tail <-- new_node
            # Now the last node in the list is new_node, so reassign the tail.
            self.tail = new_node
```



Figure 1.3: Appending a new node to the end of a nonempty doubly linked list. The red arrows are the new connections. Note that the `tail` attribute is adjusted.

### ACHTUNG!

The `is` comparison operator is **not** the same as the `==` comparison operator. While `==` checks for numerical equality, `is` evaluates whether or not two objects are at the same location in memory.

```
# This comparison evaluates to True since the numerical values are the same.
>>> 7 == 7.0
True

# 7 is an int and 7.0 is a float, so they cannot be stored at the same
# location in memory. Therefore 7 'is not' 7.0.
>>> 7 is 7.0
False
```

For numerical comparisons, always use `==`. When comparing to built-in Python constants such as `None`, `True`, `False`, or `NotImplemented`, use `is` instead.

## find()

The `LinkedList` class only explicitly keeps track of the first and last nodes in the list via the `head` and `tail` attributes. To access any other node, we must use each successive node's `next` and `prev` attributes.

```
>>> my_list = LinkedList()
>>> my_list.append(2)
>>> my_list.append(4)
>>> my_list.append(6)

# To access each value, we use the 'head' attribute of the LinkedList
# and the 'next' and 'value' attributes of each node in the list.
>>> my_list.head.value
2
>>> my_list.head.next.value
4
>>> my_list.head.next.next.value
6
>>> my_list.head.next.next is my_list.tail
True
>>> my_list.tail.prev.prev is my_list.head
True
```

**Problem 2.** Add a method called `find(self, data)` to the `LinkedList` class that returns the first node in the list containing `data` (return the actual `LinkedListNode` object, not its `value`). If no such node exists, or if the list is empty, raise a `ValueError` with an appropriate error message. (Hint: if `current` is assigned to one of the nodes the list, what does the following line do?)

```
current = current.next
```

## Magic Methods

Endowing data structures with magic methods makes it much easier to use it intuitively. Consider, for example, how a Python list responds to built-in functions like `len()`. At the bare minimum, we should give our linked list the same functionality.

**Problem 3.** Add magic methods to the `LinkedList` class so it behaves more like the built-in Python list.

1. Write the `__len__()` method so that the length of a `LinkedList` instance is equal to the number of nodes in the list. To accomplish this, consider adding an attribute that tracks the current size of the list. It should be updated every time a node is successfully added or removed.
2. Write the `__str__()` method so that when a `LinkedList` instance is printed, its output matches that of a Python list. Entries are separated by a comma and one space, and strings are surrounded by single quotes. Note the difference between the string representations of the following lists:

```
>>> num_list = [1, 2, 3]
>>> str_list = ['1', '2', '3']
>>> print(num_list)
[1, 2, 3]
>>> print(str_list)
['1', '2', '3']
```

## remove()

In addition to adding new nodes to the end of a list, it is also useful to remove nodes and insert new nodes at specified locations. To delete a node, all references to the node must be removed. Then Python will automatically delete the object, since there is no way for the user to access it. Naïvely, this might be done by finding the previous node to the one being removed, and setting its `next` attribute to `None`.

```
class LinkedList(object):
    # ...
    def remove(self, data):
        """Attempt to remove the first node containing 'data'.
        This method incorrectly removes additional nodes.
        """
        # Find the target node and sever the links pointing to it.
        target = self.find(data)
        target.prev.next = None           # -/-> target
        target.next.prev = None          # target <-/-
```

Removing all references to the target node will delete the node (see Figure 1.4). However, the nodes before and after the target node are no longer linked.

```
>>> my_list = LinkedList()
>>> for i in xrange(10):
...     my_list.append(i)
...
>>> print(my_list)
[0, 1, 2, 3, 4, 5, 6, 7, 8, 9]

>>> my_list.remove(4)           # Removing a node improperly results in
>>> print(my_list)              # the rest of the chain being lost.
[0, 1, 2, 3]                   # Should be [0, 1, 2, 3, 5, 6, 7, 8, 9].
```



Figure 1.4: Naïve Removal for Doubly linked Lists. Deleting all references pointing to *C* deletes the node, but it also separates nodes *A* and *B* from node *D*.

This can be remedied by pointing the previous node's `next` attribute to the node after the deleted node, and similarly changing that node's `prev` attribute. Then there will be no reference to the removed node and it will be deleted, but the chain will still be connected.



Figure 1.5: Correct Removal for Doubly linked Lists. To avoid gaps in the chain, nodes *B* and *D* must be linked together.

**Problem 4.** Modify the `remove()` method given above so that it correctly removes the first node in the list containing the specified data. Account for the special cases of removing the first, last, or only node.



**ACHTUNG!**

Python keeps track of the variables in use and automatically deletes a variable if there is no access to it. In many other languages, leaving a reference to an object without explicitly deleting it could cause a serious memory leak. See <https://docs.python.org/2/library/gc.html> for more information on Python's auto-cleanup system.

**insert()**

**Problem 5.** Add a method called `insert(self, data, place)` to the `LinkedList` class that inserts a new node containing `data` immediately before the first node in the list containing `place`. Account for the special case of inserting before the first node.

See Figure 1.6 for an illustration. Note that since `insert()` places a new node before an existing node, it is not possible to use `insert()` to put a new node at the end of the list or in an empty list (use `append()` instead).

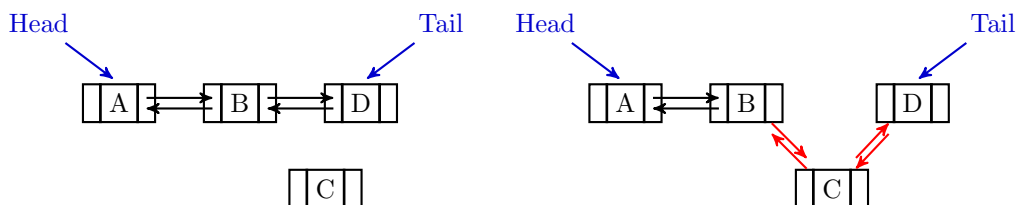


Figure 1.6: Insertion for Doubly linked Lists.

**NOTE**

The temporal complexity for inserting to the beginning or end of a linked list is  $O(1)$ , but inserting anywhere else is  $O(n)$ , where  $n$  is the number of nodes in the list. This is quite slow compared other data structures. In the next lab we turn our attention to *trees*, special kinds of linked lists that allow for much quicker sorting and data retrieval.

**Restricted-Access Lists**

It is sometimes wise to restrict the user's access to the some of the data within a structure. The three most common and basic restricted-access structures are *stacks*, *queues*, and *dequeues*. Each structure restricts the user's access differently, making them ideal for different situations.

- **Stack:** *Last In, First Out* (LIFO). Only the last item that was inserted can be accessed. A stack is like a pile of plates: the last plate put on the pile is (or should be) the first one to be taken off. Stacks usually have two main methods: `push()`, to insert new data, and `pop()`, to remove and return the last piece of data inserted.
- **Queue** (pronounced “cue”): *First In, First Out* (FIFO). New nodes are added to the end of the queue, but an existing node can only be removed or accessed if it is at the front of the queue. A queue is like a line at the bank: the person at the front of the line is served next, while newcomers add themselves to the back of the line. Queues also usually have a `push()` and a `pop()` method, but `push()` inserts data to the end of the queue while `pop()` removes and returns the data at the front of the queue.<sup>1</sup>
- **Deque** (pronounced “deck”): a double-ended queue. Data can be inserted or removed from either end, but data in the middle is inaccessible. A deque is like a deck of cards, where only the top and bottom cards are readily accessible. A deque has two methods for insertion and two for removal, usually called `append()`, `appendleft()`, `pop()`, and `popleft()`.

**Problem 6.** Write a `Deque` class that inherits from the `LinkedList` class.

1. Use inheritance to implement the following methods:

- `pop(self)`: Remove the last node in the list and return its data.
- `popleft(self)`: Remove the first node in the list and return its data.
- `appendleft(self, data)`: Insert a new node containing `data` at the beginning of the list.

The `LinkedList` class already implements the `append()` method.

2. Override the `remove()` method with the following:

```
def remove(*args, **kwargs):  
    raise NotImplementedError("Use pop() or popleft() for removal")
```

This effectively disables `remove()` for the `Deque` class, preventing the user from removing a node from the middle of the list.

3. Disable the `insert()` method as well.

---

<sup>1</sup>`push()` and `pop()` for queues are sometimes called `enqueue()` and `dequeue()`, respectively)

**NOTE**

The `*args` argument allows the `remove()` method to receive any number of positional arguments without raising a `TypeError`, and the `**kwargs` argument allows it to receive any number of keyword arguments. This is the most general form of a function signature.

Python lists have `append()` and `pop()` methods, so they can be used as stacks. However, data access and removal from the front is much slower, as Python lists are not implemented as linked lists.

The `collections` module in the standard library has a `deque` object, implemented as a doubly linked list. This is an excellent object to use in practice instead of a Python list when speed is of the essence and data only needs to be accessed from the ends of the list.

**Problem 7.** Write a function that accepts the name of a file to be read and a file to write to. Read the first file, adding each line to the end of a deque. After reading the entire file, pop each entry off of the end of the deque one at a time, writing the result to a line of the second file.

For example, if the file to be read has the list of words on the left, the resulting file should have the list of words on the right.

My homework is too hard for me.	I am a mathematician.
I do not believe that	Programming is hard, but
I can solve these problems	I can solve these problems
Programming is hard, but	I do not believe that
I am a mathematician.	My homework is too hard for me.

You may use a Python list, your `Deque` class, or `collections.deque` for the deque. Test your function on the file `english.txt`, which contains a list of over 58,000 English words in alphabetical order.

## Additional Material

### Improvements to the Linked List Class

1. Add a keyword argument to the constructor so that if an iterable is input, each element of the iterable is immediately added to the list. This makes it possible to cast an iterable as a `LinkedList` the same way that an iterable can be cast as one of Python's standard data structures.

```
>>> my_list = [1, 2, 3, 4, 5]
>>> my_linked_list = LinkedList(my_list)    # Cast my_list as a LinkedList.
>>> print(my_linked_list)
[1, 2, 3, 4, 5]
```

2. Add new methods:
  - `count()`: return the number of occurrences of a specified value.
  - `reverse()`: reverse the ordering of the nodes (in place).
  - `rotate()`: rotate the nodes a given number of steps to the right (in place).
  - `sort()`: sort the nodes by their data (in place).
3. Implement more magic methods:
  - `__max__()`: return the greatest element.
  - `__min__()`: return the least element.
  - `__getitem__()` and `__setitem__()`: enable standard bracket indexing.
  - `__iter__()`: support `for` loop iteration, the `iter()` built-in function, and the `in` statement.

### Other Linked List

The `LinkedList` class can also be used as the backbone for other data structures.

1. A *sorted list* adds new nodes strategically so that the data is always kept in order. A `SortedLinkedList` class that inherits from the `LinkedList` class should have a method called `add(self, data)` that inserts a new node containing `data` before the first node in the list that has a `value` that is greater or equal to `data` (thereby preserving the ordering). Other methods for adding nodes should be disabled.

A linked list is **not** an ideal implementation for a sorted list (try sorting `english.txt`).

2. In a *circular linked list*, the “last” node connects back to the “first” node. Thus a reference to the tail is unnecessary.

## Lab 2

# Data Structures II: Trees

**Lab Objective:** A Tree is a linked list where each node in the list may refer to more than one other node. This structural flexibility makes trees more useful and efficient than regular linked lists in many applications. Many trees are most easily constructed recursively, so we begin with an overview of recursion. We then implement a recursively structured doubly linked Binary Search Tree. Finally, we compare the standard linked list, our Binary Search Tree, and an AVL tree to illustrate the relative strengths and weaknesses of each structure.

## Recursion

A *recursive* function is one that calls itself. When the function is executed, it continues calling itself until it reaches a specified *base case* where the solution to the problem is known. The function then exits without calling itself again, and each previous function call is resolved.

As a simple example, consider the function that sums all positive integers from 1 to some integer  $n$ . This function may be represented recursively:

$$f(n) = \sum_{i=1}^n i = n + \sum_{i=1}^{n-1} i = n + f(n-1)$$

$f(n)$  may be calculated by recursively calculating  $f(n-1)$ , which calculates  $f(n-2)$ , and so on. The recursion halts with the base case  $f(1) = 1$ .

```
def recursive_sum(n):  
    """Calculate the sum of all positive integers in [1, n] recursively."""  
    # Base Case: the sum of all positive integers in [1, 1] is 1.  
    if n == 1:  
        return 1  
  
    # If the base case hasn't been reached, the function recurses by calling  
    # itself on the next smallest integer. The result of that call, plus the  
    # particular 'n' from this call, gives the result.  
    else:  
        return n + recursive_sum(n-1)
```

The computer calculates `recursive_sum(5)` with a sequence of function calls.

```
# To find the recursive_sum(5), calculate recursive_sum(4).
# But to find recursive_sum(4), calculate recursive_sum(3).
# This continues until the base case is reached.

recursive_sum(5)      # return 5 + recursive_sum(4)
  recursive_sum(4)      # return 4 + recursive_sum(3)
    recursive_sum(3)    # return 3 + recursive_sum(2)
      recursive_sum(2)  # return 2 + recursive_sum(1)
        recursive_sum(1) # Base case: return 1.
```

Substituting the values that resulted from each call unwinds the recursion.

```
recursive_sum(5)      # return 5 + 10
  recursive_sum(4)      # return 4 + 6
    recursive_sum(3)    # return 3 + 3
      recursive_sum(2)  # return 2 + 1
        recursive_sum(1) # Base case: return 1.
```

So `recursive_sum(5)` returns 15 (which is correct, since  $1 + 2 + 3 + 4 + 5 = 15$ ).

Many problems that can be solved by iterative methods can also be solved (often more intuitively) with a recursive approach. Consider the function  $g : \mathbb{N} \rightarrow \mathbb{N}$  that calculates the  $n^{\text{th}}$  Fibonacci number:

$$g(n) = g(n-1) + g(n-2), \quad g(0) = 0, \quad g(1) = 1$$

The mathematical function itself is defined recursively, so it makes sense for an implementation to use recursion. Compare the following iterative method implementing  $g$  to its recursive equivalent.

```
def iterative_fib(n):
    """Calculate the nth Fibonacci number iteratively."""
    fibonacci = []          # Initialize an empty list.
    fibonacci.append(0)     # Append 0 (the 0th Fibonacci number).
    fibonacci.append(1)     # Append 1 (the 1st Fibonacci number).
    for i in range(1, n):
        # Starting at the third entry, calculate the next number
        # by adding the last two entries in the list.
        fibonacci.append(fibonacci[-1] + fibonacci[-2])
    # When the entire list has been loaded, return the nth entry.
    return fibonacci[n]

def recursive_fib(n):
    """Calculate the nth Fibonacci number recursively."""
    # The base cases are the first two Fibonacci numbers.
    if n == 0:              # Base case 1: the 0th Fibonacci number is 0.
        return 0
    elif n == 1:            # Base case 2: the 1st Fibonacci number is 1.
        return 1
    # If this call isn't a base case, the function recurses by calling
    # itself to calculate the previous two Fibonacci numbers.
    else:
        return recursive_fib(n-1) + recursive_fib(n-2)
```

This time, the sequence of function calls is slightly more complicated because `recursive_fib()` calls itself twice at each step.

```

recursive_fib(5)      # The original call makes two additional calls:
    recursive_fib(4)      # this one...
        recursive_fib(3)
            recursive_fib(2)
                recursive_fib(1)      # Base case 2: return 1
                recursive_fib(0)      # Base case 1: return 0
            recursive_fib(1)      # Base case 2: return 1
        recursive_fib(2)
            recursive_fib(1)      # Base case 2: return 1
            recursive_fib(0)      # Base case 1: return 0
    recursive_fib(3)      # ...and this one.
        recursive_fib(2)
            recursive_fib(1)      # Base case 2: return 1
            recursive_fib(0)      # Base case 1: return 0
        recursive_fib(1)      # Base case 2: return 1

```

The sum of all of the base case results, from top to bottom, is  $1 + 0 + 1 + 1 + 0 + 1 + 0 + 1 = 5$ , so `recursive_fib(5)` returns 5 (correctly). The key to recursion is understanding the base cases correctly and making correct recursive calls.

**Problem 1.** The following code defines a simple class for singly linked lists.

```

class SinglyLinkedListNode(object):
    """Simple singly linked list node."""
    def __init__(self, data):
        self.value, self.next = data, None

class SinglyLinkedList(object):
    """A very simple singly linked list with a head and a tail."""
    def __init__(self):
        self.head, self.tail = None, None
    def append(self, data):
        """Add a Node containing 'data' to the end of the list."""
        n = SinglyLinkedListNode(data)
        if self.head is None:
            self.head, self.tail = n, n
        else:
            self.tail.next = n
            self.tail = n

```

Rewrite the following iterative function for finding data in a linked list using recursion. Use instances of the `SinglyLinkedList` class to test your function.

```

def iterative_search(linkedlist, data):
    """Search 'linkedlist' iteratively for a node containing 'data'."""
    current = linkedlist.head
    while current is not None:
        if current.value == data:
            return current
        current = current.next
    raise ValueError(str(data) + " is not in the list.")

```

(Hint: define an inner function to perform the actual recursion.)

**ACHTUNG!**

It is **not** usually better to rewrite an iterative method recursively. In Python, a function may only call itself 999 times. On the 1000<sup>th</sup> call, a `RuntimeError` is raised to prevent a stack overflow. Whether or not recursion is appropriate depends on the problem to be solved and the algorithm used to solve it.

## Trees

A *tree* data structure is a specialized linked list. Trees are more difficult to build than standard linked lists, but they are almost always more efficient. While the computational complexity of finding a node in a linked list is  $O(n)$ , a well-built, balanced tree will find a node with a complexity of  $O(\log n)$ . Some types of trees can be constructed quickly but take longer to retrieve data, while others take more time to build and less time to retrieve data.

The first node in a tree is called the *root*. The root node points to other nodes, called children. Each child node in turn points to its children. This continues on each branch until its end is reached. A node with no children is called a *leaf node*.

Mathematically, a tree is a directed graph with no cycles. Therefore a linked lists as a graph qualifies as a tree, albeit a boring one. The head node is the root node, and it has one child node. That child node also has one child node, which in turn has one child. The last node in the list is the only leaf node.

Other kinds of trees may be more complicated.

## Binary Search Trees

A *binary search tree* (BST) data structure is a tree that allows each node to have up to two children, usually called `left` and `right`. The left child of a node contains data that is less than its parent node's data. The right child's data is greater.

The tree on the right in Figure 2.1 is an example of a of binary search tree. In practice, binary search tree nodes have attributes that keep track of their data, their children, and (in doubly linked trees) their parent.

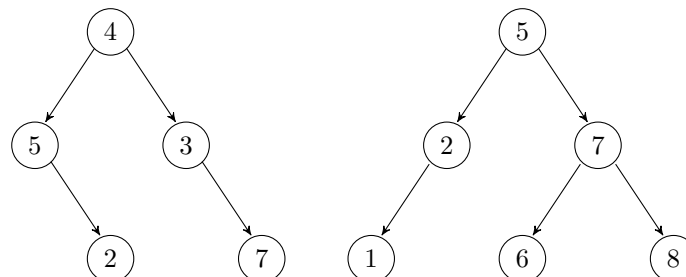


Figure 2.1: Both of these graphs are trees, but only the tree on the right is a binary search tree. How could the graph on the left be altered to make it a BST?



```

class BSTNode(object):
    """A Node class for Binary Search Trees. Contains some data, a
    reference to the parent node, and references to two child nodes.
    """
    def __init__(self, data):
        """Construct a new node and set the data attribute. The other
        attributes will be set when the node is added to a tree.
        """
        self.value = data
        self.prev = None      # A reference to this node's parent node.
        self.left = None     # This node's value will be less than self.value
        self.right = None    # This node's value will be greater than self.value

```

The actual binary search tree class has an attribute pointing to its root.

```

class BST(object):
    """Binary Search Tree data structure class.
    The 'root' attribute references the first node in the tree.
    """
    def __init__(self):
        """Initialize the root attribute."""
        self.root = None

```

## find()

Finding a node in a binary search tree can be done recursively. Starting at the root, check if the target data matches the current node. If it does not, then if the data is less than the current node's value, search again on the left child. If the data is greater, search on the right child. Continue the process until the data is found or, if the data is not in the tree, an empty child is searched.

```

class BST(object):
    # ...
    def find(self, data):
        """Return the node containing 'data'. If there is no such node
        in the tree, or if the tree is empty, raise a ValueError.
        """

        # Define a recursive function to traverse the tree.
        def _step(current):
            """Recursively step through the tree until the node containing
            'data' is found. If there is no such node, raise a Value Error.
            """
            if current is None:                # Base case 1: dead end.
                raise ValueError(str(data) + " is not in the tree.")
            if data == current.value:         # Base case 2: data found!
                return current
            if data < current.value:          # Recursively search left.
                return _step(current.left)
            else:                             # Recursively search right.
                return _step(current.right)

        # Start the recursion on the root of the tree.
        return _step(self.root)

```

**NOTE**

Conceptually, each node of a BST partitions the data of its subtree into two halves: the data that is less than the parent, and the data that is greater. We will extend this concept to higher dimensions in the next lab.

**insert()**

To insert new data into a binary search tree, add a leaf node at the correct location. First, find the node that should be the parent of the new node. This parent node is found recursively, using a similar approach to the `find()` method. Then the new node is added as the left or right child of the parent. See Figure 2.2.

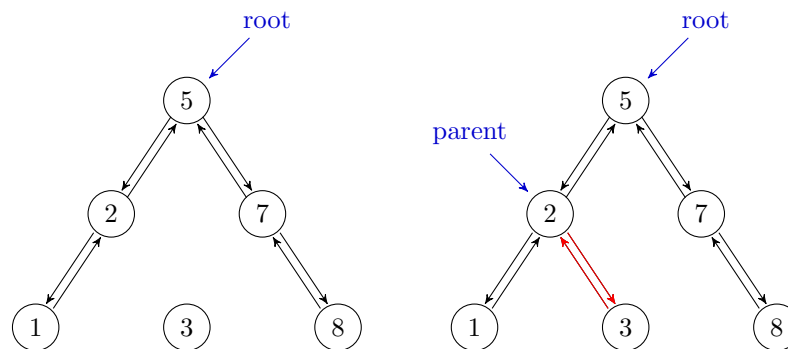


Figure 2.2: To insert a node containing 3 to the BST on the left, start at the root and recurse down the tree to find the node that should be 3's parent. Connect that parent to the child, then the child to its new parent.

**Problem 2.** Implement the `insert()` method in the `BST` class.

1. Find the parent of the new node. Consider writing a recursive method, similar to `find()`, to do this. Determine whether the new node will be the parent's left or right child, then double-link the parent and the new child.
2. Do not allow for duplicates in the tree. Raise a `ValueError` if there is already a node in the tree containing the input data.

Be sure to consider the special case of inserting to an empty tree. To test your tree, use (but do not modify) the provided `BST.__str__()` method.

---

## **remove()**

Deleting nodes from a binary search tree is more difficult than finding or inserting. Insertion always creates a new leaf node, but removal may delete any kind of node. This leads to several different cases to consider.

### **Removing a Leaf Node**

In Python, an object is automatically deleted if there are no references to it. Call the node to be removed the *target node*, and suppose it has no children. To remove the target, find the target's parent, then delete the parent's reference to the target. Then there are no references to the target, so the target node is deleted. Since the target is a leaf node, removing it does not affect the rest of the tree structure.

### **Removing a Node with One Child**

If the target node has one or more children, be careful not to delete the children when the target is removed. Simply removing the target as if it were a leaf node would delete the entire subtree originating from the target.

To avoid deleting all of the target's descendents, point the target's parent to an appropriate successor. If the target has only one child, then that child is the successor. Connect the target's parent to the successor, and double-link by setting the successor's parent to be the target node's parent. Then, since the target has no references pointing to it, it is deleted. The target's successor, however, is pointed to by the target's parent, and so it remains in the tree.

### **Removing a Node with Two Children**

Removal is more complicated if the target node has two children. To delete this kind of node, first find its immediate in-order successor. This successor is the node with the smallest value that is larger than the target's value. It may be found by moving to the right child of the target (so that its value is greater than the target's value), and then to the left for as long as possible (so that it has the smallest such value). Note that because of how the successor is chosen, any in-order successor can only have at most one child.

Once the successor is found, the target and its successor must switch places in the graph, and then the target must be removed. This can be done by simply switching the values for the target and its successor. Then the node with the target data has at most one child, and may be deleted accordingly. If the successor was chosen appropriately, then the binary search tree structure and ordering will be maintained once the deletion is finished.

The easiest way to implement this is to use recursion. First, because the successor has at most one child, remove the successor node recursively by calling `remove()` on the successor's value. Then set the data stored in the target node as the successor's value. See Figure 2.3.

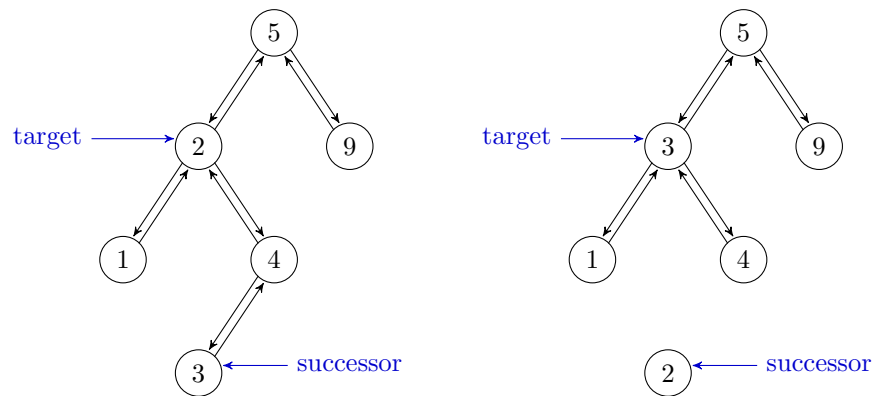


Figure 2.3: To remove the node containing 2 from the top left BST, locate the target and its in-order successor. Delete the successor, recording its value. Finally, replace the data in the target with the data that was in the successor.

### Removing the Root Node

In each of the above cases, we must also consider the subcase where the target is the root node. If the root has no children, resetting the root or calling the constructor will do. If the root has one child, that child becomes the new root of the tree. If the root has two children, the successor becomes the new root of the tree.

**Problem 3.** Implement the `remove()` method in the `BST` class. If the tree is empty, or if the target node is not in the tree, raise a `ValueError`. Test your solutions thoroughly, accounting for all possible cases:

1. The tree is empty (`ValueError`).
2. The target is not in the tree (`ValueError`).
3. The target is the root node:
  - (a) the root is a leaf node, hence the only node in the tree.
  - (b) the root has one child.
  - (c) the root has two children.
4. The target is in the tree but is not the root:
  - (a) the target is a leaf node.
  - (b) the target has one child.
  - (c) the target has two children.

(Hints: **Before coding anything**, outline the entire function with comments and `if-else` blocks. Use the `find()` method wherever appropriate.)

## AVL Trees

Binary search trees are a good way of organizing data so that it is quickly accessible. However, pathologies may arise when certain data sets are stored using a basic binary search tree. This is best demonstrated by inserting ordered data into a binary search tree. Since the data is already ordered, each node will only have one child, and the result is essentially a linked list.

```
# Sequentially adding ordered integers destroys the efficiency of a BST.
>>> unbalanced_tree = BST()
>>> for i in range(10):
...     unbalanced_tree.insert(i)
...
# The tree is perfectly flat, so it loses its search efficiency.
>>> print(unbalanced_tree)
[0]
[1]
[2]
[3]
[4]
[5]
[6]
[7]
[8]
[9]
```

Problems also arise when one branch of the tree becomes much longer than the others, leading to longer search times.

An *AVL tree* (named after Georgy Adelson-Velsky and Evgenii Landis) is a tree that prevents any one branch from getting longer than the others. It accomplishes this by recursively “balancing” the branches as nodes are added. See Figure 2.4. The AVL’s balancing algorithm is beyond the scope of this project, but details and exercises on the algorithm can be found in Chapter 2 of the Volume II text.

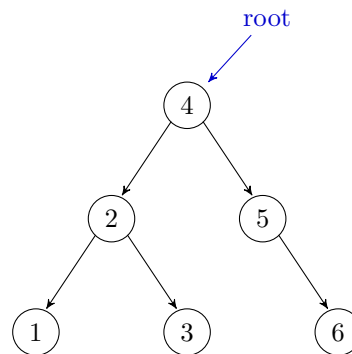


Figure 2.4: The balanced AVL tree resulting from inserting 1, 2, 3, 4, 5, and 6, in that order. After each insertion the tree rebalances if necessary.

```
>>> balanced_tree = AVL()
>>> for i in range(10):
...     balanced_tree.insert(i)
...
# The AVL tree is balanced, so it retains (and optimizes) its search efficiency.
>>> print(balanced_tree)
[3]
[1, 7]
[0, 2, 5, 8]
[4, 6, 9]
```

**Problem 4.** Write a function to compare the build and search times of the data structures we have implemented so far.

Read the file `english.txt`, adding the contents of each line to a list of data. For various values of  $n$ , repeat the following:

1. Get a subset of  $n$  **random** items from the data set.  
(Hint: use a function from the `random` or `np.random` modules.)
2. Time (separately) how long it takes to load a new `SinglyLinkedList`, a BST, and an AVL with the  $n$  items.
3. Choose 5 **random** items from the subset, and time how long it takes to find all 5 items in each data structure. Use the `find()` method for the trees, but to avoid exceeding the maximum recursion depth, use the provided `iterative_search()` function from Problem 1 to search the `SinglyLinkedList`.

Report your findings in a single figure with two subplots: one for build times, and one for search times. Use log scales if appropriate.

## Conclusion

Every data structure has advantages and disadvantages. Recognizing when an application may take advantage of a certain structure, especially when that structure is more complicated than a Python list or set, is an important skill. Choosing structures wisely often results in huge speedups and easier data maintenance.

---

## Additional Material

### Improvements to the BST

The following are a few ideas for improving the `BST` class.

1. Add a keyword argument to the constructor so that if an iterable is input, each element of the iterable is immediately added to the tree. This makes it possible to cast other iterables as a `BST`, like Python's standard data structures.
2. Add an attribute that keeps track of the number of items in the tree. Use this attribute to implement the `__len__()` magic method.
3. Add a method for translating the `BST` into a sorted Python list using a depth-first search.  
(Hint: examine the provided `__str__()` method carefully.)

### Other Trees

There are many variations on the Binary Search Tree, each with its own advantages and disadvantages. Consider writing classes for the following structures.

1. A *B-Tree* is a tree whose nodes can contain more than one piece of data and point to more than one other node. See Chapter 2 of the Volume II text for details.
2. The nodes of a *Red-Black Tree* are labeled either red or black. The tree satisfies the following rules.
  - (a) Every leaf node is black.
  - (b) Red nodes only have black children.
  - (c) Every (directed) path from a node to any of its descendent leaf nodes contains the same number of black nodes.

When a node is added that violates one of these constraints, the tree is rebalanced and recolored.

3. A *Splay Tree* includes an additional operation, called splaying, that makes a specified node the root of the tree. Splaying several nodes of interest makes them easier to access because they will be close to the root.





## Lab 3

# Data Structures III: K-D Trees

**Lab Objective:** *Nearest neighbor search is an optimization problem that arises in applications such as computer vision, pattern recognition, internet marketing, and data compression. In this lab we solve the problem efficiently using a k-d tree, then use SciPy's k-d tree to implement a handwriting recognition algorithm.*

## The Nearest Neighbor Search Problem

Suppose you move into a new city with several post offices. Since your time is valuable, you wish to know which post office is closest to your home. This is called the nearest neighbor search problem, and it has many applications.

In general, suppose that  $X$  is a collection of data, called a *training set*. Let  $y$  be any point (often called the *target* point) in the same space as the data in  $X$ . The nearest neighbor search problem determines the point in  $X$  that is closest to  $y$ . For example, in the post office problem the set  $X$  could be addresses or latitude and longitude data for each post office in the city. Then  $y$  would be the data that represents your new home, and the task is to find the closest post office in  $X$  to  $y$ .

**Problem 1.** Roughly speaking, a function that measures distance between two points in a set is called a *metric*.<sup>a</sup> The *euclidean metric* measures the distance between two points in  $\mathbb{R}^n$  with the familiar distance formula:

$$d(\mathbf{x}, \mathbf{y}) = \sqrt{\sum_{i=1}^n (x_i - y_i)^2} = \|\mathbf{x} - \mathbf{y}\|_2$$

Write a function that accepts two 1-dimensional NumPy arrays and returns the euclidean distance between them. Raise a `ValueError` if the arrays don't have the same number of entries.

(Hint: NumPy already has some functions to help do this quickly.)

<sup>a</sup>Metrics and metric spaces are examined in detail in Chapter 5 of Volume I.

Consider again the post office example. One way to find out which post office is closest is to drive from home to each post office, measure the mileage, and then choose the post office that is the closest. This is called an *exhaustive search*. More precisely, we measure the distance of  $y$  to each point in  $X$ , and choose the point with the smallest distance. This method is inefficient however, and only feasible for relatively small training sets.

**Problem 2.** Write a function that solves the nearest neighbor search problem by exhaustively checking all of the distances between a given point and each point in a data set. The function should take in a set of data points (as an  $m \times k$  NumPy array, where each row represents one of the  $m$  points in the data set) and a single target point (as a 1-dimensional NumPy array with  $k$  entries). Return the point in the training set that is closest to the target point and its distance from the target.

The complexity of this algorithm is  $O(mk)$ , where  $k$  is the number of dimensions and  $m$  is the number of data points.

## K-D Trees

A  $k$ - $d$  tree is a special kind of binary search tree for high dimensional data (i.e., more dimensions than 1). While a binary search tree excludes regions of the number line from a search until the search point is found, a  $k$ - $d$  tree works on regions of  $\mathbb{R}^k$ . So long as the data in the tree meets certain dimensionality requirements, similar efficiency gains may be made.

Recall that to search for a point in a binary search tree, we start at the root, and if the point we are searching for is less than the root we proceed down the left branch of the tree. If it is larger, we proceed down the right branch. By doing this, we exclude a region of the number line (and therefore the subtree in the opposite direction) from our search. By eliminating this region from consideration, we have far fewer points to search and the efficiency of our search is greatly increased.

Like a binary search tree, a  $k$ - $d$  tree starts with a root node with a depth, or level, of 0. At the  $i^{th}$  level, the nodes to the left of a parent have a lower value in the  $i^{th}$  dimension. Nodes to the right have a greater value in the  $i^{th}$  dimension. At the next level, we do the same for the next dimension. For example, consider data in  $\mathbb{R}^3$ . The root node partitions the data according to the first dimension. The children of the root partition according to the second dimension, and the grandchildren along the third. See Figure 3.1 for an example in  $\mathbb{R}^2$ .

As with any other data structure, the first task is to construct a node class to store data. A `KDNode` is similar to a `BSTNode`, except it has another attribute called `axis`. The `axis` attribute tells us which dimension of  $\mathbb{R}^k$  to split on.

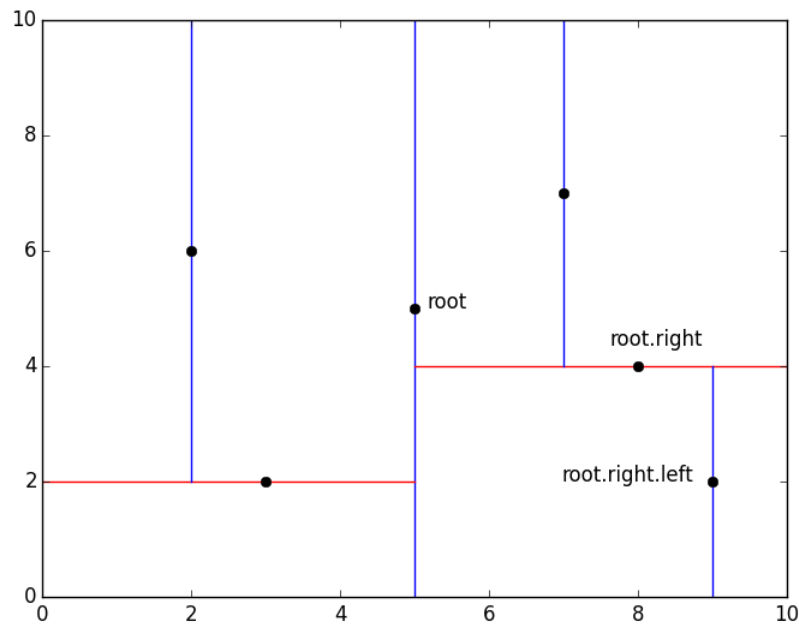


Figure 3.1: A regular binary search tree partitions  $\mathbb{R}$ , but a  $k$ -d tree partitions  $\mathbb{R}^k$ . The above graph illustrates the partition for a  $k$ -d tree loaded with the points (5, 5), (8, 4), (3, 2), (7, 7), (2, 6), and (9, 2), in that order. To find the point (9, 2), we start at the root. Since the  $x$ -coordinate of (9, 2) is greater than the  $x$ -coordinate of (5, 5), we move into the region to the right of the middle blue line, thus excluding all points  $(x, y)$  with  $x < 5$ . Next we compare (9, 2) to the root's right child, (8, 4). Since the  $y$ -coordinate of (9, 2) is less than the  $y$ -coordinate of (8, 4), we move below the red line on the right, thus excluding all points  $(x, y)$  with  $y > 4$ . We have now found (9, 2), since it is the left child of (8, 4).

**Problem 3.** Copy the `BSTNode` class from the previous lab. Write a `KDNode` class that inherits from `BSTNode`.

Modify the constructor so that a `KDNode` can only hold a NumPy array (of type `np.ndarray`). If any other data type is given, raise a `TypeError`. Also create an `axis` attribute (set it to `None` or 0 for now).

The major difference between a  $k$ -d tree and a binary search tree is how the data is compared at each depth level. Though we don't need to use a `find()` method in solving the nearest neighbor problem, we provide the  $k$ -d tree version of `find()` as an instructive example.

In the `find()` method, every comparison in the recursive `_step()` function compares the data of `target` and `current` based on the `axis` attribute of `current`. This way

if each existing node in the tree has the correct `axis`, the correct comparisons are made as we descend through the tree.

```
# Copy or import the BST class from the previous lab.

class KDT(BST):
    """A k-dimensional binary search tree object.
    Used to solve the nearest neighbor problem efficiently.

    Attributes:
        root (KDTNode): the root node of the tree. Like all other
            nodes in the tree, the root houses data as a NumPy array.
        k (int): the dimension of the tree (the 'k' of the k-d tree).
    """

    def find(self, data):
        """Return the node containing 'data'. If there is no such node
        in the tree, or if the tree is empty, raise a ValueError.
        """

        # Define a recursive function to traverse the tree.
        def _step(current):
            """Recursively step through the tree until the node containing
            'data' is found. If there is no such node, raise a Value Error.
            """
            if current is None:
                # Base case 1: dead end.
                raise ValueError(str(data) + " is not in the tree")
            elif np.allclose(data, current.value):
                # Base case 2: data found!
                return current
            elif data[current.axis] < current.value[current.axis]:
                return _step(current.left)
            else:
                return _step(current.right)

        # Start the recursion on the root of the tree.
        return _step(self.root)
```

#### Problem 4. Finish implementing the KDT class.

1. Override the `insert()` method. To insert a new node, find the node that should be the parent of the new node by recursively descending through the tree as in the `find()` method (see figure 3.2 for a geometric example). Note that the `k` attribute of the will have to be set at some point.

The `axis` attribute of the new node will be one more than that axis of the parent node. If the last dimension of the data has been reached, start `axis` over at 0.

2. To solve the nearest neighbor search problem, we need only create the *k*-d tree once. Then we can use it multiple times with different target points. To prevent the user from altering the tree, disable the `remove()` method. Raise a `NotImplementedError` if the method is called, and allow

it to receive any number of arguments.

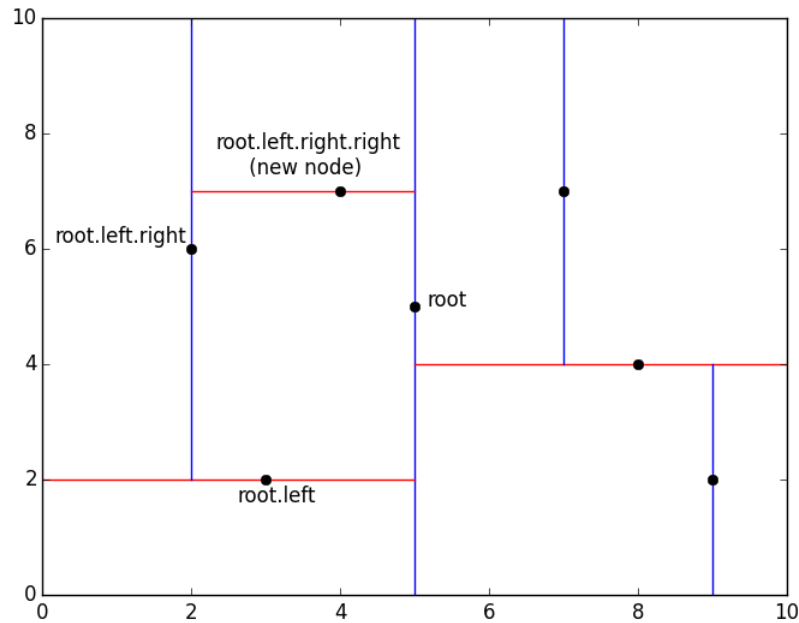


Figure 3.2: To insert the point (4, 7) into the  $k$ -d tree of figure 3.1, we find the node that will be the new node's parent. Start at the root, (5, 5). Since the  $x$ -coordinate of (4, 7) is less than the  $x$ -coordinate of (5, 5), we move into the region to the left of the middle blue line, to the root's left child, (3, 2). The  $y$ -coordinate of (4, 7) is greater than the  $y$ -coordinate of (3, 2), so we move above the red line on the left, to the right child (2, 6). Now we return to comparing the  $x$ -coordinates, and since  $4 > 2$  and (2, 6) has no right child, we install (4, 7) as the right child of (2, 6).

Using a  $k$ -d tree to solve the nearest neighbor search problem requires some care. At first glance, it appears that a procedure similar to `find()` or `insert()` will immediately yield the result. However, this is not always the case (see Figure 3.3).

To correctly find the nearest neighbor we will keep track of the target point, the current search node, current best point, and current minimum distance. Start at the root node. Then the current search node and current best point will be root, and the current minimum distance will be the euclidean distance from `root` to `target`. We then proceed recursively as in the `find()` method. As we find better points (nearer neighbors), we update the appropriate variables accordingly.

Once we have reached the bottom of the tree, we will have a good guess for the nearest neighbor. However, we are not guaranteed to have arrived at the correct point. One way to ensure that we have arrived at the correct point is to draw a hypersphere with a radius of the current minimum distance around the candidate

nearest neighbor. If this hypersphere does not intersect any of the hyperplanes that split the  $k$ -d tree, then we know that we have found a best point.

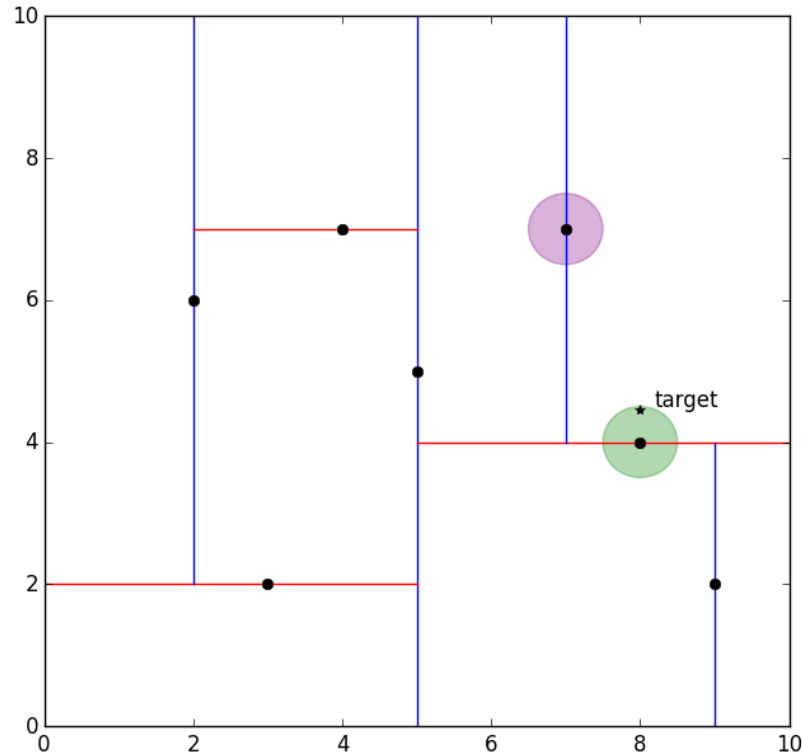


Figure 3.3: Suppose we want to find the point in the  $k$ -d tree of figure 3.2 that is closest to  $(8, 4.5)$ . First we record the distance from the root to the target as the current minimum distance (about 3.04), then travel down the tree to the right. The right child,  $(8, 4)$ , is only .5 units away from the target (the green circle), so we update the minimum distance. Since  $(8, 4)$  is not a leaf in the tree, we could continue down to the left child,  $(7, 7)$ . However, this leaf node is much further from the target (the purple circle). To ensure that we terminate the algorithm correctly we check to see if the hypersphere of radius .5 around the current node (the green circle) intersects with any other hyperplanes. Since it does not, we stop descending down the tree and conclude (correctly) that  $(8, 4)$  is the nearest neighbor.

While we can not easily draw the correct hypersphere, there is an equivalent procedure that has a straightforward implementation in Python. Before we finally decide to descend in one direction, we add the minimum distance to the  $i^{th}$  entry of the target point's data, where  $i$  is the axis of the candidate nearest neighbor. If this sum is greater than the  $i^{th}$  entry of the current search node, then the hypersphere would necessarily intersect one of the hyperplanes drawn by the tree (why?).

We summarize the algorithm below.

---

**Algorithm 3.1** *k*-d tree nearest neighbor search
 

---

```

1: Given a set of data and a target, build a k-d tree out of the data set.
2: procedure SEARCH(current, neighbor, dist)
3:   if current is None then                                     ▷ Base case.
4:     return neighbor, dist
5:   index ← current.axis
6:   if metric(current, target) < dist then
7:     neighbor ← current                                         ▷ Update the best estimate.
8:     dist ← metric(current, target)
9:   if target[index] < current.value[index] then                 ▷ Recurse left.
10:    neighbor, dist ← Search(current.left, neighbor, dist)
11:    if target[index] + dist ≥ current.value[index] then
12:      neighbor, dist ← Search(current.right, neighbor, dist)
13:  else                                                         ▷ Recurse right.
14:    neighbor, dist ← Search(current.right, neighbor, dist)
15:    if target[index] - dist ≤ current.value[index] then
16:      neighbor, dist ← Search(current.left, neighbor, dist)
17:  return neighbor, dist
18: Start SEARCH() at the root of the tree.
  
```

---

**Problem 5.** Use Algorithm 3.1 to write a function that solves the nearest neighbor search problem by searching through a *k*-d tree (your `KDT` object). The function should take in a data set and a single target point. Return the nearest neighbor in the data set and the distance from the nearest neighbor to the target point, as in Problem 2 (be sure to return a NumPy array, not a `KDTNode` for the neighbor).

To test your function, use SciPy's built-in `KDTree` object. This structure behaves like the `KDT` class, but its operations are heavily optimized. To solve the nearest neighbor problem, initialize the tree with data, then 'query' the tree with the target point. The `query` method returns a tuple of the minimum distance and the index of the nearest neighbor in the data.

```

>>> from scipy.spatial import KDTree

# Initialize the tree with data (in this example we use random data).
>>> data = np.random.random((100,5))
>>> target = np.random.random(5)
>>> tree = KDTree(data)

# Query the tree and print the minimum distance.
>>> min_distance, index = tree.query(target)
>>> print(min_distance)
0.309671532426

# Print the nearest neighbor by indexing into the tree's data.
  
```

```
>>> print(tree.data[index])  
[ 0.68001084  0.02021068  0.70421171  0.57488834  0.50492779]
```

## Handwriting Recognition

### Classification

Suppose that we are given a training set of data as well as a set of *labels* that describe each datum in the training set. For example, suppose that we had a training set containing the incomes and debt levels of  $N$  individuals. Along with this data, we have a set  $N$  labels that state whether the individual has filed for bankruptcy. The classification problem is to try and assign the correct label to an unlabelled data point.

### $k$ -Nearest Neighbors

In our previous work, we used a  $k$ -d tree to find the nearest neighbor of a target point. A more general problem is to find the  $k$  nearest neighbors to a point (using some metric to measure “distance” between data points). In classification, we find the  $k$  nearest neighbors, we let each neighbor “vote” to decide what label to give the new point. For example, consider the bankruptcy case in the previous section. If we find the 10 nearest neighbors to a new individual, and 8 of them went bankrupt, then we would predict that the individual will also go bankrupt. On the other hand, if 7 of the nearest neighbors had not filed for bankruptcy, we would predict that the individual was at low risk for bankruptcy.

### The Handwriting Recognition Problem

The problem of recognizing handwritten letters and numbers with a computer has many applications. A computer image may be thought of a vector in  $\mathbb{R}^n$ , where  $n$  is the number of pixels in the image and the entries represent how bright each pixel is. If two people write the same number, we would expect the vectors representing a scanned image of those number to be close in the euclidean metric. This insight means that given a training set of scanned images along with correct labels, we may confidently infer the label of a new scanned image.

### sklearn

The `sklearn` module contains powerful tools for solving the nearest neighbor problem. To start nearest neighbors classification, we import the `neighbors` module from `sklearn`. This module has a class for setting up a  $k$ -nearest neighbors classifier.

```
# Import the neighbors module  
>>> from sklearn import neighbors  
  
# Create an instance of a k-nearest neighbors classifier.  
# 'n_neighbors' determines how many neighbors to give votes to.
```



```
# 'weights' may be 'uniform' or 'distance.' The 'distance' option
# gives nearer neighbors more weight.
# 'p=2' instructs the class to use the euclidean metric.
>>> nbrs = neighbors.KNeighborsClassifier(n_neighbors=8, weights='distance', p=2)
```

The `nbrs` object has two useful methods for classification. The first, `fit`, will take arrays of data (the training set) and labels and put them into a  $k$ -d tree. This can then be used to find  $k$ -nearest neighbors, much like the `kdt` class that we implemented previously.

```
# 'points' is some NumPy array of data
# 'labels' is a NumPy array of labels describing the data in points.
>>> nbrs.fit(points, labels)
```

The second method, `predict`, will do a  $k$ -nearest neighbor search on the  $k$ -d tree and use the result to attach a label to unlabelled points.

```
# 'testpoints' is an array of unlabeled points.
# Perform the search and calculate the accuracy of the classification.
>>> prediction = nbrs.predict(testpoints)
>>> np.average(prediction/testlabels)
```

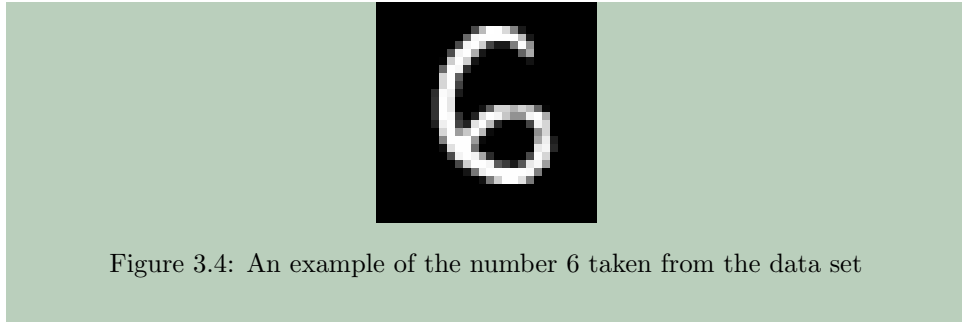
**Problem 6.** The United States Postal Service has made a collection of labeled hand written digits available to the public, provided in `PostalData.npz`. We will use this data for  $k$ -nearest neighbor classification. This data set may be loaded by using the following command:

```
labels, points, testlabels, testpoints = np.load('PostalData.npz').items()
```

This contains a training set and a test set. The first entry of each array is a name, so `points[1]` and `labels[1]` are the actual points and labels to use. Each point is an image that is represented by a flattened  $28 \times 28$  matrix of pixels. The corresponding label indicates which number was written.

Classify the testpoints with `n_neighbors` as 1, 4 or 10, and with `weights` as `'uniform'` or `'distance'`. For each trial print a report indicating how your classifier performs in terms of percentage of correct classifications. Which combination gives the most correct classifications? (Hint: define an inner function that takes in `n_neighbors` and `weights` as arguments calls the neighbors functions appropriately)

A similar classification process is used by the United States Postal Service to automatically determine the zip code to send a letter to.



## Lab 4

# Breadth-First Search and the Kevin Bacon Problem

**Lab Objective:** *Graph theory has many practical applications. A graph may represent a complex system or network, and analyzing the graph often reveals critical information about the network. In this lab we learn to store graphs as adjacency dictionaries, implement a breadth-first search to identify the shortest path between two nodes, then use the NetworkX package to solve the so-called “Kevin Bacon problem.”*

## Graphs in Python

Computers can represent mathematical graphs using various kinds of data structures. In previous labs, we stored graphs as trees and linked lists. For non-tree graphs, perhaps the most common data structure is an adjacency matrix, where each row of the matrix corresponds to a node in the graph and the entries of the row indicate which other nodes the current node is connected to. For more on adjacency matrices, see chapter 2 of the Volume II text.

Another common graph data structure is an *adjacency dictionary*, a Python dictionary with a key for each node in the graph. The dictionary values are lists containing the nodes that are connected to the key. For example, the following is an adjacency dictionary for the graph in Figure 4.1:

```
# Python dictionaries are used to store adjacency dictionaries.
>>> adjacency_dictionary = {'A':['B', 'C', 'D', 'E'], 'B':['A', 'C'],
                             'C':['B', 'A', 'D'], 'D':['A', 'C'], 'E':['A']}

# The nodes are stored as the dictionary keys.
>>> print(adjacency_dictionary.keys())
['A', 'C', 'B', 'E', 'D']

# The values are the nodes that the key is connected to.
>>> print(adjacency_dictionary['A'])
>>> ['B', 'C', 'D', 'E']           # A is connected to B, C, D, and E.
```

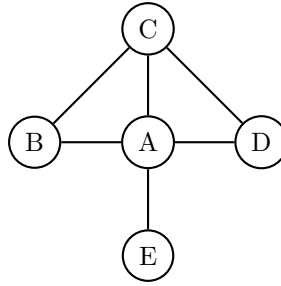


Figure 4.1: A simple graph with five vertices.

**Problem 1.** Implement the `__str__()` method in the provided `Graph` class. Print each node in the graph, followed by a list of the neighboring nodes separated by semicolons.

(Hint: consider using the `join()` method for strings.)

```

>>> my_dictionary = {'A':['C', 'B'], 'C':['A'], 'B':['A']}
>>> graph = Graph(my_dictionary)
>>> print(graph)
A: C; B
C: A
B: A

```

## Breadth-First Search

Many graph theory problems are solved by finding the shortest path between two nodes in the graph. To find the shortest path, we need a way to strategically search the graph. Two of the most common searches are depth-first search (DFS) and breadth-first search (BFS). In this lab, we focus on BFS. For details on DFS, see the chapter 2 of the Volume II text.

A BFS traverses a graph as follows: begin at a starting node. If the starting node is not the target node, explore each of the starting node's neighbors. If none of the neighbors are the target, explore the neighbors of the starting node's neighbors. If none of those neighbors are the target, explore each of their neighbors. Continue the process until the target is found.

As an example, we will do a programmatic BFS on the graph in Figure 4.1 one step at a time. Suppose that we start at node *C* and we are searching for node *E*.

```

# Start at node C
>>> start = 'C'
>>> current = start

# The current node is not the target, so check its neighbors
>>> adjacency_dictionary[current]
['B', 'A', 'D']

# None of these are E, so go to the first neighbor, B

```

```

>>> current = adjacency_dictionary[start][0]
>>> adjacency_dictionary[current]
['A', 'C']

# None of these are E either, so move to the next neighbor
# of the starting node, which is A
>>> current = adjacency_dictionary[start][1]
>>> adjacency_dictionary[current]
['B', 'C', 'D', 'E']

# The last entry of this list is our target node, and the search terminates.

```

You may have noticed that some problems in the previous approach that would arise in a more complicated graph. For example, what prevents us from entering a cycle? How can we algorithmically determine which nodes to visit as we explore deeper into the graph?

## Implementing Breadth-First Search

We solve these problems using a queue. Recall that a *queue* is a type of limited-access list. Data is inserted to the back of the queue, but removed from the front. Refer to the end of the Data Structures I lab for more details.

A queue is helpful in a BFS to keep track of the order in which we will visit the nodes. At each level of the search, we add the neighbors of the current node to the queue. The `collections` module in the Python standard library has a `deque` object that we will use as our queue.

```

# Import the deque object and start at node C
>>> from collections import deque
>>> current = 'C'

# The current node is not the target, so add its neighbors to the queue.
>>> visit_queue = deque()
>>> for neighbor in adjacency_dictionary[current]:
...     visit_queue.append(neighbor)
...
>>> print(visit_queue)
deque(['B', 'A', 'D'])

# Move to the next node by removing from the front of the queue.
>>> current = visit_queue.popleft()
>>> print(current)
B
>>> print(visit_queue)
deque(['A', 'D'])

# This isn't the node we're looking for, but we may want to explore its
# neighbors later. They should be explored after the other neighbors
# of the first node, so add them to the end of the queue.
>>> for neighbor in adjacency_dictionary[current]:
...     visit_queue.append(neighbor)
...
>>> print(visit_queue)
deque(['A', 'D', 'A', 'C'])

```

We have arrived at a new problem. The nodes *A* and *C* were added to the queue to be visited, even though *C* has already been visited and *A* is next in line.

We can prevent these nodes from being added to the queue again by creating a set of nodes to contain all nodes that have already been visited, or that are marked to be visited. Checking set membership is very fast, so this additional data structure has minimal impact on the program's speed (and is faster than checking the deque).

In addition, we keep a list of the nodes that have actually been visited to track the order of the search. By checking the set at each step of the algorithm, the previous problems are avoided.

```
>>> current = 'C'
>>> marked = set()
>>> visited = list()
>>> visit_queue = deque()

# Visit the start node C.
>>> visited.append(current)
>>> marked.add(current)

# Add the neighbors of C to the queue.
>>> for neighbor in adjacency_dictionary[current]:
...     visit_queue.append(neighbor)
...     # Since each neighbor will be visited, add them to marked as well.
...     marked.add(neighbor)
...
# Move to the next node by removing from the front of the queue.
>>> current = visit_queue.popleft()
>>> print(current)
B
>>> print(visit_queue)
['A', 'D']

# Visit B. Since it isn't the target, add B's neighbors to the queue.
>>> visited.append(current)
>>> for neighbor in adjacency_dictionary[current]:
...     visit_queue.append(neighbor)
...     marked.add(neighbor)
...

# Since C is visited and A is in marked, the queue is unchanged.
>>> print(visit_queue)
deque(['A', 'D'])
```

**Problem 2.** Implement the `traverse()` method in the `Graph` class using a BFS. Start from a specified node and proceed until all nodes in the graph have been visited. Return the list of visited nodes. If the starting node is not in the adjacency dictionary, raise a `ValueError`.

## Shortest Path

In a BFS, as few neighborhoods are explored as possible before finding the target. Therefore, the path taken to get to the target must be the shortest path.

Examine again the graph in Figure 4.1. The shortest path from *C* to *E* is start at *C*, go to *A*, and end at *E*. During a BFS, *A* is visited because it is one of *C*'s neighbors, and *E* is visited because it is one of *A*'s neighbors. If we knew programmatically that *A* was the node that visited *E*, and that *C* was the node that visited *A*, we could retrace our steps to reconstruct the search path.

To implement this idea, initialize a new dictionary before starting the BFS. When a node is added to the visit queue, add a key-value pair to the dictionary where the key is the node that is visited and the value is the node that is visiting it. When the target node is found, step back through the dictionary until arriving at the starting node, recording each step.

**Problem 3.** Implement the `shortest_path()` method in the `Graph` class using a BFS. Begin at a specified starting node and proceed until a specified target is found. Return a list containing the node values in the shortest path from the start to the target (including the endpoints). If either of the inputs are not in the adjacency graph, raise a `ValueError`.

## Network X

NetworkX is a Python package for creating, manipulating, and exploring large graphs. It contains a graph object constructor as well as methods for adding nodes and edges to the graph. It also has methods for recovering information about the graph and its structure.

A node can be an int, a string, or a Python object, and an edge can be weighted or unweighted. There are several ways to add nodes and edges to the graph, some of which are listed below.

Function	Description
<code>add_node()</code>	Add a single node to the graph.
<code>add_nodes_from()</code>	Add a list of nodes to the graph.
<code>add_edge()</code>	Add an edge between two nodes.
<code>add_edges_from()</code>	Add a list of edges to the graph.

```
# Create a new graph object using networkX
>>> import networkx as nx
>>> nx_graph = nx.Graph()

>>> nx_graph.add_node('A')
>>> nx_graph.add_node('B')
>>> nx_graph.add_edge('A', 'B')
>>> nx_graph.add_edge('A', 'C') # Node 'C' is added to the graph
>>> nx_graph.add_edges_from([('A', 'D'), ('A', 'E'), ('B', 'C')])
```

```
# We can also add weighted edges to the graph
>>> nx_graph.add_edge('C', 'D', weight=0.5)

# Nodes and edges are easy to access
>>> print(nx_graph.nodes())
['A', 'C', 'B', 'E', 'D']

>>> print(nx_graph.edges())
[('A', 'C'), ('A', 'B'), ('A', 'E'), ('A', 'D'), ('C', 'B'), ('C', 'D')]

>>> print(nx_graph.get_edge_data('C', 'D'))
{'weight': 0.5}

# With small graphs, we can visualize the graph with nx.draw()
>>> from matplotlib import pyplot as plt
>>> nx.draw(nx_graph)
>>> plt.show()
```

**Problem 4.** Write a function that accepts an adjacency dictionary. Create a `networkx` object, load it with the graph information from the dictionary, and return it.

## The Kevin Bacon Problem

“The 6 Degrees of Kevin Bacon” is a well-known parlor game. The game is played by naming an actor, then trying to find a chain of actors that have worked with each other leading to Kevin Bacon. For example, Samuel L. Jackson was in the film *Captain America: The First Avenger* with Peter Stark, who was in *X-Men: First Class* with Kevin Bacon. Thus Samuel L. Jackson has a “Bacon number” of 2. Any actors who have been in a movie with Kevin Bacon have a Bacon number of 1.

**Problem 5.** Write a `BaconSolver` class to solve the Kevin Bacon problem.

The file `movieData.txt` contains data from about 13,000 movies released over the course of several years. A single movie is listed on each line, followed by a sequence of actors that starred in it. The movie title and actors’ names are separated by a ‘/’ character. The actors are listed by last name first, followed by their first name.

Implement the constructor of `BaconSolver`. Accept a filename to pull data from and generate a dictionary where each key is a movie title and each value is a list of the actors that appeared in the movie. Store the collection of values in the dictionary (the actors) as a class attribute, avoiding duplicates. Convert the dictionary to a `NetworkX` graph and store it as another class attribute. Note that in the graph, actors only have movies as neighbors, and movies only have actors as neighbors. (Hint: recall the `split()` method for strings.)



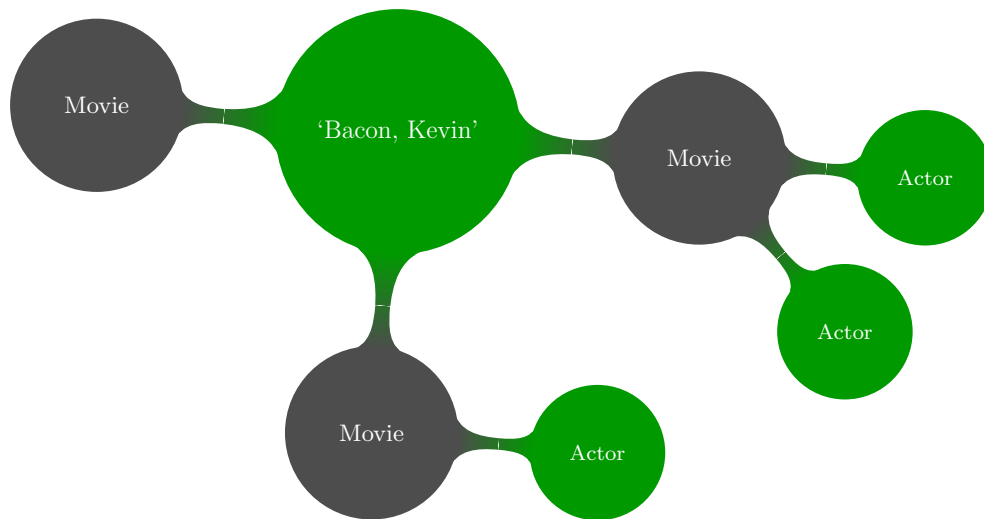


Figure 4.2: A small subgraph demonstrating the structure of the bacon graph.

### ACHTUNG!

Because of the size of the dataset, **do not** attempt to visualize the graph with `nx.draw()`. The visualization tool in NetworkX is only effective on relatively small graphs. In fact, graph visualization in general remains a challenging and ongoing area of research.

NetworkX is equipped with a variety of methods to aid in the analysis of graphs. A selected few are listed below.

Function	Description
<code>adjacency_matrix()</code>	Returns the adjacency matrix as a SciPy sparse matrix.
<code>dijkstra_path()</code>	Returns the shortest path from a source to a target in a weighted graph.
<code>has_path()</code>	Returns True if the graph has a path from a source to a target.
<code>prim_mst()</code>	Returns a minimum spanning tree for a weighted graph.
<code>shortest_path()</code>	Returns the shortest path from a source to a target.

```
# Verify nx_graph has a path from 'C' to 'E'
>>> nx.has_path(nx_graph, 'C', 'E')
True

# The shortest_path method is implemented with a
# bidirectional BFS (starting from both ends)
>>> nx.shortest_path(nx_graph, 'C', 'E')
['C', 'A', 'E']
```

**Problem 6.** Use NetworkX to implement the `path_to_bacon()` method. Accept start and target values (actors' names) and return a list with the shortest path from the start to the target. Set Kevin Bacon as the default target. If either of the inputs are not contained in the stored collection of dictionary values (if either input is not an actor's name), raise a `ValueError`.

```
>>> movie_graph = BaconSolver("movieData.txt")
>>> movie_graph.path_to_bacon("Jackson, Samuel L.")
['Jackson, Samuel L.', 'Captain America: The First Avenger', 'Stark,
Peter', 'X-Men: First Class', 'Bacon, Kevin']
```

**Problem 7.** Implement the `bacon_number()` method in the `BaconSolver` class. Accept start and target values and return the number of actors in the shortest path from start to target. Note that this is different than the number of entries in the shortest path list, since movies do not contribute to an actor's Bacon number.

Also implement the `average_bacon()` method. Compute the average Bacon number across all of the actors in the stored collection of actors. Exclude any actors that are not connected to Kevin Bacon (their theoretical Bacon number would be infinity). Return the average Bacon number and the number of actors not connected at all to Kevin Bacon.

As an aside, the prolific Paul Erdős is considered the Kevin Bacon of the mathematical community. Someone with an “Erdős number” of 2 co-authored a paper with someone who co-authored a paper with Paul Erdős.

---

## Additional Material

### Depth-First Search

A *depth-first search* (DFS) takes the opposite approach of a breadth-first search. Instead of checking all neighbors of a single node before moving on, it checks the first neighbor, then their first neighbor, then their first neighbor, and so on until reaching a leaf node. Then the algorithm back tracks to the previous node and checks its second neighbor. A DFS is sometimes more useful than a BFS, but a BFS is usually better<sup>1</sup> at finding the shortest path.

Consider adding a keyword argument to the `traverse()` method of the `Graph` class that specifies whether to use a BFS (the default) or a DFS. This can be done by changing a single line of the BFS code.

### Improvements to the `BaconSolver` Class

Consider adding a `plot_bacon()` method in the `BaconSolver` class that produces a simple histogram displaying the frequency of the Bacon numbers in the data set.

---

<sup>1</sup><https://xkcd.com/761/>



## Lab 5

# Markov Chains

**Lab Objective:** A Markov chain is a collection of states with specified probabilities for transitioning from one state to another. They are characterized by the fact that the future behavior of the system depends only on its current state.

Markov chains have far ranging applications. In this lab, we learn to construct, analyze, and interact with Markov chains and apply a Markov chain to a natural language processing problem.

## State Space Models

Many systems can be described by a finite number of states. For example, a board game where players move around the board based on die rolls can be modeled by a Markov chain. Each space represents a state, and a player is said to be in a state if their piece is currently on the corresponding space. In this case, the probability of moving from one space to another only depends on the player's current location; where the player was on a previous turn does not affect their current turn.

Finite Markov chains have an associated *transition matrix* that stores the information about the transitions between the states in the chain. The  $(i, j)$ th entry of the matrix gives the probability of moving from state  $j$  to state  $i$ . Thus each of the columns of the transition matrix must sum to 1.

### NOTE

A transition matrix where the columns sum to 1 is called *column stochastic* (or *left stochastic*). The rows of a *row stochastic* (or *right stochastic*) transition matrix each sum to 1 and the  $(i, j)$ th entry of the matrix is the probability of moving from state  $i$  to state  $j$ . Both representations are common, but in this lab we exclusively use column stochastic transition matrices for consistency.

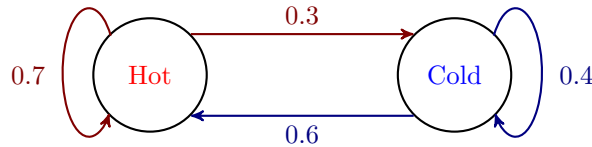
Consider a very simple weather model where the probability of being hot or cold depends on the weather of the previous day. If the probability that tomorrow is hot

given that today is hot is 0.7, and the probability that tomorrow is cold given that today is cold is 0.4, then by assigning hot to the 0<sup>th</sup> row and column, and cold to the 1<sup>st</sup> row and column, this Markov chain has the following transition matrix:

$$\begin{array}{cc} & \begin{array}{cc} \text{hot today} & \text{cold today} \end{array} \\ \begin{array}{c} \text{hot tomorrow} \\ \text{cold tomorrow} \end{array} & \begin{bmatrix} 0.7 & 0.6 \\ 0.3 & 0.4 \end{bmatrix} \end{array}$$

If it is hot today, we examine the 0th column of the matrix. There is a 70% chance that tomorrow will be hot (0th row) and a 30% chance that tomorrow will be cold (1st row). Conversely, if it is cold today, there is a 60% chance that tomorrow will be hot and a 40% chance that tomorrow will be cold.

Markov chains can be represented by a *state diagram*, a type of directed graph. The nodes in the graph are the states, and the edges indicate the state transition probabilities. The Markov chain described above has the following state diagram.



**Problem 1.** Transition matrices for Markov chains are efficiently stored as NumPy arrays. Write a function that accepts an integer  $n$  and returns the transition matrix for a random Markov chain with  $n$  states. (Hint: use array broadcasting to avoid looping.)

## Simulating State Transitions

A single draw from a *binomial distribution* with parameters  $n$  and  $p$  indicates the number of successes out of  $n$  independent experiments, each with probability  $p$  of success. The classic example is a series of coin flips, where  $p$  is the probability that the coin lands heads side up. NumPy's `random` module has an efficient tool, `binomial()`, for drawing from a binomial distribution.

```
>>> import numpy as np

# Draw from the binomial distribution with n = 1 and p = .5 (flip 1 coin).
>>> np.random.binomial(1, .5)
0                                # The coin flip resulted in tails.
```

Consider again the simple weather model and suppose that today is hot. The column that corresponds to “hot” in the transition matrix is  $[0.7, 0.3]$ . To determine whether tomorrow is hot or cold, draw from the binomial distribution with  $n = 1$  and  $p = 0.3$ . If the draw is 1, which has 30% likelihood, then tomorrow is cold. If the draw is 0, which has 70% likelihood, then tomorrow is hot. The following function implements this idea.

```
def forecast():
    """Forecast tomorrow's weather given that today is hot."""
    transition = np.array([[0.7, 0.6], [0.3, 0.4]])

    # Sample from a binomial distribution to choose a new state.
    return np.binomial(1, transition[1, 0])
```

**Problem 2.** Modify `forecast()` so that it accepts an integer parameter `days` and runs a simulation of the weather for the number of days given. Return a list containing the day-by-day weather predictions (0 for hot, 1 for cold). Assume the first day is hot, but do not include the data from the first day in the list of predictions. The resulting list should therefore have `days` entries.

## Larger Chains

The `forecast()` function makes one random draw from a binomial distribution to simulate a state change. Larger Markov chains require draws from a *multinomial distribution*, a multivariate generalization of the binomial distribution. A draw from a multinomial distribution parameters  $n$  and  $(p_1, p_2, \dots, p_k)$  indicates which of  $k$  outcomes occurs in  $n$  different experiments. In this case the classic example is a series of dice rolls, with 6 possible outcomes of equal probability.

```
>>> die_probabilities = np.array([1./6, 1./6, 1./6, 1./6, 1./6, 1./6])

# Draw from the multinomial distribution with n = 1 (roll a single die).
>>> np.random.multinomial(1, die_probabilities)
array([0, 0, 0, 1, 0, 0])    # The roll resulted in a 4.
```

**Problem 3.** Let the following matrix be the transition matrix for a Markov chain modeling weather with four states: hot, mild, cold, and freezing.

	hot	mild	cold	freezing
hot	0.5	0.3	0.1	0
mild	0.3	0.3	0.3	0.3
cold	0.2	0.3	0.4	0.5
freezing	0	0.1	0.2	0.2

Write a new function that accepts an integer parameter and runs the same kind of simulation as `forecast()`, but that uses this new four-state transition matrix. This time, assume that the first day is mild. Return a list containing the day-to-day results (0 for hot, 1 for mild, 2 for cold, and 3 for freezing).

## General State Distributions

For a Markov chain with  $n$  states, the probability of being in each of the states can be encoded by a single  $n \times 1$  vector  $\mathbf{x}$ , called a *state distribution vector*. The entries of  $\mathbf{x}$  must be nonnegative and sum to 1. Then the  $i$ th entry  $x_i$  of  $\mathbf{x}$  is the probability of being in state  $i$ . For example, the state distribution vector  $\mathbf{x} = [0.8, 0.2]^T$  corresponding to the 2-state weather model of Problem 2 indicates that there is a 80% chance that today is hot and a 20% chance that today is cold. On the other hand, the vector  $\mathbf{x} = [0, 1]^T$  implies that today is, with 100% certainty, cold.

If  $A$  is an  $n \times n$  transition matrix for a Markov chain and  $\mathbf{x}$  is a state distribution vector, then  $A\mathbf{x}$  is also a state distribution vector. In fact, if  $\mathbf{x}^{(k)}$  is the state distribution vector corresponding to a certain time  $k$ , then  $\mathbf{x}^{(k+1)} = A\mathbf{x}^{(k)}$  contains the probabilities of being in each state after allowing the system to transition again. For the weather model, this means that if there is an 80% chance that it will be hot 5 days from now, written  $\mathbf{x}^{(5)} = [0.8, 0.2]^T$ , then since

$$\mathbf{x}^{(6)} = A\mathbf{x}^{(5)} = \begin{bmatrix} 0.7 & 0.6 \\ 0.3 & 0.4 \end{bmatrix} \begin{bmatrix} 0.8 \\ 0.2 \end{bmatrix} = \begin{bmatrix} 0.68 \\ 0.32 \end{bmatrix},$$

there is a 68% chance that 6 days from now will be a hot day.

## Convergent Transition Matrices

Given an initial state distribution vector  $\mathbf{x}^{(0)}$ , defining  $\mathbf{x}^{(k+1)} = A\mathbf{x}^{(k)}$  yields the following significant relation.

$$\mathbf{x}^{(k)} = A\mathbf{x}^{(k-1)} = A(A\mathbf{x}^{(k-2)}) = A(A(A\mathbf{x}^{(k-3)})) = \dots = A^k\mathbf{x}^{(0)}$$

This indicates that the  $(i, j)$ th entry of  $A^k$  is the probability of transition from state  $j$  to state  $i$  in  $k$  steps. For the transition matrix of the 2-state weather model, something curious happens to  $A^k$  for even small values of  $k$ .

$$A = \begin{bmatrix} 0.7 & 0.6 \\ 0.3 & 0.4 \end{bmatrix} \quad A^2 = \begin{bmatrix} 0.67 & 0.66 \\ 0.33 & 0.34 \end{bmatrix} \quad A^3 = \begin{bmatrix} 0.667 & 0.666 \\ 0.333 & 0.334 \end{bmatrix}$$

As  $k \rightarrow \infty$ , the entries of  $A^k$  converge, written as follows.

$$\lim_{k \rightarrow \infty} A^k = \begin{bmatrix} 2/3 & 2/3 \\ 1/3 & 1/3 \end{bmatrix}. \quad (5.1)$$

In addition, for any initial state distribution vector  $\mathbf{x}^{(0)} = [a, b]^T$ ,  $a + b = 1$ ,

$$\lim_{k \rightarrow \infty} \mathbf{x}^{(k)} = \lim_{k \rightarrow \infty} A^k \mathbf{x}^{(0)} = \begin{bmatrix} 2/3 & 2/3 \\ 1/3 & 1/3 \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} 2(a+b)/3 \\ (a+b)/3 \end{bmatrix} = \begin{bmatrix} 2/3 \\ 1/3 \end{bmatrix}.$$

Thus as  $k \rightarrow \infty$ ,  $\mathbf{x}^{(k)} \rightarrow \mathbf{x} = [2/3, 1/3]^T$ , regardless of the initial state distribution  $\mathbf{x}^{(0)}$ . So according to this model, no matter the weather today, the probability that it is hot a week from now is approximately 66.67%. In fact, approximately 2 out of 3 days in the year should be hot.



## Steady State Distributions

The state distribution  $\mathbf{x} = [2/3, 1/3]^T$  has another important property.

$$A\mathbf{x} = \begin{bmatrix} 7/10 & 3/5 \\ 3/10 & 2/5 \end{bmatrix} \begin{bmatrix} 2/3 \\ 1/3 \end{bmatrix} = \begin{bmatrix} 14/30 + 3/15 \\ 6/30 + 2/15 \end{bmatrix} = \begin{bmatrix} 2/3 \\ 1/3 \end{bmatrix} = \mathbf{x}.$$

Any  $\mathbf{x}$  satisfying  $A\mathbf{x} = \mathbf{x}$  is called a *steady state distribution* or a *stable fixed point* of  $A$ . In other words, a steady state distribution is an eigenvector of  $A$  with corresponding eigenvalue  $\lambda = 1$ .

Every Markov chain has at least one steady state distribution. If some power  $A^k$  of  $A$  has all positive (nonzero) entries, then the steady state distribution is unique.<sup>1</sup> In this case,  $\lim_{k \rightarrow \infty} A^k$  is the matrix whose columns are all equal to the unique steady state distribution, as in (5.1). Under these circumstances, the steady state distribution  $\mathbf{x}$  can be found by iteratively calculating  $\mathbf{x}^{(k+1)} = A\mathbf{x}^{(k)}$ , as long as the initial vector  $\mathbf{x}^{(0)}$  is a state distribution vector.

### ACHTUNG!

Though every Markov chain has at least one steady state distribution, the procedure described above fails if  $A^k$  fails to converge. Consider the following example.

$$A = \begin{bmatrix} 0 & 0 & 1 \\ 0 & 1 & 0 \\ 1 & 0 & 0 \end{bmatrix}, \quad A^k = \begin{cases} A & \text{if } k \text{ is odd} \\ I & \text{if } k \text{ is even} \end{cases}$$

In this case as  $k \rightarrow \infty$ ,  $A^k$  oscillates between two different matrices.

Furthermore, the steady state distribution is not always unique; the transition matrix defined above, for example, has infinitely many.

**Problem 4.** Write a function that accepts an  $n \times n$  transition matrix  $A$ , a convergence tolerance  $\epsilon$ , and a maximum number of iterations  $N$ . Generate a random state distribution vector  $\mathbf{x}^{(0)}$  and calculate  $\mathbf{x}^{(k+1)} = A\mathbf{x}^{(k)}$  until  $\|\mathbf{x}^{(k-1)} - \mathbf{x}^{(k)}\| < \epsilon$ . If  $k$  exceeds  $N$ , raise a `ValueError` to indicate that  $A^k$  does not converge. Return the approximate steady state distribution  $\mathbf{x}$  of  $A$ .

To test your function, use Problem 1 to generate a random transition matrix  $A$ . Verify that  $A\mathbf{x} = \mathbf{x}$  and that the columns of  $A^k$  approach  $\mathbf{x}$  as  $k \rightarrow \infty$ . To compute  $A^k$ , use NumPy's (very efficient) algorithm for computing matrix powers.

```
>>> A = np.array([[.7, .6],[.3, .4]])
>>> np.linalg.matrix_power(A, 10)      # Compute A^10.
array([[ 0.66666667,  0.66666667],
       [ 0.33333333,  0.33333333]])
```

<sup>1</sup>This is a consequence of the *Perron-Frobenius theorem*, which is presented in conjunction with spectral calculus in Volume I.

Finally, use your function to validate the results of Problems 2 and 3:

1. Calculate the steady state distributions corresponding to the transition matrices for each simulation.
2. Run each simulation for a large number of days and verify that the results match the steady state distribution (for example, check that approximately  $2/3$  of the days are hot for the smaller weather model).

#### NOTE

Problem 4 is a special case of the *power method*, an algorithm for calculating an eigenvector of a matrix corresponding to the eigenvalue of largest magnitude. The general version of the power method, together with a discussion of its convergence conditions, will be discussed in another lab.

## Using Markov Chains to Simulate English

One of the original applications of Markov chains was to study natural languages.<sup>2</sup> In the early 20th century, Markov used his chains to model how Russian switched from vowels to consonants. By mid-century, they had been used as an attempt to model English. It turns out that Markov chains are, by themselves, insufficient to model very good English. However, they can approach a fairly good model of bad English, with sometimes amusing results.

By nature, a Markov chain is only concerned with its current state. Thus a Markov chain simulating transitions between English words is completely unaware of context or even of previous words in a sentence. For example, a Markov chain's current state may be the word "continuous." Then the chain would say that the next word in the sentence is more likely to be "function" rather than "raccoon." However, without the context of the rest of the sentence, even two likely words stringed together may result in gibberish.

We restrict ourselves to a subproblem of modeling the English of a specific file. The transition probabilities of the resulting Markov chain reflect the sort of English that the source authors speak. Thus the Markov chain built from *The Complete Works of William Shakespeare* differs greatly from, say, the Markov chain built from a collection of academic journals. We call the source collection of works in the next problems the *training set*.

<sup>2</sup>The term *natural language* refers to a spoken language, like English or Russian. See <http://langvillea.people.cofc.edu/MCapps7.pdf> for some details on the early applications of Markov chains, including the study of natural languages.

## Making the Chain

With the weather models of the previous sections, we chose a fixed number of days to simulate. However, English sentences are of varying length, so we do not know beforehand how many words to choose (how many state transitions to make) before ending the sentence. To capture this feature, we include two extra states in our Markov model: a *start state* (\$start) marking the beginning of a sentence, and a *stop state* (\$stop) marking the end. Thus a training set with  $N$  unique words has an  $(N + 2) \times (N + 2)$  transition matrix.

The start state only transitions to words that appear at the beginning of a sentence in the training set, and only words that appear at the end of a sentence in the training set transition to the stop state. The stop state is called an *absorbing state* because once we reach it, we cannot transition back to another state.

After determining the states in the Markov chain, we need to determine the transition probabilities between the states and build the corresponding transition matrix. Consider the following small training set from Dr. Seuss as an example.

I am Sam Sam I am.  
Do you like green eggs and ham?  
I do not like them, Sam I am.  
I do not like green eggs and ham.

If we include punctuation (so “ham?” and “ham.” are counted as distinct words) and do not alter the capitalization (so “Do” and “do” are also different), there are 15 unique words in this training set:

I   am   Sam   am.   Do   you   like   green  
eggs   and   ham?   do   not   them,   ham.

With start and stop states, the transition matrix should be  $17 \times 17$ . Each state must be assigned a row and column index in the transition matrix. An easy way to do this is to assign the states an index based on the order that they appear in the training set. Thus our states and the corresponding indices will be as follows:

\$start	I	am	Sam	...	ham.	\$stop
0	1	2	3	...	15	16

The start state should transition to the words “I” and “Do”, and the words “am.”, “ham?”, and “ham.” should each transition to the stop state. We first count the number of times that each state transitions to another state:

	\$start	I	am	Sam		ham.	\$stop
\$start	0	0	0	0	...	0	0
I	3	0	0	2	...	0	0
am	0	1	0	0	...	0	0
Sam	0	0	1	1	...	0	0
	⋮	⋮	⋮	⋮	⋱	⋮	⋮
ham.	0	0	0	0	...	0	0
\$stop	0	0	0	0	...	1	1

Now divide each column by its sum so that each column sums to 1.

	\$start	I	am	Sam		ham.	\$stop
\$start	0	0	0	0	...	0	0
I	3/4	0	0	2/3	...	0	0
am	0	1/5	0	0	...	0	0
Sam	0	0	1	1/3	...	0	0
	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
ham.	0	0	0	0	...	0	0
\$stop	0	0	0	0	...	1	1

The 3/4 indicates that 3 out of 4 times, the sentences in the training set start with the word “I”. Similarly, the 2/3 and 1/3 tell us that “Sam” is followed by “I” twice and by “am” once in the training set. Note that “am” (without a period) always transitions to “Sam” and that “ham.” (with a period) always transitions to the stop state. Finally, to avoid a column of zeros, we place a 1 in the bottom right hand corner of the matrix (so the stop state always transitions to itself).

The entire procedure of creating the transition matrix for the Markov chain with words from a file as states is summarized below.

---

**Algorithm 5.1** Convert a training set of sentences into a Markov chain.

---

- 1: **procedure** MAKETRANSITIONMATRIX
  - 2:     Count the number of unique words in the training set.
  - 3:     Initialize a square array of zeros of the appropriate size to be the transition matrix (remember to account for the start and stop states).
  - 4:     Initialize a list of states, beginning with "\$start".
  - 5:     **for** each sentence in the training set **do**
  - 6:         Split the sentence into a list of words.
  - 7:         Add each **new** word in the sentence to the list of states.
  - 8:         Convert the list of words into a list of indices indicating which row and column of the transition matrix each word corresponds to.
  - 9:         Add 1 to the entry of the transition matrix corresponding to transitioning from the start state to the first word of the sentence.
  - 10:        **for** each consecutive pair  $(x, y)$  of words in the list of words **do**
  - 11:            Add 1 to the entry of the transition matrix corresponding to transitioning from state  $x$  to state  $y$ .
  - 12:         Add 1 to the entry of the transition matrix corresponding to transitioning from the last word of the sentence to the stop state.
  - 13:     Make sure the stop state transitions to itself.
  - 14:     Normalize each column by dividing by the column sums.
-

**Problem 5.** Write a class called `SentenceGenerator`. The constructor should accept a filename (the training set). Read the file and build a transition matrix from its contents as described in Algorithm 5.1.

You may assume that the file has one complete sentence written on each line, and your implementation may be either column- or row-stochastic.

**Problem 6.** Add a method to the `SentenceGenerator` class called `babble()`. Begin at the start state and use the strategy from Problem 3 to repeatedly transition through the object's Markov chain. Keep track of the path through the chain and the corresponding sequence of words. When the stop state is reached, stop transitioning to terminate the simulation. Return the resulting sentence as a single string.

For example, your `SentenceGenerator` class should be able to create random sentences that sound somewhat like Yoda speaking.

```
>>> yoda = SentenceGenerator("yoda.txt")
>>> for _ in xrange(25):
...     print(yoda.babble())
...
Impossible to my size, do not!
For eight hundred years old to enter the dark side of Congress there is.
But beware of the Wookiees, I have.
Fear leads to eat as well.
But agree on this, we must, and find your weapon!
Hear you fear of the Force.
A Jedi must go.
Fear is upon me by a fight.
Never his ally in you.
Or I mean you it appears to answer that strong.
Hard to let go of a long time have I have.
Obi-Wan, my choice is.
Luke, when gone am I, the Force be with him.
Told you are, no harm.
Impossible to learn he is.
Inform the Force, but the dark, path as is ready.
Unexpected this move by Darth Vader.
At an end this kind?
A master and decisively we have.
Much anger there are, no more, no less.
What know you Count, this boy's future is.
Heard from the Force.
Will he begins?
So certain, are worse.
Death is time have the dark place we will be when sensing the way of
the Force.
```

## Additional Material

### Large Training Sets

The approach in Problems 5 and 6 begins to fail as the training set grows larger. For example, a single Shakespearean play may not be large enough to cause memory problems, but *The Complete Works of William Shakespeare* certainly will.

To accommodate larger data sets, consider use a sparse matrix from `scipy.sparse` for the transition matrix instead of a regular NumPy array. Specifically, construct the transition matrix as a `lil_matrix` (which is easy to build incrementally), then convert it to the `csc_matrix` format (which supports fast column operations). Ensure that the process still works on small training sets, then proceed to larger training sets. How are the resulting sentences different if a very large training set is used instead of a small training set?

### Variations on the English Model

Choosing a different state space for the English Markov model produces different results. Consider modifying your `SentenceGenerator` class so that it can determine the state space in a few different ways. The following ideas are just a few possibilities.

- Let each punctuation mark have its own state. In the example training set, instead of having two states for the words “ham?” and “ham.”, there would be three states: “ham”, “?”, and “.”, with “ham” transitioning to both punctuation states.
- Model paragraphs instead of sentences. Add a `$startParagraph` state that always transitions to `$startSentence` and a `$stopParagraph` state that is sometimes transitioned to from `$stopSentence`.
- Let the states be individual letters instead of individual words. Be sure to include a state for the spaces between words. We will explore this particular state space choice more in Volume III together with hidden Markov models.
- Construct the state space so that the next state depends on both the current and previous states. This kind of Markov chain is called a *Markov chain of order 2*. This way, every set of three consecutive words in a randomly generated sentence should be part of the training set, as opposed to only every consecutive pair of words coming from the set.
- Instead of generating random sentences from a single source, simulate a random conversation between  $n$  people. Construct a Markov chain  $M_i$ , for each person,  $i = 1, \dots, n$ , then create a Markov chain  $C$  describing the conversation transitions from person to person; in other words, the states of  $C$  are the  $M_i$ . To create the conversation, generate a random sentence from the first person using  $M_1$ . Then use  $C$  to determine the next speaker, generate a random sentence using their Markov chain, and so on.

---

## Natural Language Processing Tools

The Markov model of Problems 5 and 6 is a *natural language processing* application. Python's `nltk` module (natural language toolkit) has many tools for parsing and analyzing text for these kinds of problems. For example, `nltk.sent_tokenize()` reads a single string and splits it up into sentences.

```
>>> from nltk import sent_tokenize
>>> with open("yoda.txt", 'r') as yoda:
...     sentences = sent_tokenize(yoda.read())
...
>>> print(sentences)
['Away with your weapon!',
 'I mean you no harm.',
 'I am wondering - why are you here?',
 ...]
```

The `nltk` module is **not** part of the Python standard library. For instructions on downloading, installing, and using `nltk`, visit <http://www.nltk.org/>.





## Lab 6

# Fourier I: The Discrete Fourier Transform

**Lab Objective:** *The analysis of periodic functions has many applications in pure and applied mathematics, especially in settings dealing with sound waves. The Fourier transform provides a way to analyze such periodic functions. In this lab, we implement the discrete Fourier transform and explore digital audio signals.*

## Sound Waves

Sound is the way that we perceive vibrations in matter. These vibrations travel in waves. Sound waves have two important characteristics that determine what we hear, or whether or not we can hear it. *Frequency* is a measurement of the number of occurrences in a certain time, and determines the pitch of the sound. Only certain frequencies are perceptible to the human ear. The second characteristic is *intensity* or *amplitude*, and determines the volume of the sound. Sound waves correspond physically to continuous functions, but computers can approximate sound waves using discrete measurements. Indeed, discrete measurements can be made indistinguishable to the human ear from a truly continuous wave. Usually, sound waves are of a sinusoidal nature (with some form of decay), and the frequency is related to the wavelength, and the intensity to the wave amplitude.

## Digital Audio Signals

*Digital Audio Signals* are how computers can approximate sound waves, and have two key components that relate to the frequency and amplitude of sound waves: samples, and sampling rate. A sample is a measurement of the amplitude of a sound wave at a specific instant in time. The sampling rate corresponds to the sound frequency.

If we know at what rate a set of samples were taken, then we can reconstruct the wave exactly as it was recorded. If we don't know the sampling rate, then our frequencies will be unknown. In most applications, this sample rate will be measured in the number of samples taken per second, Hertz (Hz). The standard rate for high quality audio is 44100 equally spaced samples per second, or 44.1 kHz.

**Problem 1.** Write a class called `signal` for storing digital audio signals. The constructor should accept a sample rate (an integer) and an array of samples (a NumPy array). Store these inputs as attributes.

Write a method called `plot()` that generates the graph of the sound wave. Use the sample rate to label the x-axis in terms of seconds. See Figure 6.1 for an example.

## Wave File Format

One of the most common audio file formats across operating systems is the *wave* format, also called *wav* after its file extension. It is a lightweight, common standard that is in wide use. SciPy has built-in tools to read and create *wav* files. To read in a *wav* file, we can use the `read()` function that returns the file's sample rate and samples. See Figure 6.1.

```
# Read from the sound file.
>>> from scipy.io import wavfile
>>> rate, wave = wavfile.read('tada.wav')

# To visualize the data, use the Signal class's plot function.
>>> sig = Signal(rate, wave)
>>> sig.plot()
```

Writing a signal to a file is also simple. We use `wavfile.write()`, specifying the name of the new file, the sample rate, and the array of samples.

```
# Write a random signal sampled at a rate of 44100 Hz to my_sound.wav.
>>> wave = sp.random.randint(-32767, 32767, 30000)
>>> samplerate = 44100
>>> wavfile.write('my_sound.wav', samplerate, wave)
```

## Scaling

The `wavfile.write()` function expects an array of 16 bit integers for the samples (whole numbers between  $-32767$  and  $32767$ ). Therefore, waves may need to be scaled and converted to integers before being written to a file.

```
# Generate random samples between -0.5 and 0.5.
>>> samples = sp.random.random(30000) - 0.5
# Scale the wave so that the samples are between -32767 and 32767.
>>> samples *= 32767 * 2
# Cast the samples as 16 bit integers.
>>> samples = sp.int16(samples)
```

The scaling technique in the above example works, but only because we knew beforehand that the values were in the interval  $[-\frac{1}{2}, \frac{1}{2}]$ . If the entries of a wave are not scaled properly, the operating system may not know how to play the file.

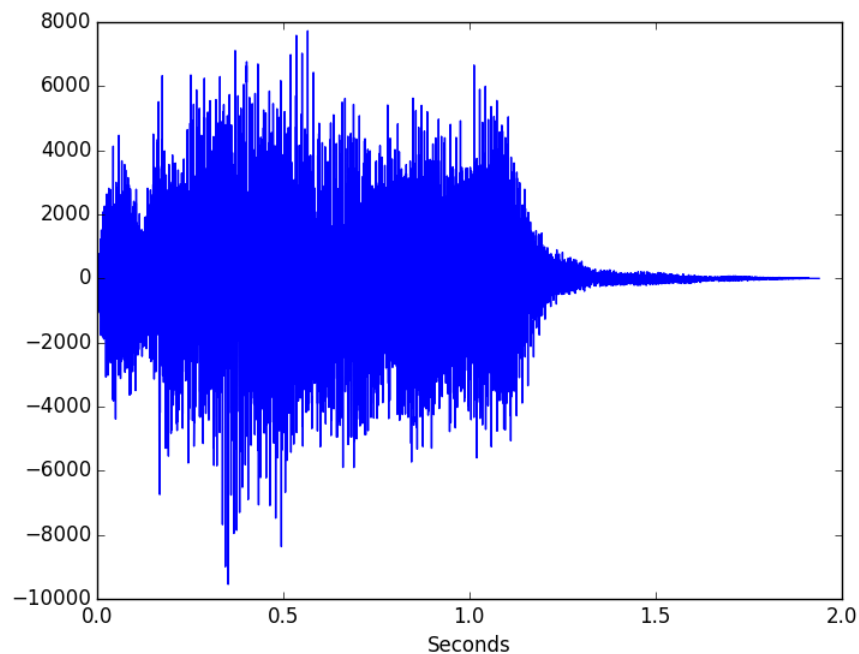


Figure 6.1: The soundwave of `tada.wav`.

**Problem 2.** Add a method to the `signal` class called `export()` that accepts a file name and generates a `.wav` file from the sample rate and the array of samples. Scale the array of samples appropriately before writing to the output file. Ensure that your scaling technique is valid for arbitrary arrays of samples. Note that some arrays will not need to be scaled.

## Creating Sounds in Python

In order to generate a sound in python, we need to sample the corresponding sinusoidal wave and then save it as an audio file. For example, suppose that we want to generate a sound with a frequency of 500 Hertz for 10 seconds.

```
>>> samplerate = 44100
>>> frequency = 500
>>> length = 10          # Length in seconds of the desired sound.
```

Recall the the function  $\sin(x)$  has a period of  $2\pi$ . To create sounds, however, we want the period of our wave to be 1, corresponding to 1 second. Thus, we will sample from the function

$$\sin(2\pi x f)$$

where  $f$  is our desired frequency.

```
# The lambda keyword is a shortcut for creating a one-line function.
>>> wave_function = lambda x: sp.sin(2*sp.pi*x*frequency)
```

In the following code, we generate a signal using three steps: first, we find the correct step size given the sample rate. Next, we generate the points at which we wish to sample the wave. Finally, we sample the wave by passing the sample points to `wave_function`. Then we can use our `Signal` class to plot the soundwave or write it to a file.

```
# Calculate the step size, the sample points, and the sample values.
>>> stepsize = 1./samplerate
>>> sample_points = sp.arange(0, length, stepsize)
>>> samples = wave_function(sample_points)

# Use the Signal class to write the sound to a file.
>>> sinewave = Signal(samplerate, samples)
>>> sinewave.export("sine.wav")
```

The `export()` method should take care of scaling and casting the entries as 16-bit integers.

**Problem 3.** The ‘A’ note occurs at a frequency of 440 Hertz. Generate the sine wave that corresponds to an ‘A’ note being played for 5 seconds.

Once you have successfully generated the ‘A’ note, experiment with different frequencies to generate different notes. The following table shows some frequencies that correspond to common notes. Octaves of these notes are obtained by doubling or halving these frequencies.

Note	Frequency
A	440
B	493.88
C	523.25
D	587.33
E	659.25
F	698.46
G	783.99
A	880

Implement a function outside of the `Signal` class that accepts a frequency and a duration and returns an instance of the `Signal` class corresponding to the desired soundwave. Sample at a rate of 44100 samples per second to create these sounds.

## Discrete Fourier Transform

### Some Technicalities

Under the right conditions, a continuous periodic function may be represented as a sum of sine waves:

$$f(x) = \sum_{k=-\infty}^{\infty} c_k \sin kx$$

where the constants  $c_k$  are called the *Fourier coefficients*.

Such a transform also exists for discrete periodic functions. Whereas the frequencies present in the continuous case are multiples of a sine wave with a period of 1, the discrete case is somewhat different. The Fourier coefficients in the discrete case represent the amplitudes of sine waves whose periods are multiples of a “fundamental frequency.” The fundamental frequency is a sine wave with a period length equal to the amount of time of the signal.

The  $k^{\text{th}}$  coefficient of a signal  $\{x_0, \dots, x_{N-1}\}$  is calculated with the following formula:

$$c_k = \sum_{n=0}^{N-1} x_n e^{-\frac{2\pi i k n}{N}} \quad (6.1)$$

where  $i$  is the square root of  $-1$ . This process is done for each  $k$  from 0 to  $N - 1$ . Thus there are just as many Fourier coefficients as samples from the original signal.

**Problem 4.** Write a function that accepts a NumPy array and computes the discrete Fourier transform of the array using Equation 6.1. Return the array of calculated coefficients.

SciPy has several methods for calculating the DFT of an array. Use `scipy.fft()` or `scipy.fftpack.fft()` to check your implementation. The naive method is significantly slower than SciPy’s implementation, so test your function only on small arrays. When you have your method working, try to optimize it so that you can calculate each coefficient  $c_k$  in just one line of code.

## Plotting the DFT

The graph of the Fourier transform of a sound file is useful in a variety of applications. While the graph of the original signal gives information about the amplitude of a soundwave at certain points, the graph of the discrete Fourier transform shows which frequencies are present in the signal. Often, this information is of greater importance than how the wave changes in time. Frequencies present in the signal have non-zero coefficients. The magnitude of these coefficients corresponds to how influential the frequency is in the signal. For example, the sounds that we generated in the previous section contained only one frequency. If we created an ‘A’ note at 440 Hz, then the graph of the DFT would appear as in Figure 6.2.

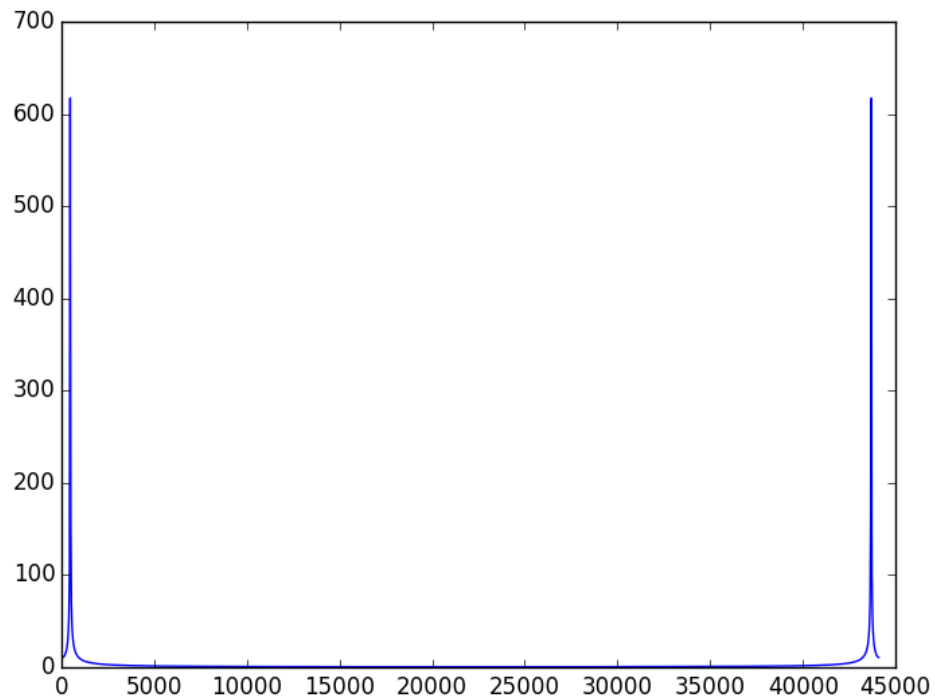


Figure 6.2: The magnitude of the coefficients of the discrete Fourier transform of an ‘A’ note. Notice that there are two spikes in the graph, the first around 440 on the x-axis. This second spike is due to symmetries inherent in the DFT. For our purposes we will mostly be concerned with the left side of the DFT plot.

On the other hand, the DFT of a more complicated sound wave will have many frequencies present. Some of these frequencies correspond to the different tones present in the signal. See Figure 6.3 for an example.

### Fixing the x-axis

If we take the DFT of a signal and then plot it without any other considerations, the x-axis will correspond to the index of the coefficients in the DFT and not their frequencies. In a previous section, we mention that the “fundamental frequency” for the DFT corresponds to a sine wave whose period is the same as the length of the signal. Thus, if unchanged, the x-axis gives us the number of times a particular sine wave cycles throughout the whole signal. If we want to label the x-axis with the frequencies measured in Hertz, or cycles per second, we will need to convert the units. Fortunately, the bitrate is measured in samples per second. Therefore, if we divide the frequency (given by the index) by the number of samples, and multiply by the sample rate, we end up with cycles per second, or Hertz.

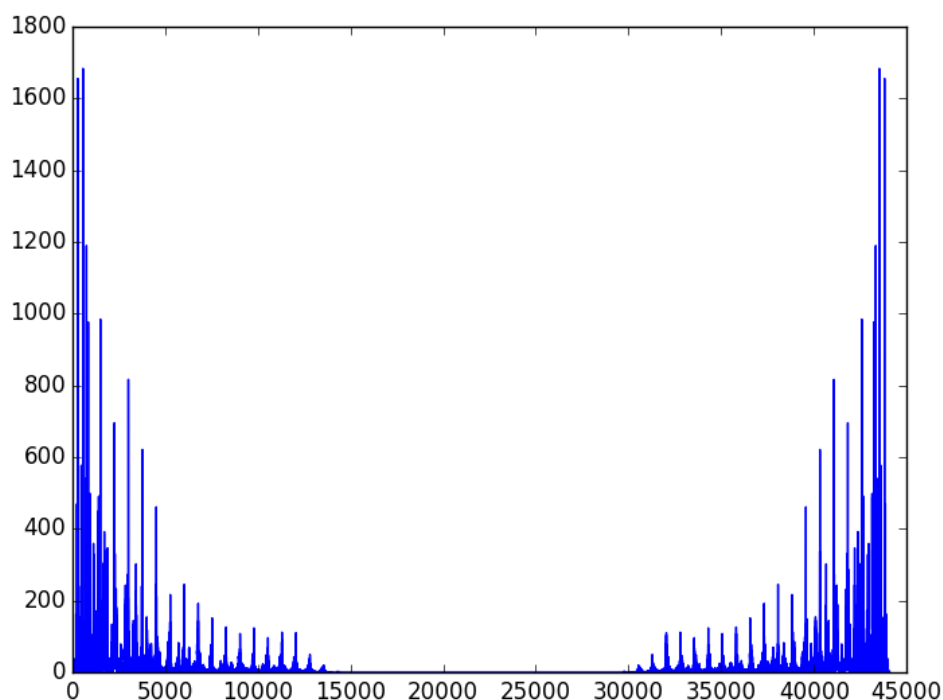


Figure 6.3: The discrete Fourier transform of `tada.wav`. Each spike in the graph corresponds to a frequency that is present in the signal.

$$\frac{\text{cycles}}{\text{samples}} \times \frac{\text{samples}}{\text{second}} = \frac{\text{cycles}}{\text{second}}$$

```
# Calculate the DFT and the x-values that correspond to the coefficients. Then
# convert the x-values so that they measure frequencies in Hertz.
>>> dft = sp.fft(signal)
>>> x_vals = sp.arange(1, len(dft)+1, 1)*1. # Make them floats

# x_vals now corresponds to frequencies measured in cycles per signal length.
>>> x_vals = x_vals/len(signal)
>>> x_vals = x_vals*rate
```

**Problem 5.** Update the `plot()` method in the `signal` class so that it generates a single plot with two subplots: the original soundwave, and the magnitude of the coefficients of the DFT (as in Figure 6.3). Use one of SciPy's FFT implementations to calculate the DFT.

**Problem 6.** A chord is a conjunction of several notes played together. We can create a chord in Python by adding several sound waves together. For example, to create a (minor) chord with ‘A’, ‘C’, and ‘E’ notes, we generate the sound waves for each, as in the prior problem, and then add them together.

Create several chords and observe the plot of their DFT. There should be as many spikes as there are notes in the plot. Then create a sound that changes over time.

(Hints: you may consider implementing the `__add__()` magic method for the `Signal` class. NumPy’s `np.hstack()` and `np.vstack()` may also be helpful.)



## Lab 7

# Filtering and Convolution

**Lab Objective:** *The Fourier transform reveals things about an audio signal that are not immediately apparent from the soundwave. In this lab we learn to filter noise out of a signal using the discrete Fourier transform, and explore the effect of convolution on sound files.*

## Cleaning up a Noisy Signal

Digital audio signals can be used to produce actual sound waves. When you play a digital audio signal on your computer, the signal is sent to a speaker, which vibrates, producing sound waves. When more than one speaker is used, they can both produce the same signal, or each could produce a different signal. When there is only one signal, we say that the sound is *monaural*, or simply *mono*. When speakers produce different signals, we say that the overall signal is *stereophonic*, or *stereo*. Usually stereo means two, but there may be any number of signals (5.1 surround sound, for instance, has 5).

Listen to `Noisysignal1.wav`. This is a mono recording of a (probably familiar) voice with some annoying noise over it. The plot of the soundwave isn't very descriptive; in fact, it looks like static. See Figure 7.1a.

However, if we take the Fourier transform of the signal, we see that the static in Figure 7.1a is the result of some concentrated high-frequency noise. (In this case, artificially added). See Figure 7.1b.

The noise can be removed by setting the coefficients of the high frequencies to zero. Since the discrete Fourier transform is symmetric, if we set coefficient  $j$  to 0, then we must set coefficient  $N - j$  to 0 as well, where  $N$  is the number of coefficients. Then we calculate the inverse Fourier transform to get a new, clean signal.

```
>>> rate,data = wavfile.read('Noisysignal1.wav')

# Calculate the Fourier transform
>>> fsig = sp.fft(data, axis = 0)

# Coefficients 10000 to 20000 were chosen by inspecting the
# plot of the Fourier transform.
```

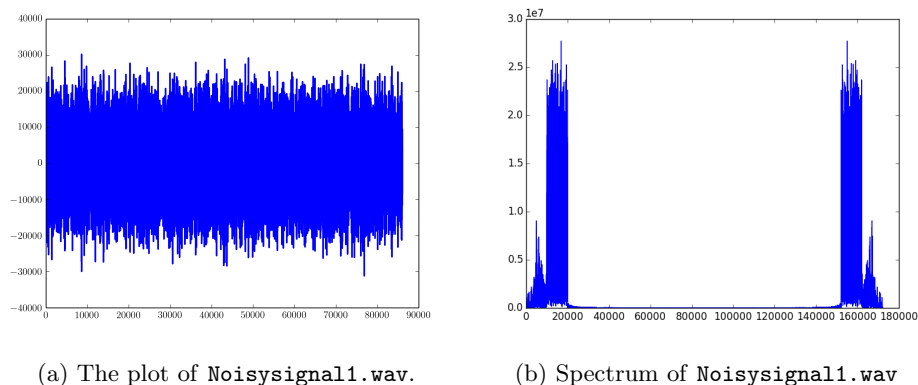


Figure 7.1

```
>>> for j in xrange(10000, 20000):
...     # Set the chosen coefficients to 0
...     fsig[j] = 0
...     fsig[-j] = 0

# Calculate the inverse Fourier transform, cast it as real,
# and scale it to be compatible with the wavfile format.
>>> newsig = sp.ifft(fsig)
>>> newsig = sp.real(newsig)
>>> newsig = sp.int16(newsig / sp.absolute(newsig).max() * 32767)
```

Now we can save the resulting cleaned-up signal `newsig` to a `.wav` file. The plot of the wave now reveals individual syllables as they are spoken. See Figure 7.2.

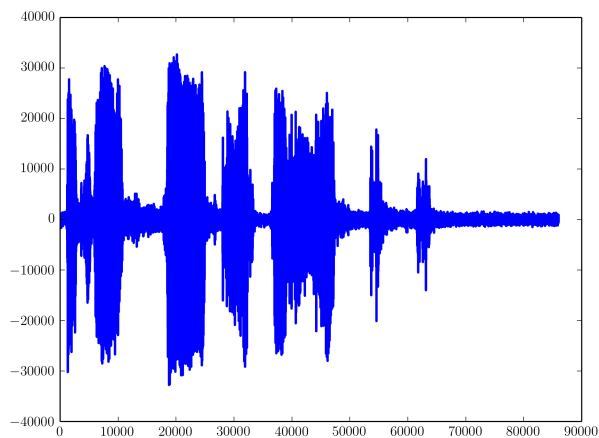


Figure 7.2: The plot of Noisysignal1.wav after being cleaned.

**Problem 1.** Listen to `Noisysignal2.wav`. You will probably just hear noise. Inspect the discrete Fourier transform to see where there is noise. Remove the noise using the technique described above in order to make the cleaned-up signal audible. What does the voice say? Who is the speaker? (If you don't know the answer to this last question, try a quick Google search.)

The DFT is commonly used in sound filtering, though identifying the particular frequencies to zero out can be difficult.

## Filtering and Convolution

The DFT is useful for more than filtering noise out of a signal. Suppose we have a recording of a musical piece played in a small, carpeted room with essentially no acoustics (little or no echo), and suppose we would like to apply an effect to make it sound as if the piece were played in a large concert hall or some other room. The DFT makes this possible when used together with the idea of *convolution*.

When a balloon is popped in large, echoic room, although the sound of the actual pop only lasts a few milliseconds, the sound echoes about the room for up to several seconds. This echoing sound is referred to as the *impulse response* of the room, and is a way of approximating the acoustics of a room.

First, we need a recording of how the room responds to a short pulse of sound. Effective ways of producing a loud sound approximating a pulse—other than creating an actual pulse with a computer—include firing a (preferably blank) gunshot, popping a balloon, or, if neither of those options are available, clapping the hands one time.

Recall that we model sound with discrete samples of a soundwave in rapid succession. When these sounds are played back, the ear perceives them as a continuous soundwave. In other words, sound playback is a series of pulses of varying intensities, similar to the pulse in an impulse response. If we “mix” the individual sounds of an instrument in a carpeted room with the impulse response from a concert hall, then the new soundwave will sound as if the instrument is being played in the concert hall.

This “mixing” is better referred to as *convolution*. With the impulse response, we can see how sound echoes and decays. This “echoicness” can then be combined with each audio sample to reproduce the echo at the appropriate time and amplitude. Since audio needs to be sampled frequently (44100 samples per second is standard) to create smooth playback, a recording of a song can contain tens of millions of samples (one minutes at 44100 samples per second gives 2646000 samples). Each of these samples needs to be combined with the impulse response, which may be several seconds long. This may be starting to seem computationally infeasible or at least very difficult, but surprisingly, it is not. The key is to recognize that this process can be described as a convolution: namely, the final sound is simply the convolution of the our original sound with the impulse response. In other words, it is the original sound with the echoes of the previous  $n$  samples, where  $n$  is the

number of samples in the impulse response. We can calculate convolutions quickly using the convolution theorem:

$$\mathcal{F}(f * g) = \mathcal{F}(f) \cdot \mathcal{F}(g)$$

where  $\mathcal{F}$  is the Fourier Transform,  $*$  is convolution, and  $\cdot$  is component-wise multiplication. Thus we calculate the convolution of two arrays by simply taking the Fourier transform of each, multiplying them pointwise, and then taking the inverse Fourier transform.

**Problem 2.** (Optional)<sup>a</sup> Find a large room or area with good acoustics, and record (an approximation to) its impulse response using a balloon pop. To record the sound, you will want to use at least a decent microphone. You may want to record it using the program Audacity<sup>b</sup> and a laptop. If you use a unidirectional microphone, be sure the microphone is pointing at the balloon when you pop it, so that the direct sound from the pop is picked up. (If you don't, the result will still be okay. However, after the convolution it will probably sound somewhat distant, as if we were standing somewhere where we couldn't hear the music directly.) If you've chosen a good room, the response should be audible for at least a full second.

Include a plot of both the waveform and spectrum of the impulse response you recorded.

<sup>a</sup>If the instructor does not require this problem then students may use the provided `balloon.wav` file which contains the sound of a balloon pop in a large room.

<sup>b</sup>Audacity is free sound manipulation software and may be downloaded at <http://audacity.sourceforge.net>

**Problem 3.** Download and listen to the file `chopin.wav`. You will hear a piano being played in a dead room with little or no acoustics. Using the Convolution Theorem, take the convolution of this signal with the impulse response recorded in the previous problem. The convolution given in the theorem is *circular*, meaning that sounds at the end of the signal will tend to mix with sounds at the beginning of the signal. To avoid this effect, add several seconds of silence (as long as the impulse response echo) to the end of `chopin.wav` by appending zeroes to the end of the signal. Also, keep in mind that the Convolution Theorem requires both signals to have the same length; therefore you will need to pad the smaller of your two *transformed* signals (namely, the transformed impulse response signal) with zeros in order to make it the same size as the other transformed signal. These zeros should be added to the middles of the transformed signal, as we need to maintain its symmetric structure. Describe the resulting sound.

To summarize:

1. Read in `chopin.wav` and the impulse response with `wavfile`,

2. Add several seconds of silence to the signal from `chopin.wav`,
3. Insert zeros into the middle of the impulse response transform so that it is the same length as `chopin.wav`,
4. Calculate the convolution of the signals,
5. And finally, calculate the inverse Fourier transform.

In some instances, a circular convolution is actually desirable. For instance, an interesting effect is achieved by taking the circular convolution of a long segment of white noise with some other (shorter) sound. We can create white noise using SciPy's `random` module:

```
# Create 10 seconds of mono white noise.
samplerate = 22050
noise = sp.int16(sp.random.randint(-32767, 32767, samplerate * 10))
```

**Problem 4.** Create white noise and listen to the resulting sound (**CAUTION:** Turn your volume *way* down! It may be very, *very* loud). This kind of noise is called “white” because it contains all frequencies with the same strength, or rather, with the same expected strength (since the amplitude of a specific frequency is a matter of chance). In order to see this, plot the spectrum of the noise.

Now we can take the circular convolution of this noise with some other sound. For instance, let's use `tada.wav`. The result is in `tada-conv.wav`. We notice that the original short sound has been sustained to an indefinite length. The result is not a set of static tones, but rather a rich sound which preserves not only the tones, but the texture, of the original sound; you can hear different tones fluctuating randomly in amplitude over time. If you were to play this `tada-conv.wav` on repeat, you would find that, because we used a circular convolution, the sound loops seamlessly from the end back to the beginning; however, most sound players are not capable of doing this properly, so you will probably hear a break in the sound. To demonstrate the “seamlessness”, we can paste together multiple copies of the sound consecutively:

```
rate, sig = wavfile.read('tada-conv.wav')
sig = sp.append(sig, sig)
sig = sp.append(sig, sig)
```

Listen to the resulting sound, and notice that we are not able to identify where the sound loops back to the beginning, because there is no break or click.



## Lab 8

# Introduction to Wavelets

**Lab Objective:** *In the context of Fourier analysis, one seeks to represent a function as a sum of sinusoids. A drawback to this approach is that the Fourier transform only captures global frequency information, and local information is lost; we can know which frequencies are the most prevalent, but not when or where they occur. The Wavelet transform provides an alternative approach that avoids this shortcoming and is often a superior analysis technique for many types of signals and images.*

## The Discrete Wavelet Transform

In wavelet analysis, we seek to analyze a function by considering its *wavelet decomposition*. The wavelet decomposition of a function is a way of expressing the function as a linear combination of a particular family of basis functions. In this way, we can represent a function by the sequence of coefficients (called *wavelet coefficients*) defining this linear combination. The mapping from a function to its sequence of wavelet coefficients is called the *discrete wavelet transform*.

This situation is entirely analogous to the discrete Fourier transform. Instead of using trigonometric functions as our basis, we use a different family of basis functions. In Wavelet analysis, we determine the family of basis functions by first starting off with a function  $\psi$  called the *wavelet* and a function  $\phi$  called the *scaling function* (these functions are also called the mother and father wavelets, respectively). We then generate countably many basis functions (sometimes called baby wavelets) from these two functions:

$$\begin{aligned}\psi_{m,k}(x) &= \psi(2^m x - k) \\ \phi_{m,k}(x) &= \phi(2^m x - k),\end{aligned}$$

where  $m, k \in \mathbb{Z}$ . The historically first, and most basic, wavelet is called the *Haar Wavelet*, given by

$$\psi(x) = \begin{cases} 1 & \text{if } 0 \leq x < \frac{1}{2} \\ -1 & \text{if } \frac{1}{2} \leq x < 1 \\ 0 & \text{otherwise.} \end{cases}$$

The associated scaling function is given by

$$\phi(x) = \begin{cases} 1 & \text{if } 0 \leq x < 1 \\ 0 & \text{otherwise.} \end{cases}$$

In the case of finitely-sampled signals and images, only finitely many wavelet coefficients are nonzero. Depending on the application, we are often only interested in the coefficients corresponding to a subset of the basis functions. Since a given family of wavelets forms an orthogonal set, we can compute the wavelet coefficients by taking inner products (i.e. by integrating). This direct approach is not particularly efficient, however. Just as there are fast algorithms for computing the fourier transform (e.g. the FFT), we can efficiently calculate wavelet coefficients using techniques from signal processing. In particular, we will use an *iterative filterbank* to compute the transform.

Let's launch into an implementation of the one-dimensional discrete wavelet transform. The key operations in the algorithm are the discrete convolution (\*) and down-sampling (*DS*). The inputs to the algorithm are a one-dimensional array  $X$  (the signal that we want to transform), a one-dimensional array  $L$  (called the *low-pass filter*), a one-dimensional array  $H$  (the *high-pass filter*), and a positive integer  $n$  (controlling to what degree we wish to transform the signal, i.e. how many wavelet coefficients we wish to compute). The low-pass and high-pass filters can be derived from the wavelet and scaling function. The low-pass filter extracts low frequency information, which gives us an approximation of the signal. This approximation highlights the overall (slower-moving) pattern without paying too much attention to the high frequency details, which to the eye (or ear) may be unhelpful noise. However, we also need to extract the high-frequency details with the high-pass filter. While they may sometimes be nothing more than unhelpful noise, there are applications where they are the most important part of the signal; for example, details are very important if we are sharpening a blurry image or increasing contrast.

For the Haar Wavelet, our filters are given by

$$L = \begin{bmatrix} \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \end{bmatrix}$$

$$H = \begin{bmatrix} -\frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \end{bmatrix}.$$

See Algorithm 8.1 and Figure 8.1 for the specifications.

---

**Algorithm 8.1** The one-dimensional discrete wavelet transform.

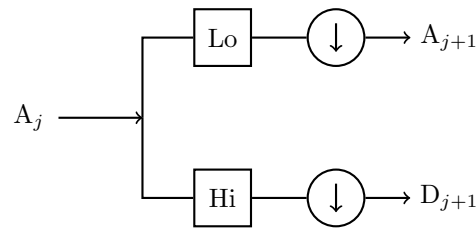
---

```

1: procedure DWT( $X, L, H, n$ )
2:    $A_i \leftarrow X$  ▷ Some initialization steps
3:   for  $i = 0 \dots n - 1$  do
4:      $D_{i+1} \leftarrow DS(A_i * H)$  ▷ High-pass filtering
5:      $A_{i+1} \leftarrow DS(A_i * L)$  ▷ Low-pass filtering
6:   return  $A_n, D_n, D_{n-1}, \dots, D_1$ .
```

---





Key:  = convolve

= downsample

Figure 8.1: The one-dimensional discrete wavelet transform implemented as a filter bank.

At each stage of the algorithm, we filter the signal into an approximation and its details. Note that the algorithm returns a sequence of one dimensional arrays

$$A_n, D_n, D_{n-1}, \dots, D_1.$$

If the input signal  $X$  has length  $2^m$  for some  $m \geq n$  and we are using the Haar wavelet, then  $A_n$  has length  $2^{m-n}$ , and  $D_i$  has length  $2^{m-i}$  for  $i = 1, \dots, n$ . The arrays  $D_i$  are outputs of the high-pass filter, and thus represent high-frequency details. Hence, these arrays are known as *details*. The array  $A_n$  is computed by recursively passing the signal through the low-pass filter, and hence it represents the low-frequency structure in the signal. In fact,  $A_n$  can be seen as a smoothed approximation of the original signal, and is called the *approximation*.

As noted earlier, the key mathematical operations are convolution and down-sampling. To accomplish the convolution, we simply use a function in SciPy.

```
>>> import numpy as np
>>> from scipy.signal import fftconvolve
>>> # initialize the filters
>>> L = np.ones(2)/np.sqrt(2)
>>> H = np.array([-1,1])/np.sqrt(2)
>>> # initialize a signal X
>>> X = np.sin(np.linspace(0,2*np.pi,16))
>>> # convolve X with L
>>> fftconvolve(X,L)
[ -1.84945741e-16  2.87606238e-01  8.13088984e-01  1.19798126e+00
  1.37573169e+00  1.31560561e+00  1.02799937e+00  5.62642704e-01
  7.87132986e-16 -5.62642704e-01 -1.02799937e+00 -1.31560561e+00
 -1.37573169e+00 -1.19798126e+00 -8.13088984e-01 -2.87606238e-01
 -1.84945741e-16]
```

The convolution operation alone gives us redundant information, so we down-sample to keep only what we need. In particular, we will down-sample by a factor of two, which means keeping only every other entry:

```
>>> # down-sample an array X
>>> sampled = X[1::2]
```

Putting these two operations together, we can obtain the approximation coefficients in one line of code:

```
>>> A = fftconvolve(X,L)[1::2]
```

Computing the detail coefficients is done in exactly the same way, replacing  $L$  with  $H$ .

**Problem 1.** Write a function that calculates the discrete wavelet transform as described above. The output should be a list of one-dimensional NumPy arrays in the following form:  $[A_n, D_n, \dots, D_1]$ .

The main body of your function should be a loop in which you calculate two arrays: the  $i$ -th approximation and detail coefficients. Append the detail coefficients array to your list, and feed the approximation array back into the loop. When the loop is finished, append the approximation array. Finally, reverse the order of your list to adhere to the required return format.

Test your function by calculating the Haar wavelet coefficients of a noisy sine signal for  $n = 4$ :

```
>>> domain = np.linspace(0, 4*np.pi, 1024)
>>> noise = np.random.randn(1024)*.1
>>> noisysin = np.sin(domain) + noise
>>> coeffs = dwt(noisysin, L, H, 4)
```

Plot your results and verify that they match the plots in Figure 8.2.

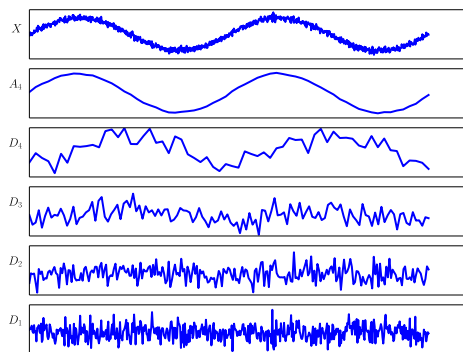


Figure 8.2: A level 4 wavelet decomposition of a signal. The top panel is the original signal, the next panel down is the approximation, and the remaining panels are the detail coefficients. Notice how the approximation resembles a smoothed version of the original signal, while the details capture the high-frequency oscillations and noise.

We can now transform a one-dimensional signal into its wavelet coefficients, but the reverse transformation is just as important. Luckily, we can reconstruct a signal from the approximation and detail coefficients. We reverse the effects of the filterbank, using slightly modified filters, essentially adding the details back into the signal at each stage until we reach the original. The Haar wavelet filters for the inverse transformation are

$$L = \begin{bmatrix} \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \end{bmatrix}$$

$$H = \begin{bmatrix} \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}} \end{bmatrix}.$$

Suppose we have the wavelet coefficients  $A_n$  and  $D_n$ . Consulting Figure 8.1, we can recreate  $A_{n-1}$  by tracing the schematic backwards:  $A_n$  and  $D_n$  are first *up-sampled*, then they are convolved with  $L$  and  $H$ , respectively, and finally added together to obtain  $A_{n-1}$ . Up-sampling means doubling the length of an array by inserting a 0 at every other position.

```
>>> # up-sample the coefficient arrays A, D
>>> up_A = np.zeros(2*A.size)
>>> up_A[::2] = A
>>> up_D = np.zeros(2*D.size)
>>> up_D[::2] = D
>>> # now convolve and add, but discard last entry
>>> A = fftconvolve(up_A,L)[: -1] + fftconvolve(up_D,H)[: -1]
```

Now that we have  $A_{n-1}$ , we repeat the process with  $A_{n-1}$  and  $D_{n-1}$  to obtain  $A_{n-2}$ . Proceed for a total of  $n$  steps (one for each  $D_n, D_{n-1}, \dots, D_1$ ) until we have obtained  $A_0$ . Since  $A_0$  is defined to be the original signal, we have finished the inverse transformation.

**Problem 2.** Write a function that calculates the inverse wavelet transform as described above. The inputs should be a list of arrays (of the same form as the output of your discrete wavelet transform function), the low-pass filter, and the high-pass filter. The output should be a single array, the recovered signal.

Note that the input list of arrays has length  $n + 1$  (consisting of  $A_n$  together with  $D_n, D_{n-1}, \dots, D_1$ ), so your code should perform the process given above  $n$  times.

In order to check your work, compute the discrete wavelet transform of a random array for different values of  $n$ , then compute the inverse transform. Compare the original signal with the recovered signal using `np.allclose`.

## The PyWavelets Module

Having implemented our own version of the basic 1-dimensional wavelet transform, we now turn to PyWavelets, a Python library for Wavelet Analysis. It provides convenient and efficient methods to calculate the one- and two-dimensional discrete Wavelet transform, as well as much more.

If you have the Anaconda distribution, then you can install PyWavelets simply with the command:

```
$ conda install -c ioos pywavelets=0.4.0
```

Once the package has been installed on your machine, type the following to get started:

```
>>> import pywt
```

Performing the discrete Wavelet transform is very simple. Below, we compute the one-dimensional transform for a sinusoidal signal.

```
>>> import numpy as np
>>> f = np.sin(np.linspace(0,8*np.pi, 256)) # build the sine wave
>>> fw = pywt.wavedec(f, 'haar') # compute the wavelet coefficients of f
```

The variable `fw` is now a list of arrays, starting with the final approximation frame, followed by the various levels of detail coefficients, just like the output of the wavelet transform function that you already coded. Plot the level 2 detail and verify that it resembles a blocky sinusoid.

```
>>> from matplotlib import pyplot as plt
>>> plt.plot(fw[-2], linestyle='steps')
>>> plt.show()
```

To reconstruct the signal, we simply call the function `waverec`:

```
>>> f_prime = pywt.waverec(fw, 'haar') # reconstruct the signal
>>> np.allclose(f_prime, f) # compare with the original
True
```

The second positional argument, as you will notice, is a string that gives the name of the wavelet to be used. We first used the Haar wavelet, with which you are already familiar. PyWavelets supports a number of different Wavelets, however, which you can list by executing the following code:

```
>>> # list the available Wavelet families
>>> print pywt.families()
['haar', 'db', 'sym', 'coif', 'bior', 'rbio', 'dmey']
>>> # list the available wavelets in the coif family
>>> print pywt.wavelist('coif')
['coif1', 'coif2', 'coif3', 'coif4', 'coif5']
```

Different wavelets have different properties; the most suitable wavelet is dependent on the specific application. See Figure 8.3 for the plots of a couple of additional wavelets.

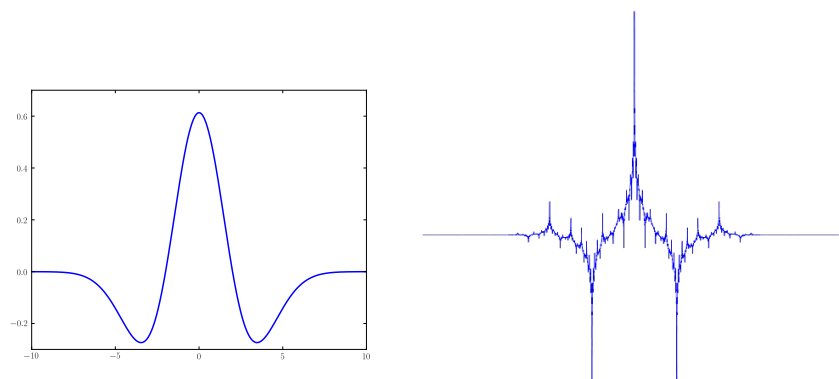


Figure 8.3: Examples of different mother wavelets.

## The 2-dimensional Wavelet Transform

We can generalize the wavelet transform for two dimensions much as we generalized the Fourier transform. This allows us to perform wavelet analysis on, for example, digital images. In particular, we can calculate the wavelet transform of a two-dimensional array by first transforming the rows, and then the columns of the array.

When implemented as an iterative filterbank, each pass through the filterbank yields an approximation plus three sets of detail coefficients rather than just one. More specifically, if the two-dimensional array  $X$  is the input to the filterbank, we obtain arrays  $LL$ ,  $LH$ ,  $HL$ , and  $HH$ , where  $LL$  is a smoothed approximation of  $X$  and the other three arrays contain wavelet coefficients capturing high-frequency oscillations in vertical, horizontal, and diagonal directions. In the jargon of signal processing, the arrays  $LL$ ,  $LH$ ,  $HL$ , and  $HH$  are called *subbands*. By recursively feeding any or all of the subbands back into the filterbank, we can decompose an input array into a collection of many subbands. This decomposition can be represented schematically by a dyadic partition of a rectangle, called a *subband pattern*. The subband pattern for one pass of the filterbank is shown in Figure 8.4, with a concrete example given in Figure 8.5.

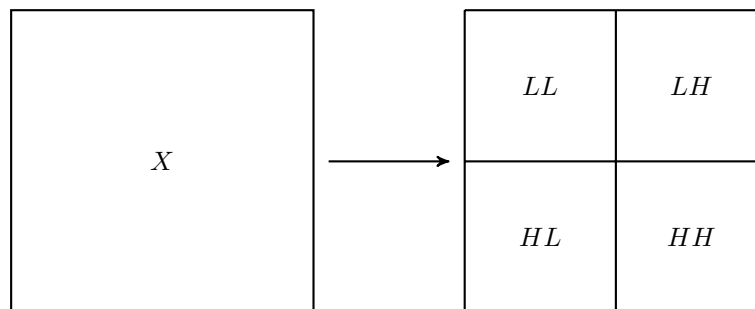


Figure 8.4: The subband pattern for one step in the 2-dimensional wavelet transform.

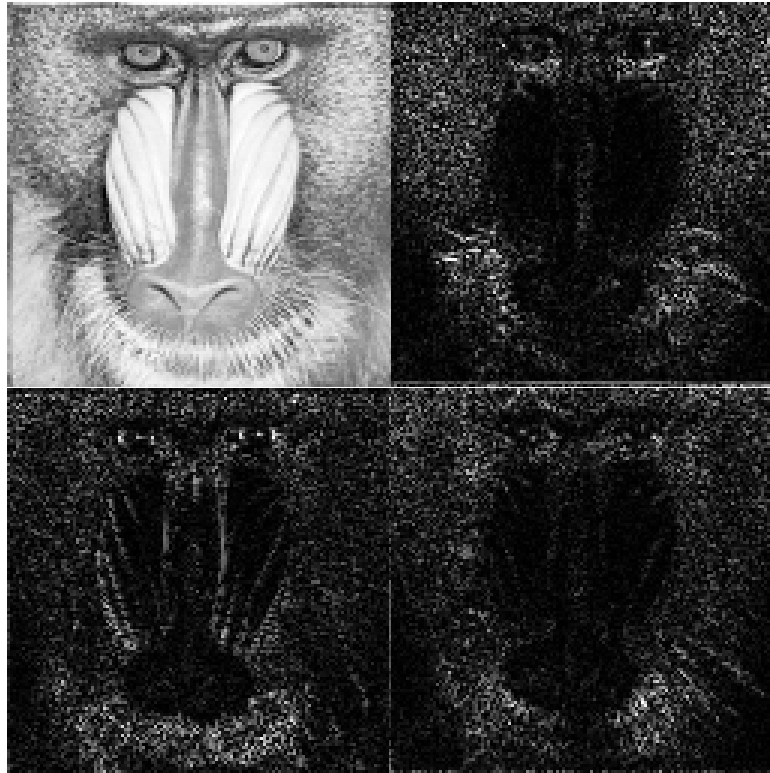


Figure 8.5: Subbands for the Mandrill image after one pass through the filterbank. Note how the upper left subband ( $LL$ ) is an approximation of the original Mandrill image, while the other three subbands highlight the stark vertical, horizontal, and diagonal changes in the image.

Original image source: <http://sipi.usc.edu/database/>.

The wavelet coefficients that we obtain from a two-dimensional wavelet transform are very useful in a variety of image processing tasks. They allow us to analyze and manipulate images in terms of both their frequency and spatial properties, and at differing levels of resolution. Furthermore, wavelet bases often have the remarkable ability to represent images in a very *sparse* manner – that is, most of the image information is captured by a small subset of the wavelet coefficients. This is the key fact for wavelet-based image compression.

PyWavelets provides a simple way to calculate the subbands resulting from one pass through the filterbank.

```
>>> from scipy.misc import imread
>>> # flag True produces a grayscale image
>>> mandrill = imread('mandrill1.png', True)
>>> # use the db4 wavelet with periodic extension
>>> lw = pywt.dwt2(mandrill, 'db4', mode='per')
```

Note that the `mode` keyword argument determines the type of extension mode (required for the convolution operation). The variable `lw` is a list. The first entry of

the list is the  $LL$ , or approximation, subband. The second entry of the list is a tuple containing the remaining subbands,  $LH$ ,  $HL$ , and  $HH$  (in that order). Plot these subbands as follows:

```
>>> plt.subplot(221)
>>> plt.imshow(np.abs(lw[0]), cmap='gray')
>>> plt.subplot(222)
>>> plt.imshow(np.abs(lw[1][0]), cmap='gray')
>>> plt.subplot(223)
>>> plt.imshow(np.abs(lw[1][1]), cmap='gray')
>>> plt.subplot(224)
>>> plt.imshow(np.abs(lw[1][2]), cmap='gray')
>>> plt.show()
```

**Problem 3.** Plot the subbands of the file `swanlake_polluted.png` as described above. Compare this with the subbands the mandrill image shown in Figure 8.5.

## Image Processing

We are now ready to use the two-dimensional wavelet transform for image processing. Wavelets are especially good at filtering out high-frequency noise from an image. Just as we were able to pinpoint the noise added to the sine wave in Figure 8.2, the majority of the noise added to an image will be contained in the final  $LH$ ,  $HL$ , and  $HH$  detail subbands of our wavelet decomposition. If we decompose our image and reconstruct it with all subbands except these final subbands, we will eliminate most of the troublesome noise while preserving the primary aspects of the image.

We perform this cleaning as follows:

```
image = imread(filename,True)
wavelet = pywt.Wavelet('haar')
WaveletCoeffs = pywt.wavedec2(image,wavelet)
new_image = pywt.waverec2(WaveletCoeffs[:-1], wavelet)
```

**Problem 4.** Write a function called `clean_image()` which accepts the name of a grayscale image file and cleans high-frequency noise out of the image. Load the image as an ndarray, and perform a wavelet decomposition using PyWavelets. Reconstruct the image using all subbands except the last set of detail coefficients, and return this cleaned image as an ndarray.

## Additional Material

### Image Compression

Numerous image compression techniques have been developed over the years to reduce the cost of storing large quantities of images. Transform methods based on Fourier and Wavelet analysis have long played an important role in these techniques; for example, the popular JPEG image compression standard is based on the discrete cosine transform. The JPEG2000 compression standard and the FBI Fingerprint Image database, along with other systems, take the wavelet approach.

The general framework for compression is fairly straightforward. First, the image to be compressed undergoes some form of preprocessing, depending on the particular application. Next, the discrete wavelet transform is used to calculate the wavelet coefficients, and these are then *quantized*, i.e. mapped to a set of discrete values (for example, rounding to the nearest integer). The quantized coefficients are then passed through an entropy encoder (such as Huffman Encoding), which reduces the number of bits required to store the coefficients. What remains is a compact stream of bits that can then be saved or transmitted much more efficiently than the original image. The steps above are nearly all invertible (the only exception being rounding), allowing us to almost perfectly reconstruct the image from the compressed bitstream. See Figure 8.6.

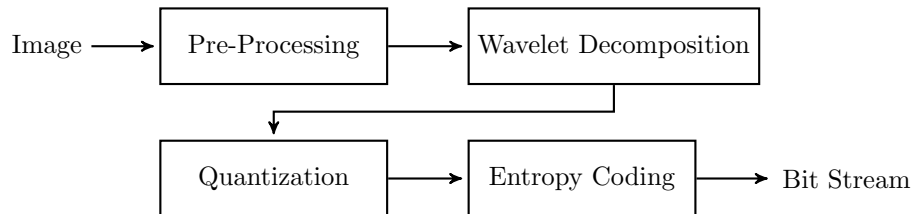


Figure 8.6: Wavelet Image Compression Schematic



## Lab 9

# Gaussian Quadrature

**Lab Objective:** *Numerical quadrature is an important numerical integration technique. The popular Newton-Cotes quadrature uses uniformly spaced points to approximate the integral, but Runge's phenomenon prevents Newton-Cotes from being effective for many functions. The Gaussian Quadrature method, on the other hand, uses carefully chosen points and weights to mitigate this problem.*

## Shifting the Interval of Integration

As with all quadrature methods, we begin by choosing a set of points  $x_i$  and weights  $w_i$  to approximate an integral.

$$\int_a^b f(x)dx \approx \sum_{i=1}^n w_i f(x_i).$$

When we do Gaussian quadrature, we are required to choose a weight function  $W(x)$ . This function determines both the  $x_i$ 's and the  $w_i$ 's. Theoretically, the weight function determines a set of orthogonal polynomials to approximate the function  $f$ .

The weight function also determines the interval over which the integration will occur. For example, we may choose the weight function as  $W(x) = 1$  over  $[-1, 1]$  to integrate functions on  $[-1, 1]$ . To calculate the definite integrate over a the arbitrary interval  $[a, b]$ , we perform a u-substitution to shift the interval of integration from  $[a, b]$  to  $[-1, 1]$ . Let

$$u = \frac{2x - b - a}{b - a}$$

so that  $u = -1$  when  $x = a$  and  $u = 1$  when  $x = b$ . Then we have

$$x = \frac{b-a}{2}u + \frac{a+b}{2} \quad \text{and} \quad dx = \frac{b-a}{2}du,$$

so the transformed integral is given by

$$\int_a^b f(x)dx = \frac{b-a}{2} \int_{-1}^1 f\left(\frac{b-a}{2}u + \frac{a+b}{2}\right) du. \quad (9.1)$$

The general quadrature formula is then given by the following equation.

$$\int_a^b f(x)dx \approx \frac{b-a}{2} \sum_i w_i f\left(\frac{(b-a)}{2}x_i + \frac{(a+b)}{2}\right)$$

**Problem 1.** Write a function that accepts a function  $f$ , interval endpoints  $a$  and  $b$ , and a keyword argument `plot` that defaults to `False`. Use (9.1) to construct a function  $g$  such that

$$\int_a^b f(x)dx = \frac{b-a}{2} \int_{-1}^1 g(u)du.$$

(Hint: this can be done in a single line using the `lambda` keyword.)

If `plot` is `True`, plot  $f$  over  $[a, b]$  and  $g$  over  $[-1, 1]$  in separate subplots. The functions probably have similar shapes, but note the difference in the scaling of the  $y$ -axis. Try  $f(x) = x^2$  and  $f(x) = (x-3)^3$  over  $[1, 4]$  as examples.

Finally, return the new function  $g$ .

## Integrating with Given Weights and Points

With the new shifted function  $g$  from Problem 1, we can write the quadrature formula as follows.

$$\int_a^b f(x)dx \approx \frac{b-a}{2} \sum_i w_i g(x_i) \quad (9.2)$$

Suppose for a given weight function  $W(x)$  and a given number of points  $n$ , we have the sample points  $\mathbf{x} = [x_1, \dots, x_n]^T$  and weights  $\mathbf{w} = [w_1, \dots, w_n]^T$  stored as 1-d NumPy arrays. The summation in (9.2) can then be calculated with the vector multiplication  $\mathbf{w}^T g(\mathbf{x})$ , where  $g(\mathbf{x}) = [g(x_1), \dots, g(x_n)]^T$ .

**Problem 2.** Write a function that accepts a function  $f$ , interval endpoints  $a$  and  $b$ , an array of points  $\mathbf{x}$ , and an array of weights  $\mathbf{w}$ . Use (9.2) and your function from Problem 1 to calculate the integral of  $f$  over  $[a, b]$ . Return the value of the integral.

To test this function, use the following 5 points and weights that accompany the constant weight function  $W(x) = 1$  (this weight function corresponds to the *Legendre polynomials*). See the next page for their definitions using NumPy.

$x_i$	$-\frac{1}{3}\sqrt{5+2\sqrt{\frac{10}{7}}}$	$-\frac{1}{3}\sqrt{5-2\sqrt{\frac{10}{7}}}$	0	$\frac{1}{3}\sqrt{5-2\sqrt{\frac{10}{7}}}$	$\frac{1}{3}\sqrt{5+2\sqrt{\frac{10}{7}}}$
$w_i$	$\frac{322-13\sqrt{70}}{900}$	$\frac{322+13\sqrt{70}}{900}$	$\frac{128}{225}$	$\frac{322+13\sqrt{70}}{900}$	$\frac{322-13\sqrt{70}}{900}$

```

import numpy as np
from math import sqrt

s1 = 2 * sqrt(10. / 7.)
points = np.array([-sqrt(5 + s1) / 3.,
                  -sqrt(5 - s1) / 3.,
                  0.,
                  sqrt(5 - s1) / 3.,
                  sqrt(5 + s1) / 3.])

s2 = 13 * sqrt(70)
weights = np.array([(322 - s2) / 900.,
                   (322 + s2) / 900.,
                   128 / 225.,
                   (322 + s2) / 900.,
                   (322 - s2) / 900.])

```

Using these points and weights should yield the approximations

$$\int_{-\pi}^{\pi} \sin(x) dx \approx 0 \quad \text{and} \quad \int_{-\pi}^{\pi} \cos(x) dx \approx 0.000196.$$

## Calculating Weights and Points

Calculating an integral when the weights and points are given is straightforward. But how are these weights and points found? There are many publications that will give tables of points for various weight functions. We will demonstrate how to find such a list using the Golub-Welsch algorithm.

### The Golub-Welsch Algorithm

The Golub-Welsch algorithm builds a tri-diagonal matrix and finds its eigenvalues. These eigenvalues are the points at which a function is evaluated for Gaussian quadrature. The weights are the length of the shifted interval of integration times the first coordinate of each eigenvector squared. We note that finding eigenvalues for a tridiagonal matrix is a well conditioned, relatively painless problem. Using a good eigenvalue solver gives the Golub-Welsch algorithm a complexity of  $O(n^2)$ . A full treatment of the Golub-Welsch algorithm may be found at <http://gubner.ece.wisc.edu/gaussquad.pdf>.

We mentioned that the choice of weight function corresponds to a class of orthogonal polynomials. An important fact about orthogonal polynomials is that any set of orthogonal polynomials  $\{u_i\}_{i=1}^N$  satisfies a three term recurrence relation

$$u_i(x) = (\gamma_{i-1}x - \alpha_i)u_{i-1}(x) - \beta_i u_{i-2}(x)$$

where  $u_{-1}(x) = 0$  and  $u_0(x) = 1$ . The coefficients  $\{\gamma_i, \alpha_i, \beta_i\}$  have been calculated for several classes of orthogonal polynomials, and may be determined for an arbitrary class using the procedure found in “Calculation of Gauss Quadrature Rules” by Golub and Welsch. Using these coefficients we may create a tri-diagonal matrix

$$J = \begin{bmatrix} a_1 & b_1 & 0 & 0 & \dots & 0 \\ b_1 & a_2 & b_2 & 0 & \dots & 0 \\ 0 & b_2 & a_3 & b_3 & \dots & 0 \\ \vdots & & & & & \vdots \\ \vdots & & & & & \vdots \\ 0 & \dots & & & & b_{N-1} \\ 0 & \dots & & b_{N-1} & & a_N \end{bmatrix}$$

Where  $a_i = \frac{-\beta_i}{\alpha_i}$  and  $b_i = (\frac{\gamma_{i+1}}{\alpha_i \alpha_{i+1}})^{\frac{1}{2}}$ . This matrix is called the Jacobi matrix.

**Problem 3.** Write a function that will accept three arrays representing the coefficients  $\{\gamma_i, \alpha_i, \beta_i\}$  from the recurrence relation above and return the Jacobi matrix.

The eigenvalues of the Jacobi matrix are the sample points  $x_i$ . The length of the shifted interval of integration (in this case 2) times the squares of the first entries of the corresponding eigenvectors give the weights.

**Problem 4.** The coefficients of the Legendre polynomials (which correspond to the weight function  $W(x) = 1$  on  $[-1, 1]$ ) are given by

$$\gamma_k = \frac{k-1}{k} \quad \alpha_k = \frac{2k-1}{k} \quad \beta_k = 0$$

Write a function that accepts an integer  $n$  representing the number of points to use in the quadrature. Calculate  $\alpha$ ,  $\beta$ , and  $\gamma$  as above, form the Jacobi matrix, then use it to find the points  $x_i$  and weights  $w_i$  that correspond to this weight function. Verify that when  $n = 5$  the points and weights match the ones given in the first part of this lab.

**Problem 5.** Write a new function that accepts a function  $f$ , bounds  $a$  and  $b$ , and  $n$  for the number of points to use. Use the previously defined functions to estimate  $\int_a^b f(x)dx$  using the coefficients of the Legendre polynomials.

This completes our implementation of the Gaussian Quadrature for a particular set orthogonal polynomials.

## Numerical Integration with SciPy

There are many other techniques for finding the weights and points for a given weighting function. SciPy's `integrate` module provides general-purpose integration tools. For example, `scipy.integrate.quadrature()` offers a reasonably fast Gaussian quadrature implementation.

**Problem 6.** The standard normal distribution is an important object of study in probability and statistic. It is defined by the probability density function  $p(x) = \frac{1}{\sqrt{2\pi}}e^{-x^2/2}$  (here we are assuming a mean of 0 and a variance of 1). This is a function that cannot be integrated symbolically.

The probability that a normally distributed random variable  $X$  will take on a value less than (or equal to) a given value  $x$  is

$$P(X \leq x) = \int_{-\infty}^x \frac{1}{\sqrt{2\pi}} e^{-t^2/2} dt$$

This function is essentially zero for values of  $x$  that lie reasonably far from the mean, so we can estimate this probability by integrating from  $-5$  to  $x$  instead of from  $-\infty$  to  $x$ .

Write a function that uses `scipy.integrate.quad()` to estimate the probability that this normally distributed random variable will take a value less than a given number  $x$  that lies relatively close to the mean. You can test your result at  $x = 1$  by comparing it with the following code:

```
from scipy.stats import norm
N = norm()
N.cdf(1)
```

# Make a standard normal random variable.  
# Integrate the pdf from -infinity to 1.



## Lab 10

# CVXOPT

**Lab Objective:** *Introduce some of the basic optimization functions available in the CVXOPT package*

Notebox: CVXOPT is not part of the standard library, nor is it included in the Anaconda distribution. To install CVXOPT, use the following commands:

for Windows: `conda install -c http://conda.anaconda.org/omnia cvxopt`

for Unix: `pip install cvxopt` End notebox.

## Linear Programs

CVXOPT is a package of Python functions and classes designed for the purpose of convex optimization. In this lab we will focus on linear and quadratic programming. A *linear program* is a linear constrained optimization problem. Such a problem can be stated in several different forms, one of which is

$$\begin{array}{ll} \text{minimize} & c^T x \\ \text{subject to} & Gx + s = h \\ & Ax = b \\ & s \geq 0. \end{array}$$

This is the formulation used by CVXOPT. In this formulation, we require that the matrix  $A$  has full row rank, and that the block matrix  $[G \ A]^T$  has full column rank.

Note that the constraint  $Gx + s = h$  includes the term  $s$ , which is not part of the objective function, and is known as the *slack variable*. Since  $s \geq 0$ , the constraint  $Gx + s = h$  is equivalent to  $Gx \leq h$ .

Consider the following example:

$$\begin{array}{ll} \text{minimize} & -4x_1 - 5x_2 \\ \text{subject to} & x_1 + 2x_2 \leq 3 \\ & 2x_1 + x_2 \leq 3 \\ & x_1, x_2 \geq 0 \end{array}$$

The final two constraints,  $x_1, x_2 \geq 0$ , need to be adjusted to be  $\leq$  constraints. This is easily done by multiplying by  $-1$ , resulting in the constraints  $-x_1, -x_2 \leq 0$ . If we define

$$G = \begin{bmatrix} 1 & 2 \\ 2 & 1 \\ -1 & 0 \\ 0 & -1 \end{bmatrix} \quad \text{and} \quad h = \begin{bmatrix} 3 \\ 3 \\ 0 \\ 0 \end{bmatrix},$$

then we can express the constraints compactly as

$$Gx \leq h, \quad \text{where} \quad x = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}.$$

By adding a slack variable  $s$ , we can write our constraints as

$$Gx + s = h,$$

which matches the form discussed above. In the case of this particular example, we ignore the extra constraint

$$Ax = b,$$

since we were given no equality constraints.

Now we proceed to solve the problem using CVXOPT. We need to initialize the arrays  $c$ ,  $G$ , and  $h$ , and then pass them to the appropriate function. CVXOPT uses its own data type for an array or matrix, and while similar to the NumPy array, it does have a few differences, especially when it comes to initialization. Below, we initialize CVXOPT matrices for  $c$ ,  $G$ , and  $h$ .

```
>>> from cvxopt import matrix
>>> c = matrix([-4., -5.])
>>> G = matrix([[1., 2., -1., 0.], [2., 1., 0., -1.]])
>>> h = matrix([ 3., 3., 0., 0.] )
```

### ACHTUNG!

Observe that CVXOPT matrices are initialized column-wise rather than row-wise (as in the case of NumPy).

Alternatively, we can initialize the arrays first in NumPy (a process with which you should be familiar), and then simply convert them to the CVXOPT matrix data type:

```
>>> import numpy as np
>>> c = np.array([-4., -5.])
>>> G = np.array([[1., 2.], [2., 1.], [-1., 0.], [0., -1.]])
>>> h = np.array([3., 3., 0., 0.])

>>> #Now convert to CVXOPT matrix type
>>> c = matrix(c)
>>> G = matrix(G)
>>> h = matrix(h)
```

Use whichever method is most convenient. In this lab, we will initialize non-



trivial matrices first as ndarrays for consistency.

Finally, be sure the entries in the matrices are floats!

Having initialized the necessary objects, we are now ready to solve the problem. We will use the CVXOPT function for linear programming `solvers.lp`, and we simply need to pass in  $c$ ,  $G$ , and  $h$  as arguments.

```
>>> from cvxopt import solvers
>>> sol = solvers.lp(c, G, h)
      pcost      dcost      gap      pres      dres      k/t
0: -8.1000e+00 -1.8300e+01 4e+00 0e+00 8e-01 1e+00
1: -8.8055e+00 -9.4357e+00 2e-01 1e-16 4e-02 3e-02
2: -8.9981e+00 -9.0049e+00 2e-03 1e-16 5e-04 4e-04
3: -9.0000e+00 -9.0000e+00 2e-05 1e-16 5e-06 4e-06
4: -9.0000e+00 -9.0000e+00 2e-07 1e-16 5e-08 4e-08
Optimal solution found.
>>> print sol['x']
[ 1.00e+00]
[ 1.00e+00]
>>> print sol['primal objective']
-8.99999981141
>>> print type(sol['x'])
<type 'cvxopt.base.matrix'>
```

## NOTE

Although it is often helpful to see the progress of each iteration of the algorithm, you may suppress this output by first running,

```
solvers.options['show_progress'] = False
```

The function `solvers.lp` returns a dictionary containing useful information. For the time being, we will only focus on the values of  $x$  and the primal objective value (i.e. the minimum value achieved by the objective function).

## ACHTUNG!

Note that the minimizer of the `solvers.lp()` function returns a `cvxopt.base.matrix` object. In order to use the minimizer again in other algebraic expressions, you need to convert it first to a flattened numpy array, which can be done quickly with `np.ravel()`. Please return all minimizers in this lab as flattened numpy arrays.

**Problem 1.** Solve the following convex optimization problem:

$$\begin{array}{ll} \text{minimize} & 2x_1 + x_2 + 3x_3 \\ \text{subject to} & x_1 + 2x_2 \geq 3 \\ & 2x_1 + 10x_2 + 3x_3 \geq 10 \\ & x_1 \geq 0 \\ & x_2 \geq 0 \\ & x_3 \geq 0 \end{array}$$

Report the values for  $x$  and the objective value that you obtain. Remember to make the necessary adjustments so that all inequality constraints are  $\leq$  rather than  $\geq$ .

The  $l_1$  minimization problem is to

$$\begin{array}{ll} \text{minimize} & \|x\|_1 \\ \text{subject to} & Ax = b. \end{array}$$

This problem can be converted into a linear program by introducing an additional vector  $u$  of length  $n$ , and then solving:

$$\begin{array}{ll} \text{minimize} & \begin{bmatrix} \mathbf{1} & 0 \end{bmatrix} \begin{bmatrix} u \\ x \end{bmatrix} \\ \text{subject to} & \begin{bmatrix} -I & I \\ -I & -I \end{bmatrix} \begin{bmatrix} u \\ x \end{bmatrix} \leq \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \\ & \begin{bmatrix} 0 & A \end{bmatrix} \begin{bmatrix} u \\ x \end{bmatrix} = b. \end{array}$$

Of course, solving this gives values for the optimal  $u$  and the optimal  $x$ , but we only care about the optimal  $x$ .

**Problem 2.** Write a function called `l1Min()` that takes a matrix  $A$  and vector  $b$  as inputs, and solves the  $l_1$  optimization problem. Report the values for  $x$  and the objective value. Remember to first discard the unnecessary  $u$  values from the minimizer.

## The Transportation Problem

Consider the following transportation problem: A piano company needs to transport thirteen pianos from their three supply centers (denoted by 1, 2, 3) to two demand centers (4, 5). Transporting a piano from a supply center to a demand center incurs a cost, listed in Table 10.3. The company wants to minimize shipping costs for the

Supply Center	Number of pianos available
1	7
2	2
3	4

Table 10.1: Number of pianos available at each supply center

Demand Center	Number of pianos needed
4	5
5	8

Table 10.2: Number of pianos needed at each demand center

pianos while meeting the demand. How many pianos should each supply center send to each demand center?

The variables  $p, q, r, s, t$ , and  $u$  must be nonnegative and satisfy the following three supply constraints and two demand constraints:

$$\begin{aligned}
 p + q &= 7 \\
 r + s &= 2 \\
 t + u &= 4 \\
 p + r + t &= 5 \\
 q + s + u &= 8
 \end{aligned}$$

The objective function is the number of pianos shipped from each location multiplied by the respective cost:

$$4p + 7q + 6r + 8s + 8t + 9u.$$

There are several ways to solve this linear program. We want our answers to be integers, and this added constraint in general turns out to be an NP-hard problem. There is a whole field devoted to dealing with integer constraints, called *integer linear programming*, which is beyond the scope of this lab. Fortunately, we can treat this particular problem as a standard linear program and still obtain integer solutions.

Here,  $G$  and  $h$  constrain the variables to be non-negative. Because CVXOPT uses the format  $Gx \leq h$ , we see that  $G$  must be a  $6 \times 6$  identity matrix multiplied by  $-1$ , and  $h$  is just a column vector of zeros. The matrices  $A$  and  $b$  represent the supply and demand constraints, since these are equality constraints. Try initializing these arrays and solving the linear program by entering the code below. (Notice that we pass more arguments to `solvers.lp` since we have equality constraints.)

```

>>> c = matrix([4., 7., 6., 8., 8., 9])
>>> G = matrix(-1*np.eye(6))
>>> h = matrix(np.zeros(6))
>>> A = matrix(np.array([[1.,1.,0.,0.,0.,0.],
                        [0.,0.,1.,1.,0.,0.],
                        [0.,0.,0.,0.,1.,1.],
                        [1.,0.,1.,0.,1.,0.],

```

Supply Center	Demand Center	Cost of transportation	Number of pianos
1	4	4	p
1	5	7	q
2	4	6	r
2	5	8	s
3	4	8	t
3	5	9	u

Table 10.3: Cost of transporting one piano from a supply center to a demand center

```

                                [0.,1.,0.,1.,0.,1.]))
>>> b = matrix([7., 2., 4., 5., 8.])
>>> sol = solvers.lp(c, G, h, A, b)
      pcost      dcost      gap      pres      dres      k/t
0:  8.9500e+01  8.9500e+01  2e+01  4e-17  2e-01  1e+00
Terminated (singular KKT matrix).
>>> print sol['x']
[ 3.00e+00]
[ 4.00e+00]
[ 5.00e-01]
[ 1.50e+00]
[ 1.50e+00]
[ 2.50e+00]
>>> print sol['primal objective']
89.5

```

Notice that some problems occurred. First, CVXOPT alerted us to the fact that the algorithm terminated prematurely (due to a singular matrix). Further, the solution that was obtained does not consist of integer entries.

So what went wrong? Recall that the matrix  $A$  is required to have full row rank, but we can easily see that the rows of  $A$  are linearly dependent. We rectify this by converting the last row of the equality constraints into *inequality* constraints, so that the remaining equality constraints define a new matrix  $A$  with linearly independent rows.

This is done as follows:

Suppose we have the equality constraint

$$x + 2y - 3z = 4.$$

This is equivalent to the pair of inequality constraints

$$x + 2y - 3z \leq 4,$$

$$x + 2y - 3z \geq 4.$$

Of course, we require only  $\leq$  constraints, so we obtain the pair of constraints

$$x + 2y - 3z \leq 4,$$

$$-x - 2y + 3z \leq -4.$$

Apply this process to the last equality constraint. You will obtain a new matrix  $G$  with several additional rows (to account for the new inequality constraints); a new vector  $h$ , also with more entries; a smaller matrix  $A$ ; a smaller vector  $b$ .

**Problem 3.** Solve the problem by converting the last equality constraint into an inequality constraint. Report the optimal values for  $x$  and the objective function.

## Quadratic Programming

Quadratic programming is similar to linear programming, one exception being that the objective function is quadratic rather than linear. The constraints, if there are any, are still of the same form. Thus  $G, h, A$ , and  $b$  are optional. The formulation that we will use is

$$\begin{aligned} & \text{minimize} && \frac{1}{2}x^\top Px + q^\top x \\ & \text{subject to} && Gx \leq h \\ & && Ax = b, \end{aligned}$$

where  $P$  is a positive semidefinite symmetric matrix. In this formulation, we require again that  $A$  has full row rank, and that the block matrix  $\begin{bmatrix} P & G & A \end{bmatrix}^\top$  has full column rank.

As an example, let us minimize the quadratic function

$$f(y, z) = 2y^2 + 2yz + z^2 + y - z.$$

Note that there are no constraints, so we only need to initialize the matrix  $P$  and the vector  $q$ . To find these, we first rewrite our function to match the formulation given above. Note that if we let

$$P = \begin{bmatrix} a & b \\ b & c \end{bmatrix}, \quad q = \begin{bmatrix} d \\ e \end{bmatrix}, \quad \text{and} \quad x = \begin{bmatrix} y \\ z \end{bmatrix},$$

then

$$\begin{aligned} \frac{1}{2}x^\top Px + q^\top x &= \frac{1}{2} \begin{bmatrix} y \\ z \end{bmatrix}^\top \begin{bmatrix} a & b \\ b & c \end{bmatrix} \begin{bmatrix} y \\ z \end{bmatrix} + \begin{bmatrix} d \\ e \end{bmatrix}^\top \begin{bmatrix} y \\ z \end{bmatrix} \\ &= \frac{1}{2}ay^2 + byz + \frac{1}{2}cz^2 + dy + ez \end{aligned}$$

Thus, we see that the proper values to initialize our matrix  $P$  and vector  $q$  are:

$$\begin{aligned} a &= 4 & d &= 1 \\ b &= 2 & e &= -1 \\ c &= 2 \end{aligned}$$

Now that we have the matrix  $P$  and vector  $q$ , we are ready to use the CVXOPT function for quadratic programming `solvers.qp`.

```
>>> P = matrix(np.array([[4., 2.], [2., 2.]])
>>> q = matrix([1., -1.]
```

```
>>> sol=solvers.qp(P, q)
>>> print(sol['x'])
[-1.00e+00]
[ 1.50e+00]
>>> print sol['primal objective']
-1.25
```

**Problem 4.** Find the minimizer and minimum of

$$g(x, y, z) = \frac{3}{2}x^2 + 2xy + xz + 2y^2 + 2yz + \frac{3}{2}z^2 + 3x + z$$

**Problem 5.** The  $l_2$  minimization problem is to

$$\begin{array}{ll} \text{minimize} & \|x\|_2 \\ \text{subject to} & Ax = b. \end{array}$$

This problem is equivalent to a quadratic program, since  $\|x\|_2 = \sqrt{x^\top x}$ . Write a function called `l2Min()` that takes a matrix  $A$  and vector  $b$  as inputs and solves the  $l_2$  minimization problem. Report the values for  $x$  and the objective value.

## Allocation Models

Allocation models lead to simple linear programs. An allocation model seeks to allocate a valuable resource among competing needs. Consider the following example is taken from “Optimization in Operations Research” by Ronald L. Rardin.

The U.S. Forest service has used an allocation model to deal with the task of managing national forests. The model begins by dividing the land into a set of analysis areas. Several land management policies (also called prescriptions) are then proposed and evaluated for each area. An *allocation* is how much land (in acreage) in each unique analysis area will be assigned to each of the possible prescriptions. We seek to find the best possible allocation, subject to forest-wide restrictions on land use.

The file `ForestData.npy` contains data for a fictional national forest (you can also find the data in Table ??). There are 7 areas of analysis and 3 prescriptions for

each of them.

Column 1:  $i$ , area of analysis

Column 2:  $s_i$ , size of the analysis area (in thousands of acres)

Column 3:  $j$ , prescription number

Column 4:  $p_{i,j}$ , net present value (NPV) per acre of in area  $i$  under prescription  $j$

Column 5:  $t_{i,j}$ , protected timber yield per acre in area  $i$  under prescription  $j$

Column 6:  $g_{i,j}$ , protected grazing capability per acre for area  $i$  under prescription  $j$

Column 7:  $w_{i,j}$ , wilderness index rating (0 to 100) for area  $i$  under prescription  $j$

Let  $x_{i,j}$  be the amount of land in area  $i$  allocated to prescription  $j$ . Under this

Forest Data						
Analysis Area, $i$	Acres (1000)'s $s_i$	Prescription $j$	NPV, (per acre) $p_{i,j}$	Timber, (per acre) $t_{i,j}$	Grazing, (per acre) $g_{i,j}$	Wilderness Index, $w_{i,j}$
1	75	1	503	310	0.01	40
		2	140	50	0.04	80
		3	203	0	0	95
2	90	1	675	198	0.03	55
		2	100	46	0.06	60
		3	45	0	0	65
3	140	1	630	210	0.04	45
		2	105	57	0.07	55
		3	40	0	0	60
4	60	1	330	112	0.01	30
		2	40	30	0.02	35
		3	295	0	0	90
5	212	1	105	40	0.05	60
		2	460	32	0.08	60
		3	120	0	0	70
6	98	1	490	105	0.02	35
		2	55	25	0.03	50
		3	180	0	0	75
7	113	1	705	213	0.02	40
		2	60	40	0.04	45
		3	400	0	0	95

notation, an allocation is just a vector consisting of the  $x_{i,j}$ 's. For this particular example, the allocation vector is of size  $7 \cdot 3 = 21$ . Our goal is to find the allocation vector that maximizes net present value, while producing at least 40 million board-feet of timber, at least 5 thousand animal-unit months of grazing, and keeping the average wilderness index at least 70.

Of course, the allocation vector is also constrained to be nonnegative, and all of the land must be allocated precisely.

Note that since acres are in thousands, we will divide the constraints of timber and animal months of grazing by 1000 in our problem setup, and compensate for

this after we obtain a solution. We can summarize our problem as follows:

$$\begin{aligned}
 & \text{maximize} && \sum_{i=1}^7 \sum_{j=1}^3 p_{i,j} x_{i,j} \\
 & \text{subject to} && \sum_{j=1}^3 x_{i,j} = s_i \text{ for } i = 1, \dots, 7 \\
 & && \sum_{i=1}^7 \sum_{j=1}^3 t_{i,j} x_{i,j} \geq 40,000 \\
 & && \sum_{i=1}^7 \sum_{j=1}^3 g_{i,j} x_{i,j} \geq 5 \\
 & && \frac{1}{788} \sum_{i=1}^7 \sum_{j=1}^3 w_{i,j} x_{i,j} \geq 70 \\
 & && x_{i,j} \geq 0 \text{ for } i = 1, \dots, 7 \text{ and } j = 1, 2, 3
 \end{aligned}$$

**Problem 6.** Solve the problem above. Return the minimizer  $x$  of  $x_{i,j}$ 's. Also return the maximum total net present value, which will be equal to the primal objective of the appropriately minimized linear function, multiplied by -1000. (This final multiplication after we have obtained a solution changes our answer to be a maximum, and compensates for the data being in thousands of acres).

You can learn more about CVXOPT at <http://abel.ee.ucla.edu/cvxopt/documentation/>.



## Lab 11

# The Simplex Method

**Lab Objective:** *The Simplex Method is a straightforward algorithm for finding optimal solutions to optimization problems with linear constraints and cost functions. Because of its simplicity and applicability, this algorithm has been named one of the most important algorithms invented within the last 100 years. In this lab, we implement a standard Simplex solver for the primal problem.*

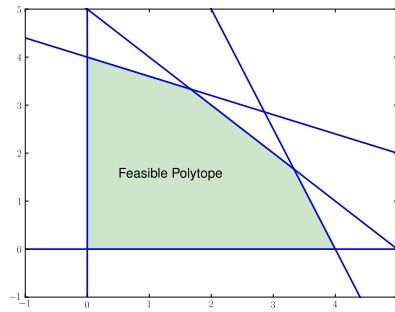
## Standard Form

The Simplex Algorithm accepts a linear constrained optimization problem, also called a *linear program*, in the form given below:

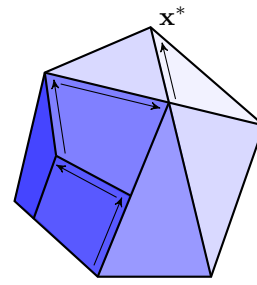
$$\begin{array}{ll}\text{maximize} & \mathbf{c}^T \mathbf{x} \\ \text{subject to} & \mathbf{A} \mathbf{x} \preceq \mathbf{b} \\ & \mathbf{x} \succeq \mathbf{0}\end{array}$$

Note that any linear program can be converted to standard form, so there is no loss of generality in restricting our attention to this particular formulation.

Such an optimization problem defines a region in space called the *feasible region*, the set of points satisfying the constraints. Because the constraints are all linear, the feasible region forms a geometric object called a *polytope*, having flat faces and edges (see Figure 11.1). The Simplex Algorithm jumps among the vertices of the feasible region searching for an optimal point. It does this by moving along the edges of the feasible region in such a way that the objective function is always increased after each move.



(a) The feasible region for a linear program with 2-dimensional constraints.



(b) The feasible region for a linear program with 3-dimensional constraints.

Figure 11.1: If an optimal point exists, it is one of the vertices of the polyhedron. The simplex algorithm searches for optimal points by moving between adjacent vertices in a direction that increases the value of the objective function until it finds an optimal vertex.

Implementing the Simplex Algorithm is straightforward, provided one carefully follows the procedure. We will break the algorithm into several small steps, and write a function to perform each one. To become familiar with the execution of the Simplex algorithm, it is helpful to work several examples by hand.

## The Simplex Solver

Our program will be more lengthy than many other lab exercises and will consist of a collection of functions working together to produce a final result. It is important to clearly define the task of each function and how all the functions will work together. If this program is written haphazardly, it will be much longer and more difficult to read than it needs to be. We will walk you through the steps of implementing the Simplex Algorithm as a Python class.

For demonstration purposes, we will use the following linear program.

$$\begin{array}{ll}
 \text{maximize} & 3x_0 + 2x_1 \\
 \text{subject to} & x_0 - x_1 \leq 2 \\
 & 3x_0 + x_1 \leq 5 \\
 & 4x_0 + 3x_1 \leq 7 \\
 & x_0, x_1 \geq 0.
 \end{array}$$

## Accepting a Linear Program

Our first task is to determine if we can even use the Simplex algorithm. Assuming that the problem is presented to us in standard form, we need to check that the feasible region includes the origin.

**Problem 1.** Write a class that accepts the arrays  $\mathbf{c}$ ,  $A$ , and  $\mathbf{b}$  of a linear optimization problem in standard form. In the constructor, check that the system is feasible at the origin<sup>a</sup>. That is, check that  $A\mathbf{x} \preceq \mathbf{b}$  when  $\mathbf{x} = \mathbf{0}$ . Raise a `ValueError` if the problem is not feasible at the origin.

<sup>a</sup>For now, we only check for feasibility at the origin. A more robust solver sets up the auxiliary problem and solves it to find a starting point if the origin is infeasible.

## Adding Slack Variables

The next step is to convert the inequality constraints  $A\mathbf{x} \preceq \mathbf{b}$  into equality constraints by introducing a slack variable for each constraint equation. If the constraint matrix  $A$  is an  $m \times n$  matrix, then there are  $m$  slack variables, one for each row of  $A$ . Grouping all of the slack variables into a vector  $\mathbf{w}$  of length  $m$ , the constraints now take the form  $A\mathbf{x} + \mathbf{w} = \mathbf{b}$ . In our example, we have

$$\mathbf{w} = \begin{bmatrix} x_2 \\ x_3 \\ x_4 \end{bmatrix}$$

When adding slack variables, it is useful to represent all of your variables, both the original primal variables and the additional slack variables, in a convenient manner. One effective way is to refer to a variable by its subscript. For example, we can use the integers 0 through  $n - 1$  to refer to the original (non-slack) variables  $x_0$  through  $x_{n-1}$ , and we can use the integers  $n$  through  $n + m - 1$  to track the slack variables (where the slack variable corresponding to the  $i$ th row of the constraint matrix is represented by the index  $n + i - 1$ ).

We also need some way to track which variables are *basic* (non-zero) and which variables are *nonbasic* (those that have value 0). A useful representation for the variables is a Python list (or NumPy array), where the elements of the list are integers. Since we know how many basic variables we have ( $m$ ), we can partition the list so that all the basic variables are kept in the first  $m$  locations, and all the non-basic variables are stored at the end of the list. The ordering of this list is important. In particular, if  $i \leq m$ , the  $i$ th element of the list represents the basic variable corresponding to the  $i$ th row of  $A$ . Henceforth we will refer to this list as the *index list*.

Initially, the basic variables are simply the slack variables, and their values correspond to the values of the vector  $\mathbf{b}$ . In our example, we have 2 primal variables  $x_0$  and  $x_1$ , and we must add 3 slack variables. Thus, we instantiate the following index list:

```
>>> L = [2, 3, 4, 0, 1]
```

Notice how the first 3 entries of the index list are 2, 3, 4, the indices representing the slack variables. This reflects the fact that the basic variables at this point are exactly the slack variables.

As the Simplex Algorithm progresses, however, the basic variables change, and it will be necessary to swap elements in our index list. For example, suppose the variable represented by the index 4 becomes nonbasic, while the variable represented by index 0 becomes basic. In this case we swap these two entries in the index list.

```
>>> L[2], L[3] = L[3], L[2]
>>> L
[2, 3, 0, 4, 1]
```

Now our index list tells us that the current basic variables have indices 2, 3, 0.

**Problem 2.** Design and implement a way to store and track all of the basic and non-basic variables.

Hint: Using integers that represent the index of each variable is useful for Problem 4.

## Creating a Tableau

After we have determined that our program is feasible, we need to create the *tableau* (sometimes called the *dictionary*), a data structure to track the state of the algorithm. You may structure the tableau to suit your specific implementation. Remember that your tableau will need to include in some way the slack variables that you created in Problem 2.

There are many different ways to build your tableau. One way is to mimic the tableau that is often used when performing the Simplex Algorithm by hand. Define

$$\bar{A} = \begin{bmatrix} A & I_m \end{bmatrix},$$

where  $I_m$  is the  $m \times m$  identity matrix, and define

$$\bar{\mathbf{c}} = \begin{bmatrix} \mathbf{c} \\ \mathbf{0} \end{bmatrix}.$$

That is,  $\bar{\mathbf{c}} \in \mathbb{R}^{n+m}$  such that the first  $n$  entries are  $\mathbf{c}$  and the final  $m$  entries are zeros. Then the initial tableau has the form

$$T = \begin{bmatrix} 0 & -\bar{\mathbf{c}}^T & 1 \\ \mathbf{b} & \bar{A} & \mathbf{0} \end{bmatrix} \quad (11.1)$$

The columns of the tableau correspond to each of the variables (both primal and slack), and the rows of the tableau correspond to the basic variables. Using the convention introduced above of representing the variables by indices in the index list, we have the following correspondence:

$$\text{column } i \Leftrightarrow \text{index } i - 2, \quad i = 2, 3, \dots, n + m + 1,$$

and

$$\text{row } j \Leftrightarrow L_{j-1}, \quad j = 2, 3, \dots, m + 1,$$

where  $L_{j-1}$  refers to the  $(j-1)$ th entry of the index list.

For our example problem, the initial index list is

$$L = (2, 3, 4, 0, 1),$$

and the initial tableau is

$$T = \begin{bmatrix} 0 & -3 & -2 & 0 & 0 & 0 & 1 \\ 2 & 1 & -1 & 1 & 0 & 0 & 0 \\ 5 & 3 & 1 & 0 & 1 & 0 & 0 \\ 7 & 4 & 3 & 0 & 0 & 1 & 0 \end{bmatrix}.$$

The third column corresponds to index 1, and the fourth row corresponds to index 4, since this is the third entry of the index list.

The advantage of using this kind of tableau is that it is easy to check the progress of your algorithm by hand. The disadvantage is that pivot operations require careful bookkeeping to track the variables and constraints.

**Problem 3.** Add a method to your Simplex solver that will create the initial tableau as a NumPy array.

## Pivoting

Pivoting is the mechanism that really makes Simplex useful. Pivoting refers to the act of swapping basic and nonbasic variables, and transforming the tableau appropriately. This has the effect of moving from one vertex of the feasible polytope to another vertex in a way that increases the value of the objective function. Depending on how you store your variables, you may need to modify a few different parts of your solver to reflect this swapping.

When initiating a pivot, you need to determine which variables will be swapped. In the tableau representation, you first find a specific element on which to pivot, and the row and column that contain the pivot element correspond to the variables that need to be swapped. Row operations are then performed on the tableau so that the pivot column becomes an elementary vector.

Let's break it down, starting with the pivot selection. We need to use some care when choosing the pivot element. To find the pivot column, search from left to right along the top row of the tableau (ignoring the first column), and stop once you encounter the first negative value. The index corresponding to this column will be designated the *entering index*, since after the full pivot operation, it will enter the basis and become a basic variable.

Using our initial tableau  $T$  in the example, we stop at the second column:

$$T = \begin{bmatrix} 0 & \boxed{-3} & -2 & 0 & 0 & 0 & 1 \\ 2 & 1 & -1 & 1 & 0 & 0 & 0 \\ 5 & 3 & 1 & 0 & 1 & 0 & 0 \\ 7 & 4 & 3 & 0 & 0 & 1 & 0 \end{bmatrix}$$

We now know that our pivot element will be found in the second column. The entering index is thus 0.

Next, we select the pivot element from among the positive entries in the pivot column (ignoring the entry in the first row). *If all entries in the pivot column are non-positive, the problem is unbounded and has no solution.* In this case, the algorithm should terminate. Otherwise, assuming our pivot column is the  $j$ th column of the tableau and that the positive entries of this column are  $T_{i_1,j}, T_{i_2,j}, \dots, T_{i_k,j}$ , we calculate the ratios

$$\frac{T_{i_1,1}}{T_{i_1,j}}, \frac{T_{i_2,1}}{T_{i_2,j}}, \dots, \frac{T_{i_k,1}}{T_{i_k,j}},$$

and we choose our pivot element to be one that minimizes this ratio. If multiple entries minimize the ratio, then we utilize *Bland's Rule*, which instructs us to choose the entry in the row corresponding to the smallest index (obeying this rule is important, as it prevents the possibility of the algorithm cycling back on itself infinitely). The index corresponding to the pivot row is designated as the *leaving index*, since after the full pivot operation, it will leave the basis and become a nonbasic variable.

In our example, we see that all entries in the pivot column (ignoring the entry in the first row, of course) are positive, and hence they are all potential choices for the pivot element. We then calculate the ratios, and obtain

$$\frac{2}{1} = 2, \quad \frac{5}{3} = 1.66\dots, \quad \frac{7}{4} = 1.75.$$

We see that the entry in the third row minimizes these ratios. Hence, the element in the second column, third row is our designated pivot element, and our leaving index is  $L_2 = 3$ :

$$T = \begin{bmatrix} 0 & -3 & -2 & 0 & 0 & 0 & 1 \\ 2 & 1 & -1 & 1 & 0 & 0 & 0 \\ 5 & \boxed{3} & 1 & 0 & 1 & 0 & 0 \\ 7 & 4 & 3 & 0 & 0 & 1 & 0 \end{bmatrix}$$

**Problem 4.** Write a method that will determine the pivot row and pivot column according to Bland's Rule.

**Definition 11.1 (Bland's Rule).** Choose the nonbasic variable with the smallest index that has a positive coefficient in the objective function as the leaving variable. Choose the basic variable with the smallest index among all the binding basic variables.

Bland's Rule is important in avoiding cycles when performing pivots. This rule guarantees that a feasible Simplex problem will terminate in a finite number of pivots.

The next step is to swap the entering and leaving indices in our index list. In the example, we determined above that these indices are 0 and 3. We swap these

two elements in our index list, and the updated index list is now

$$L = (2, 0, 4, 3, 1),$$

so the basic variables are now given by the indices 2, 0, 4.

Finally, we perform row operations on our tableau in the following way: divide the pivot row by the value of the pivot entry. Then use the pivot row to zero out all entries in the pivot column above and below the pivot entry. In our example, we first divide the pivot row by 3, and then zero out the two entries above the pivot element and the single entry below it:

$$\begin{aligned} & \begin{bmatrix} 0 & -3 & -2 & 0 & 0 & 0 & 1 \\ 2 & 1 & -1 & 1 & 0 & 0 & 0 \\ 5 & 3 & 1 & 0 & 1 & 0 & 0 \\ 7 & 4 & 3 & 0 & 0 & 1 & 0 \end{bmatrix} \rightarrow \begin{bmatrix} 0 & -3 & -2 & 0 & 0 & 0 & 1 \\ 2 & 1 & -1 & 1 & 0 & 0 & 0 \\ 5/3 & 1 & 1/3 & 0 & 1/3 & 0 & 0 \\ 7 & 4 & 3 & 0 & 0 & 1 & 0 \end{bmatrix} \rightarrow \\ & \begin{bmatrix} 5 & 0 & -1 & 0 & 1 & 0 & 1 \\ 2 & 1 & -1 & 1 & 0 & 0 & 0 \\ 5/3 & 1 & 1/3 & 0 & 1/3 & 0 & 0 \\ 7 & 4 & 3 & 0 & 0 & 1 & 0 \end{bmatrix} \rightarrow \begin{bmatrix} 5 & 0 & -1 & 0 & 1 & 0 & 1 \\ 1/3 & 0 & -4/3 & 1 & -1/3 & 0 & 0 \\ 5/3 & 1 & 1/3 & 0 & 1/3 & 0 & 0 \\ 7 & 4 & 3 & 0 & 0 & 1 & 0 \end{bmatrix} \rightarrow \\ & \begin{bmatrix} 5 & 0 & -1 & 0 & 1 & 0 & 1 \\ 1/3 & 0 & -4/3 & 1 & -1/3 & 0 & 0 \\ 5/3 & 1 & 1/3 & 0 & 1/3 & 0 & 0 \\ 1/3 & 0 & 5/3 & 0 & -4/3 & 1 & 0 \end{bmatrix}. \end{aligned}$$

The result of these row operations is our updated Tableau, and the pivot operation is complete.

**Problem 5.** Add a method to your solver that checks for unboundedness and performs a single pivot operation from start to completion. If the problem is unbounded, raise a `ValueError`.

## Termination and Reading the Tableau

Up to this point, our algorithm accepts a linear program, adds slack variables, and creates the initial tableau. After carrying out these initial steps, it then performs the pivoting operation iteratively until the optimal point is found. But how do we determine when the optimal point is found? The answer is to look at the top row of the tableau. More specifically, before each pivoting operation, check whether all of the entries in the top row of the tableau (ignoring the entry in the first column) are nonnegative. If this is the case, then we have found an optimal solution, and so we terminate the algorithm.

The final step is to report the solution. The ending state of the tableau and index list tell us everything we need to know. The maximum value attained by the objective function is found in the upper leftmost entry of the tableau. The nonbasic variables, whose indices are located in the last  $n$  entries of the index list, all have the value 0. The basic variables, whose indices are located in the first  $m$  entries of

the index list, have values given by the first column of the tableau. Specifically, the basic variable whose index is located at the  $i$ th entry of the index list has the value  $T_{i+1,1}$ .

In our example, suppose that our algorithm terminates with the tableau and index list in the following state:

$$T = \begin{bmatrix} 5.2 & 0 & 0 & 0 & .2 & .6 & 1 \\ .6 & 0 & 0 & 1 & -1.4 & .8 & 0 \\ 1.6 & 1 & 0 & 0 & .6 & -.2 & 0 \\ .2 & 0 & 1 & 0 & -.8 & .6 & 0 \end{bmatrix}$$

$$L = (2, 0, 1, 3, 4).$$

Then the maximum value of the objective function is 5.2. The nonbasic variables have indices 3, 4 and have the value 0. The basic variables have indices 2, 0, and 1, and have values .6, 1.6, and .2, respectively. In the notation of the original problem statement, the solution is given by

$$x_0 = 1.6$$

$$x_1 = .2.$$

**Problem 6.** Write an additional method in your solver called `solve()` that obtains the optimal solution, then returns the maximum value, the basic variables, and the nonbasic variables. The basic and nonbasic variables should be represented as two dictionaries that map the index of the variable to its corresponding value.

For our example, we would return the tuple  $(5.2, \{0: 1.6, 1: .2, 2: .6\}, \{3: 0, 4: 0\})$ .

At this point, you should have a Simplex solver that is simple to use. The following code demonstrates how your solver is expected to behave:

```
>>> import SimplexSolver

# Initialize objective function and constraints.
>>> c = np.array([3., 2])
>>> b = np.array([2., 5, 7])
>>> A = np.array([[1., -1], [3, 1], [4, 3]])

# Instantiate the simplex solver, then solve the problem.
>>> solver = SimplexSolver(c, A, b)
>>> sol = solver.solve()
>>> print(sol)
(5.200,
 {0: 1.600, 1: 0.200, 2: 0.600},
 {3: 0, 4: 0})
```

If the linear program were infeasible at the origin or unbounded, we would expect the solver to alert the user by raising an error.



Note that this simplex solver is *not* fully operational. It can't handle the case of infeasibility at the origin. This can be fixed by adding methods to your class that solve the *auxiliary problem*, that of finding an initial feasible tableau when the problem is not feasible at the origin. Solving the auxiliary problem involves pivoting operations identical to those you have already implemented, so adding this functionality is not overly difficult.

## The Product Mix Problem

We now use our Simplex implementation to solve the *product mix problem*, which in its basic form can be expressed as a simple linear program. Suppose that a manufacturer makes  $n$  products using  $m$  different resources (labor, raw materials, machine time available, etc). The  $i$ th product is sold at a unit price  $p_i$ , and there are at most  $m_j$  units of the  $j$ th resource available. Additionally, each unit of the  $i$ th product requires  $a_{j,i}$  units of resource  $j$ . Given that the demand for product  $i$  is  $d_i$  units per a certain time period, how do we choose the optimal amount of each product to manufacture in that time period so as to maximize revenue, while not exceeding the available resources?

Let  $x_1, x_2, \dots, x_n$  denote the amount of each product to be manufactured. The sale of product  $i$  brings revenue in the amount of  $p_i x_i$ . Therefore our objective function, the profit, is given by

$$\sum_{i=1}^n p_i x_i.$$

Additionally, the manufacture of product  $i$  requires  $a_{j,i} x_i$  units of resource  $j$ . Thus we have the resource constraints

$$\sum_{i=1}^n a_{j,i} x_i \leq m_j \text{ for } j = 1, 2, \dots, m.$$

Finally, we have the demand constraints which tell us not to exceed the demand for the products:

$$x_i \leq d_i \text{ for } i = 1, 2, \dots, n$$

The variables  $x_i$  are constrained to be nonnegative, of course. We therefore have a linear program in the appropriate form that is feasible at the origin. It is a simple task to solve the problem using our Simplex solver.

**Problem 7.** Solve the product mix problem for the data contained in the file `productMix.npz`. In this problem, there are 4 products and 3 resources. The archive file, which you can load using the function `np.load`, contains a dictionary of arrays. The array with key `'A'` gives the resource coefficients  $a_{i,j}$  (i.e. the  $(i,j)$ -th entry of the array give  $a_{i,j}$ ). The array with key `'p'` gives the unit prices  $p_i$ . The array with key `'m'` gives the available resource units  $m_j$ . The array with key `'d'` gives the demand constraints  $d_i$ .

Report the number of units that should be produced for each product.

## Beyond Simplex

The *Computing in Science and Engineering* journal listed Simplex as one of the top ten algorithms of the twentieth century [Nash2000]. However, like any other algorithm, Simplex has its drawbacks.

In 1972, Victor Klee and George Minty published a paper with several examples of worst-case polytopes for the Simplex algorithm [Klee1972]. In their paper, they give several examples of polytopes that the Simplex algorithm struggles to solve.

Consider the following linear program from Klee and Minty.

$$\begin{array}{rcccccl}
 \max & 2^{n-1}x_1 & +2^{n-2}x_2 & +\cdots & +2x_{n-1} & +x_n & \\
 \text{subject to} & x_1 & & & & & \leq 5 \\
 & 4x_1 & +x_2 & & & & \leq 25 \\
 & 8x_1 & +4x_2 & +x_3 & & & \leq 125 \\
 & \vdots & & & & & \vdots \\
 & 2^n x_1 & +2^{n-1}x_2 & +\cdots & +4x_{n-1} & +x_n & \leq 5
 \end{array}$$

Klee and Minty show that for this example, the worst case scenario has exponential time complexity. With only  $n$  constraints and  $n$  variables, the simplex algorithm goes through  $2^n$  iterations. This is because there are  $2^n$  extreme points, and when starting at the point  $x = 0$ , the simplex algorithm goes through all of the extreme points before reaching the optimal point  $(0, 0, \dots, 0, 5^n)$ . Other algorithms, such as interior point methods, solve this problem much faster because they are not constrained to follow the edges.

## Lab 12

# Optimization with Scipy

**Lab Objective:** *The Optimize package in Scipy provides highly optimized and versatile methods for solving fundamental optimization problems. In this lab we introduce the syntax and variety of `scipy.optimize` as a foundation for unconstrained numerical optimization.*

Numerical optimization is one of the most common modern applications of mathematics. Many mathematical problems can be rewritten in terms of optimization, and unless the problem is both simple and small, usually cannot be solved analytically, and must be approximated by numerical computation.

To assist with this, the `scipy.optimize` package has several functions for minimizing, root finding, and curve fitting, of which we will introduce the most essential.

You can learn about all of the functions at <http://docs.scipy.org/doc/scipy/reference/optimize.html>.

## Local Minimization

First we will test out a few of the minimization algorithms on the Rosenbrock function, which is defined as

$$f(x, y) = (1 - x)^2 + 100(y - x^2)^2.$$

The Rosenbrock function is commonly used when evaluating the performance of an optimization algorithm. Reasons for this include the fact that its minimizer `x = np.array([1., 1.])` is found in curved valley, and so minimizing the function is non-trivial. See Figure 12.1. The Rosenbrock function is included in the `optimize` package (as `rosen`), as well as its gradient (`rosen_der`) and its hessian (`rosen_hess`).

We will use the `minimize()` function and test some of its algorithms (specified by the keyword argument “method” – see the documentation page for `minimize()`). For each algorithm, you need to pass in a callable function object for the Rosenbrock function, as well as a NumPy array giving the initial guess. For some algorithms, you will additionally need to pass in the jacobian or hessian. You may recognize some of these algorithms, and several of them will be discussed in greater detail

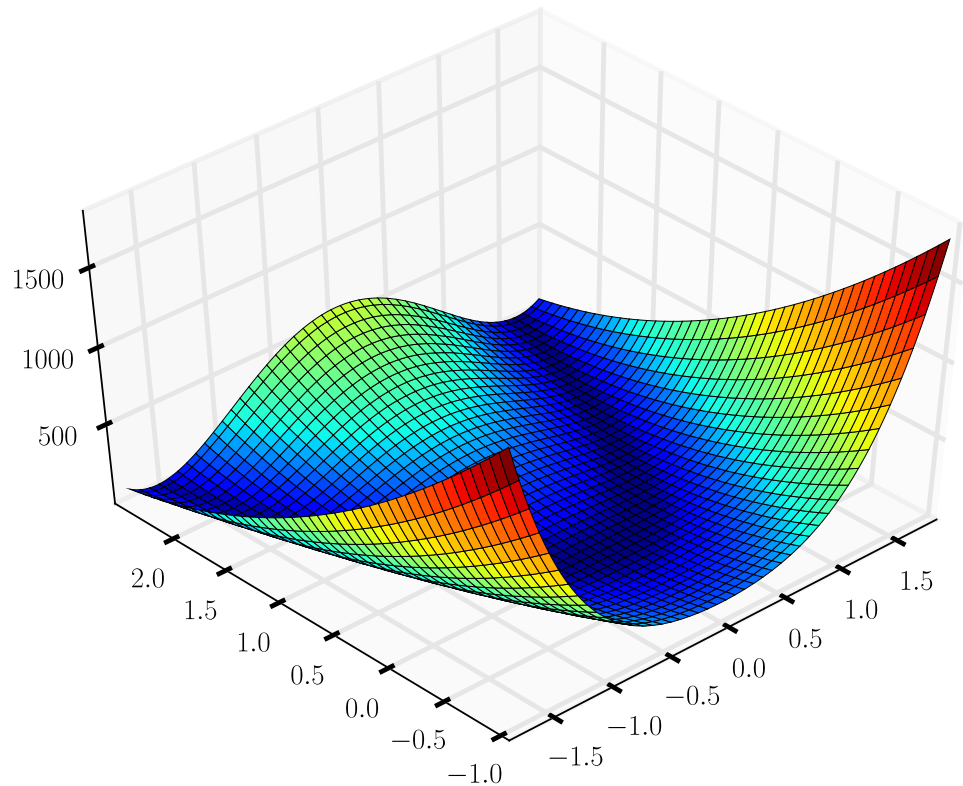


Figure 12.1:  $f(x, y) = (1 - x)^2 + 100(y - x^2)^2$

later. For this lab, you do not need to understand how they work, just how to use them.

As an example, we'll minimize the Rosenbrock with the Newton-CG method. This method often performs better by including the optional hessian as an argument, which we will do here.

```
>>> import numpy as np
>>> from scipy import optimize as opt
>>> x0 = np.array([4., -2.5])
>>> opt.minimize(opt.rosen, x0, method='Newton-CG', hess=opt.rosen_hess,
                jac=opt.rosen_der)

      fun: 1.1496545381999877e-15
      jac: array([ 1.12295570e-05, -5.63744647e-06])
message: 'Optimization terminated successfully.'
  nfev: 45
  nhev: 34
   nit: 34
  njev: 78
status: 0
success: True
   x: array([ 0.99999997,  0.99999993])
```

As the online documentation indicates, `opt.minimize()` returns an object of type `opt.optimize.OptimizeResult`.

The printed output gives you information on the performance of the algorithm. The most relevant output for this lab include

```
fun: 1.1496545381999877e-15, the obtained minimum;
nit: 96, the number of iterations the algorithm took to complete;
success: True, whether the algorithm converged or not;
x: array([ 0.99999997, 0.99999993]), the obtained minimizer.
```

Each of these outputs can be accessed either by indexing `OptimizeResult` object like a dictionary (`result['nit']`), or as attributes of a class (`result.nit`). We recommend access by indexing, as this is consistent with other optimization packages in Python.

The online documentation for `scipy.optimize.minimize()` includes other optional parameters available to users, for example, to set a tolerance of convergence. In some methods, the derivative may be optional, while it may be necessary in others. While we do not cover all possible parameters in this lab, they should be explored as needed for specific applications.

**Problem 1.** Use the `opt.minimize()` function to find the minimum of the Rosenbrock function. Test Nelder-Mead, CG, and BFGS, starting each with the initial guess `x_0 = np.array([4., -2.5])`. For each method, print whether it converged, and if so, print how many iterations it took.

Note that the hessian argument is not needed for these particular methods.

Each of these three algorithms will be explored in great detail later in Volume 2: Nelder-Mead is a variation of the Simplex algorithm, CG is a variant of the Conjugate Gradient algorithm, and BFGS is a quasi-Newton method developed by Broyden, Fletcher, Goldfarb, and Shanno.

The `minimize()` function can use various algorithms, each of which is best for certain problems. Which algorithm one uses depends on the specific nature of one's problem.

It is also important to note that in many optimization applications, very little is known about the function to optimize. These functions are often called *blackbox functions*. For example, one may be asked in the airline industry to analyze and optimize certain properties involving a segment of airplane wing. Perhaps expert engineers have designed extremely robust and complicated software to model this wing segment given certain inputs, but this function is so complicated that nobody except the experts dares to try parcing it. Briefly said, you simply don't want to understand it; nobody wants to understand it.

Fortunately, one can still optimize effectively in such situations by wisely selecting a correct algorithm. However, because so little is known about the blackbox function, one must wisely select an appropriate minimization method and follow the specifications of the problem exactly.

**Problem 2.** Minimize the `blackbox()` function in the `blackbox_function` module. You don't need to know the source code or how it works in order to minimize it. Simply select the appropriate method of `scipy.optimize.minimize()` for this problem, without passing your method a derivative. You may need to test several methods and determine which is most appropriate.

The function `blackbox()` returns a certain measure of a piecewise-linear curve between two fixed points: the origin, and the point (40,30). This function accepts a one-dimensional `ndarray` of length `m` of y-values, where `m` is the number of points of the piecewise curve excluding endpoints. These points are spaced evenly along the x-axis, so only the y-values of each point are passed into `blackbox()`.

Once you have selected a method, select an initial point with the following code:

```
y_initial = 30*np.random.random_sample(18)
```

Then plot your initial curve and minimizing curve together on the same plot, including endpoints. Note that this will require padding your array of internal y-values with the y-values of the endpoints, so that you plot a total of 20 points for each curve.

## Global Minimization via Basin Hopping

In the realm of optimization, convex functions are the most well-behaved, as any local minimum is a global minimum. However, in practice one must frequently deal with non-convex functions, and sometimes we need pick the global minimum out of many local minima.

For example, consider the function

$$z = r^2(1 + \sin^2(4r)),$$

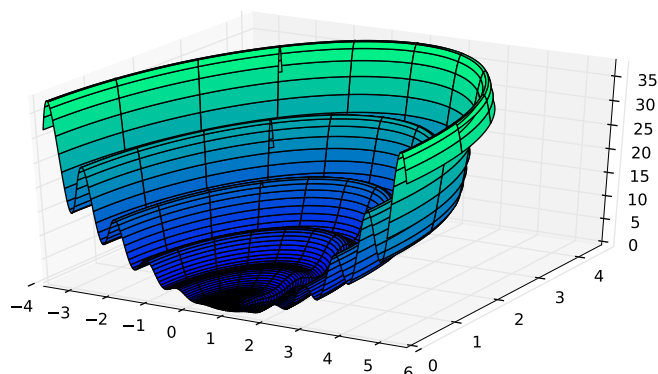
where

$$r = \sqrt{(x+1)^2 + y^2}.$$

Essentially, this is a wavy crater offset from the origin by 1 along the  $x$  axis (see Figure 12.2). The presence of many local minima proves to be a difficulty for the minimization algorithms.

For example, if we try using the Nelder-Mead method as previously, with an initial point of `x0 = np.array([-2, -2])`, the algorithm fails to find the global minimum, and instead comes to rest on a local minimum.

```
>>> def multimin(x):
>>>     r = np.sqrt((x[0]+1)**2 + x[1]**2)
>>>     return r**2 * (1+ np.sin(4*r)**2)
>>>
>>> x0 = np.array([-2, -2])
>>> res = opt.minimize(multimin, x0, method='Nelder-Mead')
final_simplex: (array([[ -2.11758025,  -2.04313668], [ -2.11748198,  -2.04319043],
```

Figure 12.2:  $z = r^2(1 + 2 \sin^2(4r))$ 

```

[-2.11751491, -2.04317242]]), array([ 5.48816866,
                                     5.48816866,  5.48816866]))

    fun: 5.488168656962328
  message: 'Optimization terminated successfully.'
     nfev: 84
       nit: 44
    status: 0
   success: True
         x: array([-2.11758025, -2.04313668])
>>> print res['x']
[-2.11758025, -2.04313668]
>>> print res['fun']
5.488168656962328
>>> print multimin([-1,0])
0.0

```

However, SciPy does have some tools to help us with these problems. Specifically, we can use the `opt.basinhopping()` function.

The `opt.basinhopping()` function uses the same minimizing algorithms (in fact, you can tell it whatever minimizing algorithm you can pass to `opt.minimize()`). However, once it settles on a minimum, it hops randomly to a new point in the domain (depending on how we set the “hopping” distance) that hopefully lies outside of the valley or basin belonging to the current local minimum. It then searches for the minimum from this new starting point, and if it finds a better minimizer, it repeats the hopping process from this new minimizer. Thus, the `opt.basinhopping()` function has multiple chances to escape a local basin and find the correct global minimum.

*Only Scipy Version 0.12+ has `opt.basinhopping`. In earlier versions, such as 0.11, you won't find it.*

**Problem 3.** Explore the documentation for the `opt.basinhopping()` function online or via IPython, and use it to find the global minimum of our `multimin()`

function with `x0 = np.array([-2, -2])`. Call it using the same Nelder-Mead algorithm with `opt.basinhopping(multimin, x0, stepsize=0.5, minimizer_kwargs={'method': 'nelder-mead'})`. Try it first with `stepsize=0.5` and then with `stepsize=0.2`.

Plot the `multimin` function using the following code:

```
xdomain = np.linspace(-3.5, 1.5, 70)
ydomain = np.linspace(-2.5, 2.5, 60)
X, Y = np.meshgrid(xdomain, ydomain)
Z = multimin((X, Y))
fig = plt.figure()
ax1 = fig.add_subplot(111, projection='3d')
ax1.plot_wireframe(X, Y, Z, linewidth=.5, color='c')
```

Plot the initial point and minima by adapting the following line:

```
ax1.scatter(x_value, y_value, z_value)
```

Why doesn't the algorithm find the global minimum with `stepsize=0.2`? Print your answer to this question, and return the true global minimum.

## Root Finding

The `optimize` package also has functions useful in root-finding. The next example, taken from the online documentation, solves the following nonlinear system of equations using `opt.root`.

$$\begin{bmatrix} x_0 + 1/2(x_0 - x_1)^3 - 1 \\ 1/2(x_1 - x_0)^3 + x_1 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}.$$

```
>>> def func(x):
>>>     return [x[0] + 0.5 * (x[0] - x[1])**3 - 1.0,
>>>             0.5 * (x[1] - x[0])**3 + x[1]]
>>> def jac(x):
>>>     return np.array([[1 + 1.5 * (x[0] - x[1])**2,
>>>                      -1.5 * (x[0] - x[1])**2],
>>>                      [-1.5 * (x[1] - x[0])**2,
>>>                      1 + 1.5 * (x[1] - x[0])**2]])
>>> sol = opt.root(func, [0, 0], jac=jac, method='hybr')
>>> print sol.x
[ 0.8411639  0.1588361]
>>> print func(sol.x)
[-1.1102230246251565e-16, 0.0]
```

**Problem 4.** Find the roots of the system

$$\begin{bmatrix} -x + y + z \\ 1 + x^3 - y^2 + z^3 \\ -2 - x^2 + y^2 + z^2 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}.$$



Return the values of  $x, y, z$  as an array.

As with `opt.minimize()`, `opt.root()` has more than one algorithm for root finding. Here we have used the `hybr` method. There are also several algorithms for scalar root finding. See the online documentation for more.

## Curve Fitting

SciPy also has methods for curve fitting wrapped by the `opt.curve_fit()` function. Just pass it data and a function to be fit. The function should take in the independent variable as its first argument and values for the fitting parameters as subsequent arguments. Examine the following example from the online documentation.

```
>>> import numpy as np
>>> import scipy.optimize as opt

>>> #the function with which to create the data and later fit it
>>> def func(x,a,b,c):
>>>     return a*np.exp(-b*x) + c

>>> #create perturbed data
>>> x = np.linspace(0,4,50)
>>> y = func(x,2.5,1.3,0.5)
>>> yn = y + 0.2*np.random.normal(size=len(x));

>>> #perform the fit
>>> popt, pcov = opt.curve_fit(func,x,yn)
```

The variable `popt` now contains the fitted parameters and `pcov` gives the covariance of the fit. See Figure 12.3 for a plot of the data and the fitted curve.

One of the most fundamental phenomena in the physical and engineering sciences is turbulent convection, wherein an unstable density gradient induces a fluid to move chaotically (basically, hot air rises). This problem is so important that experiments and numerical simulations have been pushed to their limits in the past several decades to determine the qualitative nature of the fluid's motion under an extreme forcing (think of boiling a pot of water, but instead at temperatures akin to the interior of the sun). The strength of the forcing (amount of the enforced temperature gradient) is measured by the non-dimensional Rayleigh number  $R$ . Of particular interest is to determine how well the chaotic turbulent flow transports the heat from the hot bottom to the cold top, as measured by the Nusselt number  $\nu$ . One of the primary goals of experiments, simulations, and analysis is to determine how the Nusselt number  $\nu$  depends on the Rayleigh number  $R$ , i.e. if the bottom of the pot of water is heated more strongly, how much faster does the boiling water transport heat to the top?

It is often generically believed that the Nusselt number obeys a power law of the form  $\nu = cR^\beta$ , where  $\beta \leq 1/2$ . Through some mild assumptions on the temperature, we can construct an eigenvalue problem that we solve numerically for a variety of Rayleigh numbers, thus obtaining an upper bound on the Nusselt number as  $\nu \leq cR^\beta$ . With our physical specifications of the problem, we may predict  $\beta < 1/2$ .

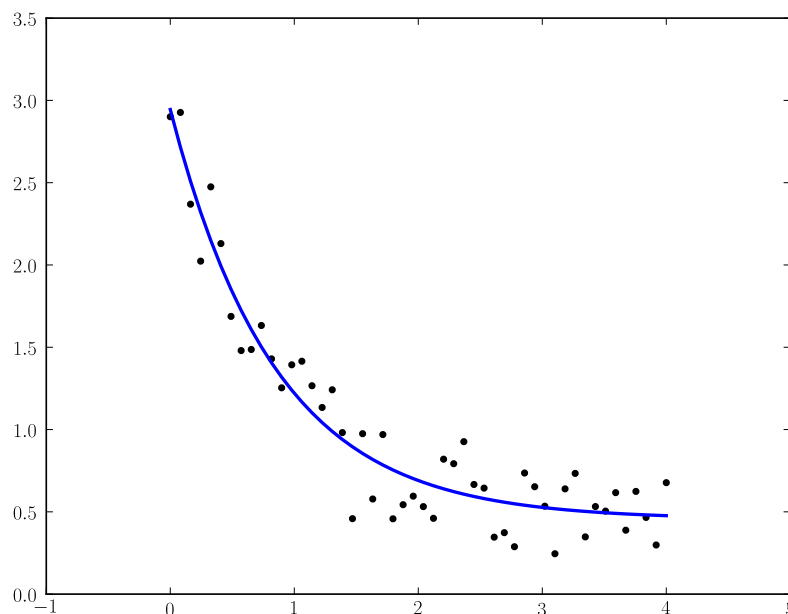


Figure 12.3: Example of perturbed data graphed with the resulting curve using the fitted parameters:  $a = 2.72$ ,  $b = 1.31$ , and  $c = 0.45$ .

**Problem 5.** Use `opt.curve_fit()` to fit a curve to data obtained from numerical simulations of convection. The data are in the file `convection.npy`. The first column is  $R$ , the Rayleigh number, and the second column is  $\nu$ , the Nusselt number. With the convection equation

$$\nu = cR^\beta,$$

use `opt.curve_fit()` to find a fit to the data using  $c$  and  $\beta$  as the fitting parameters. See Figure 12.4 for a plot of the data along with a fitted curve. Though it may be difficult to see in the figure, the first four points skew the data, and do not help us determine the appropriate long-term values of  $c$  and  $\beta$ . Thus, do not use the first four points when fitting a curve to the data, but include them in the plot.

Just so that you know that you are getting realistic values,  $c$  should be around .1, and  $\beta$  should be less than  $1/2$ . Return your values for  $c$  and  $\beta$  in a NumPy array of length 2.

The `scipy.optimize` package has many other useful functions, and is a good first resource when confronting a numerical optimization problem. See the online documentation for further details.

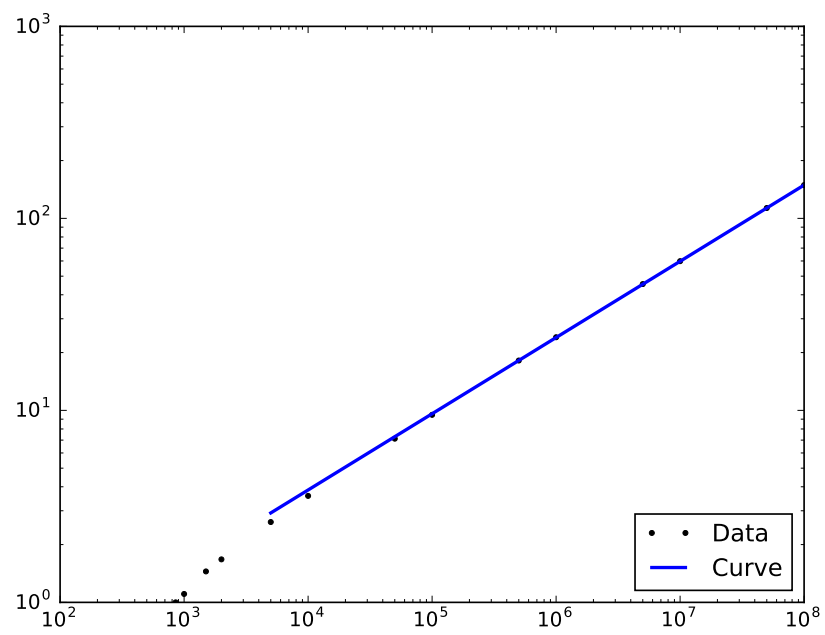


Figure 12.4: The black points are the data from `convection.npy` plotted as a scatter plot. The blue line is a fitted curve.



## Lab 13

# 1-D Optimization

**Lab Objective:** *Many high-dimensional optimization algorithms rely on one-dimensional optimization methods. In this lab, we implement four line search algorithms for optimizing scalar-valued functions defined on  $\mathbb{R}$ . We will generalize some of these approaches to high-dimensional optimization problems in subsequent labs.*

## Overview of Line Search Algorithms

Imagine you are hiking a steep mountain. When it is time to head home, thick fog gathers around, reducing visibility to just a couple of feet. How can you find your way back with such limited visibility? One strategy is to pick a downhill direction and follow that direction as far as you can, or until it starts leading upward again. Then choose another downhill direction, and take that as far as you can, repeating the process. By always choosing a downhill direction, you hope to eventually make it back to the base of the mountain.

This is the basic approach of *line search algorithms* for numerical optimization. Let  $f$  be a scalar-valued function. The goal is to find the *global minimizer*  $\mathbf{x}^*$  such that  $f(\mathbf{x}^*) \leq f(\mathbf{x})$  for all  $\mathbf{x}$  in the domain of  $f$ . After choosing an initial guess  $\mathbf{x}_0$ , we produce a sequence of approximations  $\mathbf{x}_1, \mathbf{x}_2, \mathbf{x}_3, \dots$  using the rule

$$\mathbf{x}_{k+1} = \mathbf{x}_k + \alpha_k \mathbf{p}_k. \quad (13.1)$$

The point  $\mathbf{p}_k$  is the *search direction* (which way to go) and the scalar  $\alpha_k$  is called the *step size* (how far to go). The choice of search direction and step size at each step is what defines different line search algorithms.

## Derivative versus Derivative-Free Methods

A function's derivative provides information about how the value of the function changes at each point, and can be used to determine local optima. Unfortunately, not all objective functions are differentiable, and many are difficult or costly to differentiate. Thus some line search methods utilize the derivative of the objective function, but others do not.

## Interval Approximation Methods for Unimodal Functions

A function  $f : [a, b] \rightarrow \mathbb{R}$  satisfies the *unimodal property* if it has just **one** local (hence global) minimum and is monotonic to the left and right of the minimum. The following line search methods optimize a unimodal function by partitioning the function's domain into progressively smaller intervals that contain the minimizer.

### Golden Section Search

Let  $f : [a, b] \rightarrow \mathbb{R}$  be unimodal. Starting with the closed interval  $[a, b]$ , the *golden section search* finds a smaller interval that contains  $x^*$  as follows.

Choose two points  $a'$  and  $b'$  with  $a' < b'$ . If  $f(a') \geq f(b')$ , the unimodal property guarantees that the minimizer must be in the interval  $[a', b]$ , for otherwise the function  $f$  would have a local minimum in both  $[a, a']$  and  $[a', b]$ . In the next step, we repeat the process over the interval  $[a', b]$ . If instead  $f(a') \leq f(b')$ , then we choose the interval  $[a, b']$  for the next step. Finally, if  $f(a') = f(b')$ , then it does not matter which interval is chosen.

It turns out that there is an optimal choice for the two test points  $a'$  and  $b'$ . Given the current interval  $[a, b]$ , choose  $a'$  and  $b'$  satisfying

$$\begin{aligned} a' &= a + \rho(b - a) \\ b' &= a + (1 - \rho)(b - a), \end{aligned}$$

where  $\rho = \frac{1}{2}(3 - \sqrt{5}) \approx 0.382$  (this constant is related to the famous *golden ratio*, hence the name of the algorithm).

At each step, the interval is reduced by a factor of  $1 - \rho$ , which means that after  $n$  steps, the minimizer is pinned down to within an interval approximately  $(0.618)^n$  times the length of the original interval. Note that this rate of convergence is independent of the objective function.

**Problem 1.** Write a function that accepts a callable function  $f$ , interval limits  $a$  and  $b$ , and a number of iterations `niter` to calculate. Implement the golden section search as described above, returning the midpoint of the final interval.

Use your function to minimize  $f(x) = e^x - 4x$  on the interval  $[0, 3]$ . How many steps do you need to take to get within .001 of the true minimizer?

### Bisection Algorithm

This method is similar to the Golden Ratio method, but instead of cutting our interval into two overlapping sections, we divide the interval evenly in half, and then use the derivative  $f'(x)$  to determine where the minimizer lies. This method takes advantage of the fact that a unimodal function's derivative is strictly less than 0 to the left of the minimizer, and strictly greater than 0 to the right.

For a unimodal function  $f : [a, b] \rightarrow \mathbb{R}$ , take the midpoint,  $x_1 = \frac{b+a}{2}$ . If  $f'(x_1) > 0$ , the critical point must lie in the interval  $[a, x_1]$ ; otherwise, the critical

point lies in the other half of the interval,  $[x_1, b]$ . We repeat this process on the correct interval until the desired accuracy is achieved.

At each step, the interval is reduced by a factor of two. This is slightly quicker than the factor of  $1 - \rho$  in the Golden Section search method. Like the golden section search, the convergence of this method is independent of the objective function.

**Problem 2.** Write a function that accepts a callable function  $f$ , interval limits  $a$  and  $b$ , and a number of iterations `niter` to calculate. Implement the bisection algorithm as described above, returning the midpoint of the final interval.

Use your function to minimize the same objective function as in Problem 1. How many steps do you need to take to get within .001 of the true minimizer? Time both algorithms and report which one is faster to converge.

## Newton's Method and Quasi-Newton Methods

Newton's Method, is a basic line search algorithm that uses the derivatives of the function to select a direction and step size.

To use this method, we need a function that is twice differentiable. The idea is to approximate the function with a quadratic polynomial and then solve the trivial problem of minimizing the polynomial. Doing so in an iterative manner can lead us to the actual minimizer. Let  $f$  be a function satisfying the appropriate conditions, and let us make an initial guess,  $x_0$ . The relevant quadratic approximation to  $f$  at  $x_0$  is

$$q(x) = f(x_0) + f'(x_0)(x - x_0) + \frac{1}{2}f''(x_0)(x - x_0)^2,$$

which is the second-degree Taylor polynomial for  $f$  centered at  $x_0$ . The minimum for this quadratic function is easily found by solving  $q'(x) = 0$ , and we take the obtained  $x$ -value as our new approximation. The formula for the  $(k + 1)$ -th approximation, which the reader can verify, is

$$x_{k+1} = x_k - \frac{f'(x_k)}{f''(x_k)}.$$

In the one dimensional case, there are only two search directions: to the right (+) or to the left (-). Newton's method chooses the search direction  $\mathbf{p}_k = \text{sign}(-f'(x_k)/f''(x_k))$  and the step size  $\alpha_k = |f'(x_k)/f''(x_k)|$ .

The convergence properties of this sequence depend heavily on the initial guess  $x_0$  and the function  $f$ . Roughly speaking, if  $x_0$  is sufficiently close to the actual minimizer, and if  $f$  is well-approximated by parabolas, then one can expect the sequence to converge quickly. However, there are cases when the sequence converges slowly or not at all. See Figure 13.1.

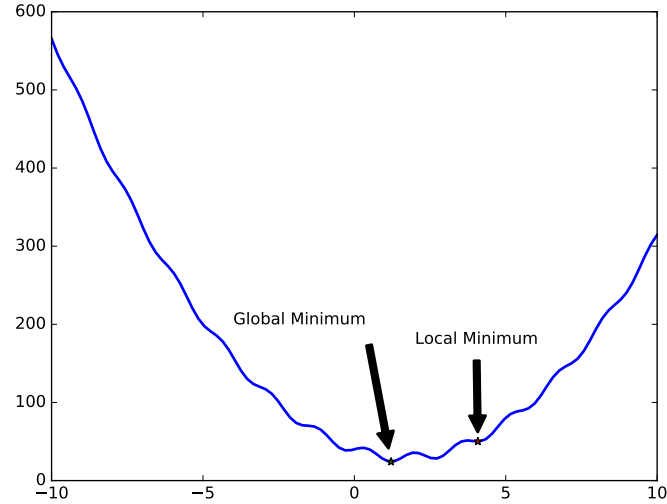


Figure 13.1: The results of Newton's Method using two different initial guesses. The global minimizer was correctly found with initial guess of 1. However, an initial guess of 4 led to only a local minimum.

**Problem 3.** Implement Newton's Method. You will write a function that takes a function and its two derivatives, as well as a starting point. It will return the minimizer.

Use this function to minimize  $f(x) = x^2 + \sin(5x)$  with an initial guess of  $x_0 = 0$ . Now try other initial guesses farther away from the true minimizer, and note when the method fails to obtain the correct answer.

## One-Dimensional Secant Method

Sometimes we would like to use Newton's Method, but for whatever reason we don't have a second derivative. Maybe calculating it is too costly or the function is not twice differentiable. In this situation we can approximate the second derivative using the first derivative. The approximation using a secant calculation, hence the name. We use the same basic algorithm as in Newton's Method, but with an approximation for the second derivative of the objective function.

$$x_{n+1} = x_n - \frac{f'(x_n)}{f''_{approx}(x_n)},$$

where we approximate the second derivative as follows:

$$f''_{approx}(x_n) = \frac{f'(x_n) - f'(x_{n-1})}{x_n - x_{n-1}}.$$

This gives us the final equation:

$$x_{n+1} = x_n - \frac{x_n - x_{n-1}}{f'(x_n) - f'(x_{n-1})} f'(x_n),$$



Notice that this equation requires two initial points (both  $x_n$  and  $x_{n-1}$ ) to calculate the next estimate.

**Problem 4.** Write a function that accepts a scalar-valued function  $f$ , its first derivative  $Df$ , and two starting points. Use the secant method to find and return the minimizer of  $f$ .

Use your function to minimize  $f(x) = x^2 + \sin(x) + \sin(10x)$  with initial guesses of  $x_0 = 0$  and  $x_1 = -1$ . Now try other initial guesses farther away from the true minimizer, and note when the method fails to obtain the correct answer.

(Hint: You may want to plot this function to understand why this problem is so sensitive to the starting point.)

## General Line Search Methods

### Step Size Calculation

Given a differentiable function  $f : \mathbb{R}^n \rightarrow \mathbb{R}$  that we wish to minimize, and assuming that we already have a current point  $\mathbf{x}_k$  and direction  $\mathbf{p}_k$  in which to search, how do we choose our step size  $\alpha_k$ ? If our step size is too small, we will not make good progress toward the minimizer, and convergence will be slow. If the step size is too large, however, we may overshoot and produce points that are far away from the solution. A common approach to pick an appropriate step size involves the *Wolfe conditions*:

$$\begin{aligned} f(\mathbf{x}_k + \alpha_k \mathbf{p}_k) &\leq f(\mathbf{x}_k) + c_1 \alpha_k \nabla f(\mathbf{x}_k)^\top \mathbf{p}_k, & (0 < c_1 < 1), \\ \nabla f(\mathbf{x}_k + \alpha_k \mathbf{p}_k)^\top \mathbf{p}_k &\geq c_2 \nabla f(\mathbf{x}_k)^\top \mathbf{p}_k, & (c_1 < c_2 < 1). \end{aligned}$$

The search direction  $\mathbf{p}_k$  is often required to satisfy  $\mathbf{p}_k^\top \nabla f(\mathbf{x}_k) < 0$ , in which case it is called a *descent direction*, since the function is guaranteed to decrease in this direction. Generally speaking, choosing a step size  $\alpha_k$  satisfying these conditions ensures that we achieve sufficient decrease in the function and also that we do not terminate the search at a point of steep decrease (since then we could achieve even better results by choosing a slightly larger step size). The first condition is known as the *Armijo condition*.

We will discuss methods of finding search directions in future labs. For now, we will discuss one simple algorithm for finding an appropriate step size which satisfies the Armijo conditions.

### Backtracking

Finding such a step size satisfying these conditions is not always an easy task, however. One simple approach, known as *backtracking*, starts with an initial step

size  $\alpha$ , and repeatedly scales it down until the Armijo condition is satisfied. That is, choose  $\alpha > 0, \rho \in (0, 1), c \in (0, 1)$ , and while

$$f(\mathbf{x}_k + \alpha \mathbf{p}_k) > f(\mathbf{x}_k) + c\alpha \nabla f(\mathbf{x}_k)^\top \mathbf{p}_k,$$

re-scale  $\alpha = \rho\alpha$ . Once the loop terminates, set  $\alpha_k = \alpha$ . Note that the value  $\nabla f(\mathbf{x}_k)^\top \mathbf{p}_k$  remains fixed for the duration of the backtracking algorithm, and hence need only be calculated once at the beginning.

**Problem 5.** Implement this backtracking algorithm using the function definition in the spec file. Your function will accept a function, its derivative, a starting point, and the direction  $\mathbf{p}$ .

## Line Search in SciPy

SciPy's `optimize` module contains implementations of various optimization algorithms, including several line search methods. In particular, the module provides a useful routine for calculating a step size satisfying the Wolfe Conditions described above, which is more robust and efficient than our simple backtracking approach. We recommend its use for the remainder of this lab. The function is called `line_search()`, and accepts several arguments. We can typically leave the keyword arguments at their default values, but we do need to pass in the objective function, its gradient, the current point, and the search direction. The following code gives an example of its usage, using the objective function  $f(x, y) = x^2 + 4y^2$ .

```
>>> import numpy as np
>>> from scipy.optimize import line_search
>>>
>>> def objective(x):
>>>     return x[0]**2 + 4*x[1]**2
>>>
>>> def grad(x):
>>>     return np.array([2*x[0], 8*x[1]])
>>>
>>> x = np.array([1., 3.]) # current point
>>> p = -grad(x)           # current search direction
>>> a = line_search(objective, grad, x, p)[0]
>>> print a
0.125649913345
```

Note that the function returns a tuple of values, the first of which is the step size.

## Lab 14

# Newton and Quasi-Newton Methods

**Lab Objective:** *Newton's method is generally useful because of its fast convergence properties. However, Newton's method requires the explicit calculation of the second derivative (i.e., the Hessian matrix) at each step, which is computationally costly. Quasi-Newton methods modify Newton's method so that the Hessian does not have to be computed at each step, thus making computations faster. This generally comes at the cost of slower convergence speed, but the increased computation speed can make these methods more effective in many cases.*

## Newton's Method

At this point, we have discussed Newton's Method several times. In the  $n$  dimensional version, the next step is given by:

$$\mathbf{x}_{k+1} = \mathbf{x}_k - D^2 f(\mathbf{x}_k)^{-1} Df(\mathbf{x}_k)^T \quad (14.1)$$

**Problem 1.** Write code implementing Newton's method in  $n$  Dimensions. Ensure that it takes its Jacobian, and Hessian as arguments and returns the minimizer. Test it on the Rosenbrock function:

$$f(x, y) = 100(y - x^2)^2 + (1 - x)^2$$

using starting points  $(-2, 2)$  and  $(10, -10)$ .

## Broyden's Method

One quasi-Newton method is known as Broyden's method. Broyden's Method is a multidimensional version of the secant method we have discussed previously. Just like the secant method approximates the second derivative of a function by using the first derivatives at nearby points, Broyden's Method uses the Jacobian to update an initial Hessian matrix.

## Broyden's Method in n Dimensions

If we have the point  $\mathbf{x}_k$  and the Hessian  $D^2f(\mathbf{x}_k)$  at that point, we can use the following equation to select our guess for the zero of the function:

$$\mathbf{x}_{k+1} = \mathbf{x}_k - D^2f(\mathbf{x}_k)^{-1}Df(\mathbf{x}_k)^T. \quad (14.2)$$

This is precisely Newton's method. However, since calculating the Hessian at each step is costly, we instead estimate the Hessian (just as we used a secant line to approximate the derivative in the one-dimensional case).

The idea is to construct the best rank-one approximation of the Hessian at each iteration. This approximation, denoted  $A_{k+1}$ , must satisfy

$$Df(\mathbf{x}_{k+1}) - Df(\mathbf{x}_k) = (\mathbf{x}_{k+1} - \mathbf{x}_k)^T A_{k+1}. \quad (14.3)$$

In multiple dimensions, this equation will be underdetermined (i.e., many  $A_{k+1}$ 's will satisfy the equation). Suppose that we have a previous estimate of the Hessian  $A_k$  at the point  $\mathbf{x}_k$  (note that for the first iteration, we plug in the starting point to the Hessian as our first approximation). We can then find the best approximation of  $A_{k+1}$  that minimizes  $\|A_{k+1} - A_k\|$ . If we define  $\mathbf{y}_k = Df(\mathbf{x}_{k+1})^T - Df(\mathbf{x}_k)^T$  and  $\mathbf{s}_k = \mathbf{x}_{k+1} - \mathbf{x}_k$ , this requirement is uniquely fulfilled by the following:

$$A_{k+1} = A_k + \frac{\mathbf{y}_k - A_k \mathbf{s}_k \mathbf{s}_k^T}{\|\mathbf{s}_k\|^2} \mathbf{s}_k^T. \quad (14.4)$$

After we have obtained the approximation of the Hessian (Equation 14.4), we can apply Equation 14.2 to find  $\mathbf{x}_{k+1}$ . We can then repeat this process until we have (presumably) converged to a zero of the function.

**Problem 2.** Write code implementing Broyden's method. Test it on the function:

$$f(x, y) = e^{x-1} + e^{1-y} + (x - y)^2$$

using starting points (2, 3) and (3, 2).

### NOTE

We can often make Broyden's method faster using the Sherman-Morrison-Woodbury Formula. This formula allows us to efficiently calculate the inverse of a matrix when we add a low rank update to that matrix. After manipulation of the Sherman-Morrison-Woodbury Formula, we obtain the following:

$$J_k^{-1} = J_{k-1}^{-1} + \frac{\Delta x_k - J_{k-1}^{-1} \Delta F_k}{\Delta x_k^T J_{k-1}^{-1} \Delta F_k} (\Delta x_k^T J_{k-1}^{-1})$$

Thus, we can calculate the inverse of the Jacobian in the first step of our

algorithm and then calculate an update to the inverse at each step using the above formula.

## BFGS

To be a descent method, we need a monotonically decreasing sequence of functions. In other words,  $f(\mathbf{x}_k) < f(\mathbf{x}_{k-1})$ . However, if the Hessian or the approximated Hessian is not positive definite, we cannot expect that  $f(\mathbf{x}_k) < f(\mathbf{x}_{k-1})$ . A drawback of Broyden's method is that the Hessian approximations are not always positive definite, even if  $D^2f(\mathbf{x}_k) > 0$ . The Broyden-Fletcher-Goldfarb-Shanno (BFGS) method is an adjustment to Broyden's method that maintains a positive-definite Hessian approximation. To do this, it makes a rank-two approximation instead of a rank-one approximation. It uses the same update of  $\mathbf{x}_k$  as Broyden's method, but with a different update of  $A_k$ :

$$A_{k+1} = A_k + \frac{\mathbf{y}_k \mathbf{y}_k^T}{\mathbf{y}_k^T \mathbf{s}_k} - \frac{A_k \mathbf{s}_k \mathbf{s}_k^T A_k}{\mathbf{s}_k^T A_k \mathbf{s}_k} \quad (14.5)$$

where  $\mathbf{y}_k$  and  $\mathbf{s}_k$  have the same definitions as given above.

**Problem 3.** Implement the BFGS method in a new function. Your function should take in the Jacobian, the Hessian, a starting point, a number of iterations, and a stopping tolerance, and return the approximated root along with the number of iterations it took. Test your implementation with the same function given in Problem 2. Experiment with different starting points. Is BFGS faster than Broyden's method? Are there cases (i.e., different starting points or varying number of iterations) where one implementation is better than the other?

## Comparing Newton and Quasi-Newton Methods

Different optimization algorithms are more efficient in different situations. If the Jacobian and Hessian are readily available and the Hessian is easily inverted, the standard Newton's Method is probably the best option. If the Hessian is not available or difficult to compute, then using Broyden's Method may be a better option. In circumstances where computing the inverse of the Hessian is difficult, BFGS will allow us to update the inverted Hessian at each step without repeatedly inverting a matrix.

**Problem 4.** Compare the performance of Newton, Broyden, and BFGS on the following functions:

$$f(x, y) = 0.26(x^2 + y^2) - 0.48xy$$

$$f(x, y) = \sin(x + y) + (x - y)^2 - 1.5x + 2.5y + 1$$

Output the number of iterations of each algorithm as well as the total time each algorithm takes to run. Calculate the time per iteration for each algorithm and compare. You should see that Newton's Method takes more time per iteration, but that it takes fewer steps than the other algorithms.

## The Gauss-Newton Method

### Non-linear Least Squares Problems

We now discuss a very important class of problems known as Least Squares problems. These are unconstrained optimization problems that seek to minimize an objective function of the form

$$f(\mathbf{x}) = \frac{1}{2} \sum_{j=1}^m r_j^2(\mathbf{x}),$$

where each  $r_i : \mathbb{R}^n \rightarrow \mathbb{R}$  is smooth, and  $m \geq n$ . Such problems arise in many scientific fields, including economics, physics, and statistics. Linear Least Squares problems form an important subclass, and can be solved directly without the need for an iterative method. At present we will focus on the non-linear case, which can be solved with a line search method.

To motivate the problem further, suppose you are given a set of data points, and you have some kind of model for the data. You need to choose particular values for the parameters in your model, and you wish to do so in a way that “best fits” the observed data. What do we mean by “best fit”? We need some way to measure the error between our model and the data set, and then minimize this error. The best fit will correspond to the choice of parameters that minimize the error function.

More formally, suppose we are given the data points  $(t_1, y_1), (t_2, y_2), \dots, (t_m, y_m)$ , where  $y_i, t_i \in \mathbb{R}$  for  $i = 1, \dots, m$ . Let  $\phi(\mathbf{x}, \mathbf{t})$  be our model for this data set, where  $\mathbf{x}$  is a vector of parameters of the model, and  $\mathbf{t} \in \mathbb{R}^n$ . We can measure the error at the  $i$ -th data point by the value

$$r_i(\mathbf{x}) := \phi(x_i, t_i) - y_i,$$

and by summing the squares of these errors, we obtain our non-linear least squares objective function:

$$f(\mathbf{x}) = \frac{1}{2} \sum_{j=1}^m r_j^2(\mathbf{x}).$$

The individual functions  $r_i$  that measure the error between the model and the data point are known as *residuals*, and we can aggregate these functions into a *residual vector*

$$\mathbf{r}(\mathbf{x}) := (r_1(\mathbf{x}), r_2(\mathbf{x}), \dots, r_m(\mathbf{x}))^T.$$

The Jacobian of  $\mathbf{r}(\mathbf{x})$  can be expressed in terms of the gradients of each  $r_i$  as follows:

$$J(\mathbf{x}) = \begin{bmatrix} \nabla r_1(\mathbf{x})^T \\ \nabla r_2(\mathbf{x})^T \\ \vdots \\ \nabla r_m(\mathbf{x})^T \end{bmatrix}$$

You can further verify that

$$\begin{aligned} \nabla f(\mathbf{x}) &= J(\mathbf{x})^T \mathbf{r}(\mathbf{x}), \\ \nabla^2 f(\mathbf{x}) &= J(\mathbf{x})^T J(\mathbf{x}) + \sum_{j=1}^m r_j(\mathbf{x}) \nabla^2 r_j(\mathbf{x}). \end{aligned}$$

That second term in the formula for  $\nabla^2 f$  involves second derivatives and can be problematic to compute. Often in practice, this term is small, either because the residuals themselves are small, or are nearly affine in a neighborhood of the solution and hence the second derivatives are small. The simplest method for solving the nonlinear least squares problem, known as the *Gauss-Newton Method*, exploits this observation, simply ignoring the second term and making the approximation

$$\nabla^2 f(\mathbf{x}) \approx J(\mathbf{x})^T J(\mathbf{x}).$$

The method then proceeds in a manner similar to Newton's Method. In particular, at the  $k$ -th iteration, we choose a search direction  $p_k$  that solves the linear system

$$J_k^T J_k p_k = -J_k^T r_k.$$

Thus, at each iteration, we find  $\mathbf{x}_{k+1}$  as follows:

$$\mathbf{x}_{k+1} = \mathbf{x}_k - (J(\mathbf{x}_k)^T J(\mathbf{x}_k))^{-1} J(\mathbf{x}_k)^T \mathbf{r}(\mathbf{x}_k). \quad (14.6)$$

**Problem 5.** Implement the Gauss-Newton Method. Your function should take the gradient of the objective function  $Df$ , the residual vector  $r$ , and the Jacobian of the residual vector  $J$ . Return the minimizer.

Test your function by using `optimize.leastsq` and comparing your minimizer with Scipy's minimizer. Use the Jacobian function, residual function, and starting point given in the example below.

Let us work through an example of a nonlinear least squares problem. Suppose we have data points generated from a sine function and slightly perturbed by gaussian noise. In Python we can generate such data as follows:

```
>>> t = np.arange(10)
>>> y = 3*np.sin(0.5*t) + 0.5*np.random.randn(10)
```

Now we write Python functions for our model, the residual vector, the Jacobian, the objective function, and the gradient. The calculations for all of these are straight forward.

```
>>> def model(x, t):
>>>     return x[0]*np.sin(x[1]*t)
>>> def residual(x):
>>>     return model(x, t) - y
>>> def jac(x):
>>>     ans = np.empty((10,2))
>>>     ans[:,0] = np.sin(x[1]*t)
>>>     ans[:,1] = x[0]*t*np.cos(x[1]*t)
>>>     return ans
>>> def objective(x):
>>>     return .5*(residual(x)**2).sum()
>>> def grad(x):
>>>     return jac(x).T.dot(residual(x))
```

By inspecting our data, we might make an initial guess for the parameters  $x_0 = (2.5, 0.6)$ . We are now ready to use our `gaussNewton` function to find the least squares solution.

```
>>> x0 = np.array([2.5,.6])
>>> x = gaussNewton(jac, residual, x0, niter=10)
```

We can plot everything together to compare our fitted model with the data and the original sine curve from which the data were generated.

```
dom = np.linspace(0,10,100)
plt.plot(t, y, 'r*')
plt.plot(dom, 3*np.sin(.5*dom), 'b--')
plt.plot(dom, x[0]*np.sin(x[1]*dom))
plt.show()
```

## Non-linear Least Squares in Python

The module `scipy.optimize` also has a method to solve non-linear least squares problem, and it is quite convenient. The function is called `leastsq`, and in its most basic use, you only need to pass in the residual function and starting point as arguments. In the example above, we simply need to execute the following code:

```
>>> from scipy.optimize import leastsq
>>> x2 = leastsq(residual, x0)[0]
```

This should give us the same answer, but much faster.

**Problem 6.** We have census data giving the population of the United States every ten years since 1790. For convenience, we have entered the data in Python below, so that you may simply copy and paste.

```
>>> #Start with the first 8 decades of data
>>> years1 = np.arange(8)
>>> pop1 = np.array([3.929, 5.308, 7.240, 9.638, 12.866,
>>>                  17.069, 23.192, 31.443])
>>>
>>> #Now consider the first 16 decades
```



```
>>> years2 = np.arange(16)
>>> pop2 = np.array([3.929, 5.308, 7.240, 9.638, 12.866,
>>>                  17.069, 23.192, 31.443, 38.558, 50.156,
>>>                  62.948, 75.996, 91.972, 105.711, 122.775,
>>>                  131.669])
```

Consider just the first 8 decades of population data. By plotting the data and having an inclination that population growth tends to be exponential, it is reasonable to hypothesize an exponential model for the population, that is,

$$\phi(x_1, x_2, x_3, t) = x_1 \exp(x_2(t + x_3)).$$

By inspection, find a reasonable initial guess for the parameters  $(x_1, x_2, x_3)$  (i.e.  $(150, .4, 2.5)$ ). Write a function for this model in Python, along with the corresponding residual vector, and fit the model using the `leastsq` function. Plot the data against the fitted curve, to see how close you are.

Now consider all 16 decades of data. If you plot your curve from above with this more complete data, you will see that the model is no longer a good fit. Instead, the data suggest a logistic model, which also arises from a differential equations treatment of population growth. Thus, your new model is

$$\phi(x_1, x_2, x_3, t) = \frac{x_1}{1 + \exp(-x_2(t + x_3))}.$$

By inspection, find a reasonable initial guess for the parameters  $(x_1, x_2, x_3)$  (i.e.  $(150, .4, -15)$ ). Again, write Python functions for the model and the corresponding residual vector, and fit the model. Plot the data against the fitted curve. It should be a good fit.



## Lab 15

# Gradient Descent Methods

**Lab Objective:** *Many optimization methods fall under the umbrella of descent algorithms. The idea is to choose an initial guess, identify a direction from this point along which the objective function decreases, and perform a line search to find a new point where the objective function is smaller than at the initial guess.*

*In this lab, we implement two major descent algorithms: the method of steepest descent, which uses the gradient of the objective function as the descent direction, and the conjugate gradient algorithm, which uses a conjugate basis as the descent directions. We then apply these techniques to linear and logistic regression problems.*

## The Method of Steepest Descent

Recall the basic idea of a line search algorithm to optimize: at the  $k$ th iteration, choose a search direction  $\mathbf{p}_k$  and a step size  $\alpha_k$ , then compute  $\mathbf{x}_{k+1} = \mathbf{x}_k + \alpha_k \mathbf{p}_k$ . If  $f : \mathbb{R}^n \rightarrow \mathbb{R}$  is a scalar-valued function, its gradient  $\nabla f : \mathbb{R}^n \rightarrow \mathbb{R}^n$  points in the direction of steepest increase of  $f$ . It follows that the opposite direction is the direction of steepest decrease, or *descent*.

The *method of steepest descent* is a line search method that uses  $\mathbf{p}_k = -\nabla f(\mathbf{x}_k)$  as the search direction. A simple version of the method chooses the step size as follows:

1. At the  $k$ th iteration, start with a step size of  $\alpha = 1$ .
2. Check that  $f(\mathbf{x}_k - \alpha \nabla f(\mathbf{x}_k)) < f(\mathbf{x}_k)$  (i.e. check that the function decreases in the search direction), and if it does, set  $\mathbf{x}_{k+1} = \mathbf{x}_k - \alpha \nabla f(\mathbf{x}_k)$ .
3. If the function does *not* decrease, set  $\alpha = \frac{\alpha}{2}$  and check the search direction again. Repeat this step until the function decreases in the search direction.
4. If  $\alpha$  is scaled below a given tolerance, terminate the iteration.

**Problem 1.** Write a function that accepts a convex objective function  $f : \mathbb{R}^n \rightarrow \mathbb{R}$ , its derivative  $Df : \mathbb{R}^n \rightarrow \mathbb{R}^n$ , an initial guess  $x_0 \in \mathbb{R}^n$ , a convergence tolerance, and a maximum number of iterations. Use the Method of Steepest Descent to compute the minimizer of  $f$ . Continue the algorithm until  $\alpha$  is less than the convergence tolerance, or until iterating the maximum number of times. Return the minimizer.

## The Conjugate-Gradient Method

Unfortunately, the method of steepest descent can be very inefficient for certain problems: depending on the geometry of the objective function, the sequence of points can “zig-zag” back and forth without making significant progress toward the true minimizer. In contrast, the *Conjugate-Gradient algorithm* ensures that the true global minimizer is reached in at most  $n$  steps. See Figure 15.1 for an illustration of this contrast.

There are many methods for solving the linear system of equations  $A\mathbf{x} = \mathbf{b}$ , each with its own pros and cons. The Conjugate-Gradient algorithm is one such method for solving large systems of equations where other methods, such as Cholesky factorization and simple Gaussian elimination, are unsuitable. However, the algorithm works equally well for optimizing convex quadratic functions, and it can even be extended to more general classes of optimization problems.

The type of linear system that Conjugate-Gradient can solve involves a matrix with special structure. Given a symmetric positive-definite  $n \times n$  matrix  $Q$  and an  $n$ -vector  $\mathbf{b}$ , we wish to find the  $n$ -vector  $\mathbf{x}$  satisfying

$$Q\mathbf{x} = \mathbf{b}.$$

A unique solution exists because positive-definiteness implies invertibility. For our purposes here, it is useful to recast this problem as an equivalent optimization problem:

$$\min_{\mathbf{x}} f(\mathbf{x}) := \frac{1}{2}\mathbf{x}^T Q \mathbf{x} - \mathbf{b}^T \mathbf{x} + \mathbf{c}.$$

Note that  $\nabla f(\mathbf{x}) = Q\mathbf{x} - \mathbf{b}$ , so that minimizing  $f$  is the same as solving the equation

$$0 = \nabla f(\mathbf{x}) = Q\mathbf{x} - \mathbf{b},$$

which is the original linear system.

## Conjugacy

Unlike the method of steepest descent, the conjugate gradient algorithm chooses a search direction based off of the matrix  $Q$  that is guaranteed to be a direction of descent, though not the direction of greatest descent.

Two vectors  $\mathbf{x}, \mathbf{y} \in \mathbb{R}^n$  are said to be *conjugate* with respect to  $Q$  if  $\mathbf{x}^T Q \mathbf{y} = 0$ . A set of vectors  $\{\mathbf{x}_0, \mathbf{x}_1, \dots, \mathbf{x}_m\}$  is said to be conjugate if each pair of vectors are conjugate to each other. Note that if  $Q = I$ , then conjugacy is the same as

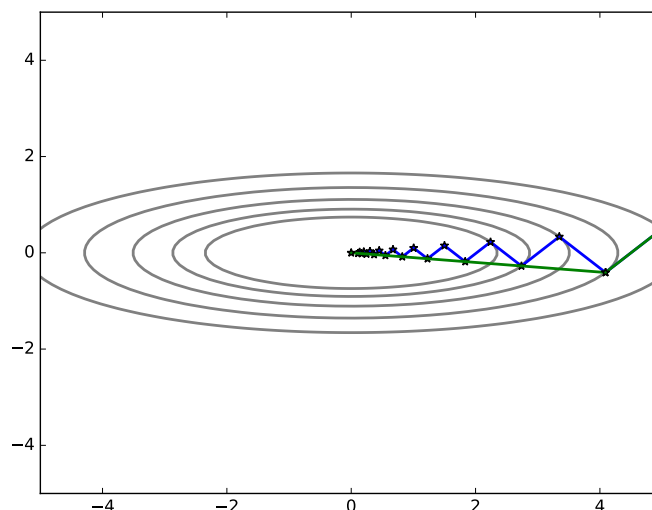


Figure 15.1: Paths traced by Steepest Descent (blue) and Conjugate-Gradient (green). Notice the zig-zagging nature of the Steepest Descent path, as opposed to the direct Conjugate-Gradient path, which finds the minimizer in 2 steps.

orthogonality. Thus, the notion of conjugacy is in some ways a generalization of orthogonality. It turns out that a conjugate set of vectors is linearly independent, and a conjugate basis—which can be constructed in a manner analogous to the Gram-Schmidt orthogonalization process—can be used to diagonalize the matrix  $Q$ . These are some of the theoretical reasons behind the effectiveness of the Conjugate-Gradient algorithm.

## The Algorithm

If we are given a set of  $n$   $Q$ -conjugate vectors, we can simply choose these as our direction vectors and follow the basic descent algorithm. Convergence to the minimizer in at most  $n$  steps is guaranteed because each iteration in the algorithm minimizes the objective function over an expanding affine subspace of dimension equal to the iteration number. Thus, at the  $n$ -th iteration, we have minimized the function over all of  $\mathbb{R}^n$ .

Unfortunately, we are not often given a set of conjugate vectors in advance, so how do we produce such a set? As mentioned earlier, a Gram-Schmidt process could be used, and the set of eigenvectors also works, but both of these options are computationally expensive. Built into the algorithm is a way to determine a new conjugate direction based only on the previous direction, which means less memory usage and faster computation. We have stated the details of Conjugate-Gradient in Algorithm 15.1.

Note that the points  $x_i$  are the successive approximations to the minimizer, the vectors  $d_i$  are the conjugate descent directions, and the vectors  $r_i$ , which actually correspond to the steepest descent directions, are used in determining the conjugate directions. The constants  $\alpha_i$  and  $\beta_i$  are used, respectively, in the line search, and

**Algorithm 15.1** Conjugate-Gradient Algorithm

---

```

1: procedure CONJUGATE-GRADIENT ALGORITHM
2:   Choose initial point  $x_0$ .
3:    $r_0 \leftarrow Qx_0 - b, d_0 \leftarrow -r_0, k \leftarrow 0$ .
4:   while  $r_k \neq 0$  do
5:      $\alpha_k \leftarrow \frac{r_k^T r_k}{d_k^T Q d_k}$ .
6:      $x_{k+1} \leftarrow x_k + \alpha_k d_k$ .
7:      $r_{k+1} \leftarrow r_k + \alpha_k Q d_k$ .
8:      $\beta_{k+1} \leftarrow \frac{r_{k+1}^T r_{k+1}}{r_k^T r_k}$ .
9:      $d_{k+1} \leftarrow -r_{k+1} + \beta_{k+1} d_k$ .
10:     $k \leftarrow k + 1$ .

```

---

in ensuring the  $Q$ -conjugacy of the descent directions.

The most numerically expensive computation in the algorithm is matrix-vector multiplication. Notice, however, that each iteration of the algorithm only requires one distinct matrix-vector multiplication,  $Qd_k$ . The rest of the operations are simply vector-vector multiplication, addition, and scalar multiplication. This makes for a very fast algorithm. As noted earlier, Conjugate-Gradient is especially preferred when  $Q$  is large and sparse. In this case, it may be possible to design a specialized sub-routine that performs matrix-vector multiplication by  $Q$ , by taking advantage of its sparseness. Doing so may lead to further speed-ups in the overall algorithm.

We now have an algorithm that can solve certain  $n \times n$  linear systems and minimize quadratic functions on  $\mathbb{R}^n$  in at most  $n$  steps, and sometimes fewer, depending on the spectrum of the matrix  $Q$ . Further improvements on convergence may be obtained by preconditioning the matrix, but we do not go into detail here.

**Problem 2.** Implement the basic Conjugate-Gradient algorithm presented above. Write a function `conjugateGradient()` that accepts a vector  $b$ , an initial guess  $x_0$ , a symmetric positive-definite matrix  $Q$ , and a default tolerance of .0001 as inputs. Continue the algorithm until  $\|r_k\|$  is less than the tolerance. Return the solution  $x^*$  to the linear system  $Qx = b$ .

## Example

We now work through an example that demonstrates the usage of the Conjugate-Gradient algorithm. We assume that we have already written the specified function in the above problem.

We must first generate a symmetric positive-definite matrix  $Q$ . This can be done by generating a random matrix  $A$  and setting  $Q = A^T A$ . So long as  $A$  is of full column rank, the matrix  $Q$  will be symmetric positive-definite.

```

>>> import numpy as np
>>> from scipy import linalg as la

>>> # initialize the desired dimension of the space

```

```

>>> n = 10

>>> # generate Q, b
>>> A = np.random.random((n,n))
>>> Q = A.T.dot(A)
>>> b = np.random.random(n)

```

At this point, check to make sure that  $Q$  is nonsingular by examining its determinant (use `scipy.linalg.det()`). Provided that the determinant is nonzero, we proceed by writing a function that performs matrix-vector multiplication by  $Q$  (we will not take advantage of sparseness just now), randomly selecting a starting point (Conjugate-Gradient is not sensitive to the location of the starting point), obtaining the answer using our function, and checking it with the answer obtained by `scipy.linalg.solve()`.

```

>>> # generate random starting point
>>> x0 = np.random.random(n)

>>> # find the solution
>>> x = conjugateGradient(b, x0, mult)

>>> # compare to the answer obtained by SciPy
>>> print np.allclose(x, la.solve(Q,b))

```

The output of the print statement should be `True`.

Time the performance of your algorithm and of `scipy.linalg.solve()` on inputs of size 100.

## Application: Least Squares and Linear Regression

The Conjugate-Gradient method can be used to solve linear least squares problems, which are ubiquitous in applied science. Recall that a least squares problem can be formulated as an optimization problem:

$$\min_x \|Ax - b\|_2,$$

where  $A$  is an  $m \times n$  matrix with full column rank,  $x \in \mathbb{R}^n$ , and  $b \in \mathbb{R}^m$ . The solution can be calculated analytically, and is given by

$$x^* = (A^T A)^{-1} A^T b,$$

or in other words, the minimizer solves the linear system

$$A^T A x = A^T b.$$

Since  $A$  has full column rank, we know that  $A^T A$  is an  $n \times n$  matrix of rank  $n$ , which means it is invertible. We can therefore conclude that  $A^T A$  is symmetric positive-definite, so we may use Conjugate-Gradient to solve the linear system and obtain the least squares solution.

Linear least squares is the mathematical underpinning of linear regression, which is a very common technique in many scientific fields. In a typical linear regression problem, we have a set of real-valued data points  $\{y_1, \dots, y_m\}$ , where each  $y_i$  is

paired with a corresponding set of predictor variables  $\{x_{i,1}, x_{i,2}, \dots, x_{i,n}\}$  with  $n < m$ . The linear regression model posits that

$$y_i = \beta_0 + \beta_1 x_{i,1} + \beta_2 x_{i,2} + \dots + \beta_n x_{i,n} + \epsilon_i$$

for  $i = 1, 2, \dots, m$ . The real numbers  $\beta_0, \dots, \beta_n$  are known as the parameters of the model, and the  $\epsilon_i$  are independent normally-distributed error terms. Our task is to calculate the parameters that best fit the data. This can be accomplished by posing the problem in terms of linear least squares: Define

$$b = [y_1, \dots, y_m]^T,$$

$$A = \begin{bmatrix} 1 & x_{1,1} & x_{1,2} & \cdots & x_{1,n} \\ 1 & x_{2,1} & x_{2,2} & \cdots & x_{2,n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & x_{m,1} & x_{m,2} & \cdots & x_{m,n} \end{bmatrix},$$

and

$$x = [\beta_0, \beta_1, \dots, \beta_n]^T.$$

Now use Conjugate-Gradient to solve the system

$$A^T A x = A^T b.$$

The solution  $x^* = [\beta_0^*, \beta_1^*, \dots, \beta_n^*]^T$  gives the parameters that best fit the data. These values can be understood as defining the hyperplane that best fits the data. See Figure 15.2.

**Problem 3.** Using your Conjugate-Gradient function, solve the linear regression problem specified by the data contained in the file `linregression.txt`. This is a whitespace-delimited text file formatted so that the  $i$ -th row consists of  $y_i, x_{i,1}, \dots, x_{i,n}$ . Use the function `numpy.loadtxt()` to load in the data. Report your solution.

## Non-linear Conjugate-Gradient Algorithms

The algorithm presented above is only valid for certain linear systems and quadratic functions, but the basic strategy may be adapted to minimize more general convex or non-linear functions. There are multiple ways to modify the algorithm, and they all involve getting rid of  $Q$ , since there is no such  $Q$  for non-quadratic functions. Generally speaking, we need to find new formulas for  $\alpha_k$ ,  $r_k$ , and  $\beta_k$ .

The scalar  $\alpha_k$  is simply the result of performing a line-search in the given direction  $d_k$ , so we may define

$$\alpha_k = \arg \min_x f(x_k + \alpha d_k).$$

The vector  $r_k$  in the original algorithm was really just the gradient of the objective function, and so we may define

$$r_k = \nabla f(x_k).$$



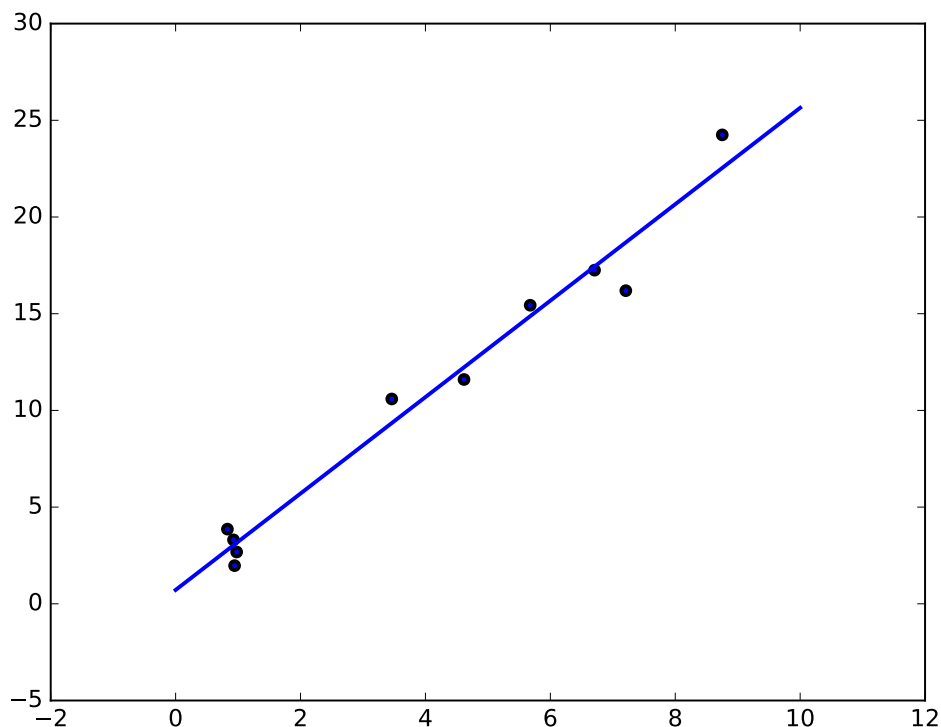


Figure 15.2: Solving the Linear Regression problem results in a best-fit hyperplane.

There are various ways to define the constants  $\beta_k$  in this more general setting, and the right choice will depend on the nature of the objective function. A well-known formula, due to Fletcher and Reeves, is

$$\beta_{k+1} = \frac{\nabla f_{k+1}^T \nabla f_{k+1}}{\nabla f_k^T \nabla f_k}.$$

Making these adjustments is not difficult, but we will opt instead to use built-in functions in Python. In particular, the SciPy module `scipy.optimize` provides a function `fmin_cg()`, which uses a non-linear Conjugate-Gradient method to minimize general functions. Using this function is easy – we only need to pass to it the objective function and an initial guess.

## Application: Logistic Regression

Logistic regression is an important technique in statistical analysis and classification. The core problem in logistic regression involves an optimization that we can tackle using nonlinear Conjugate-Gradient.

As in linear regression, we have a set of data points  $y_i$  together with predictor variables  $x_{i,1}, x_{i,2}, \dots, x_{i,n}$  for  $i = 1, \dots, m$ . However, the  $y_i$  are binary data points – that is, they are either 0 or 1. Furthermore, instead of having a linear relationship between the data points and the response variables, we assume the following

probabilistic relationship:

$$\mathbb{P}(y_i = 1 \mid x_{i,1}, \dots, x_{i,n}) = p_i,$$

where

$$p_i = \frac{1}{1 + \exp(-(\beta_0 + \beta_1 x_{i,1} + \dots + \beta_n x_{i,n}))}.$$

The parameters of the model are the real numbers  $\beta_0, \beta_1, \dots, \beta_n$ . Observe that we have  $p_i \in (0, 1)$  regardless of the values of the predictor variables and parameters.

The probability of observing the data points  $y_i$  under this model, assuming they are independent, is given by the expression

$$\prod_{i=1}^m p_i^{y_i} (1 - p_i)^{1-y_i}.$$

We seek to choose the parameters  $\beta_0, \dots, \beta_n$  that maximize this probability. To this end, define the *likelihood function*  $L : \mathbb{R}^{n+1} \rightarrow \mathbb{R}$  by

$$L(\beta_0, \dots, \beta_n) = \prod_{i=1}^m p_i^{y_i} (1 - p_i)^{1-y_i}.$$

We can now state our core problem as follows:

$$\max_{(\beta_0, \dots, \beta_n)} L(\beta_0, \dots, \beta_n).$$

Maximizing this function can be problematic for numerical reasons. By taking the logarithm of the likelihood, we have a more suitable objective function whose maximizer agrees with that of the original likelihood function, since the logarithm is strictly monotone increasing. Thus, we define the *log-likelihood function*  $l : \mathbb{R}^{n+1} \rightarrow \mathbb{R}$  by  $l = \log \circ L$ .

Finally, we multiply by  $-1$  to turn our problem into minimization. The final statement of the problem is:

$$\min_{(\beta_0, \dots, \beta_n)} -l(\beta_0, \dots, \beta_n).$$

A few lines of calculation reveal that

$$\begin{aligned} l(\beta_0, \dots, \beta_n) = & - \sum_{i=1}^m \log(1 + \exp(-(\beta_0 + \beta_1 x_{i,1} + \dots + \beta_n x_{i,n}))) + \\ & \sum_{i=1}^m y_i (\beta_0 + \beta_1 x_{i,1} + \dots + \beta_n x_{i,n}). \end{aligned}$$

The values for the parameters that we obtain are known collectively as the *maximum likelihood estimate*.

Let's work through a simple example. We will deal with just one predictor variable, and therefore two parameters. The data is given in Table 15.1. This is obviously just toy data with no meaning, but one can think of the  $y_i$  data points as indicating, for example, the presence of absence of a particular disease in subject  $i$ , with  $x_i$  being the subject's weight, or age, or something of the sort.

In the code below we initialize our data.

Table 15.1: Data for Logistic Regression Example

$y$	$x$
0	1
0	2
0	3
0	4
1	5
0	6
1	7
0	8
1	9
1	10

```
>>> y = np.array([0, 0, 0, 0, 1, 0, 1, 0, 1, 1])
>>> x = np.ones((10, 2))
>>> x[:,1] = np.array([1, 2, 3, 4, 5, 6, 7, 8, 9, 10])
```

Although we have just one predictor variable, we initialized `x` with two columns, the first of which consists entirely of ones, and the second of which contains the values of the predictor variable. This extra column of ones corresponds to the parameter  $\beta_0$ , which, as you will note, is not multiplied by any of the predictor variables in the log-likelihood function.

We next need to write a Python function that returns the value of our objective function for any value of the parameters,  $(\beta_0, \beta_1)$ .

```
>>> def objective(b):
...     #Return -1*log(1+exp(x.dot(b))), where 1 is the log likelihood.
...     return (np.log(1+np.exp(x.dot(b))) - y*(x.dot(b))).sum()
```

Finally, we minimize the objective function using `fmin_cg()`.

```
>>> guess = np.array([1., 1.])
>>> b = fmin_cg(objective, guess)
Optimization terminated successfully.
      Current function value: 4.310122
      Iterations: 13
      Function evaluations: 128
      Gradient evaluations: 32
>>> print b
[-4.35776886  0.66220658]
```

We can visualize our answer by plotting the data together with the function

$$\phi(x) = \frac{1}{1 + \exp(-\beta_0 - \beta_1 x)},$$

using the values  $\beta_0, \beta_1$  that we obtained from the minimization.

```
>>> dom = np.linspace(0, 11, 100)
>>> plt.plot(x, y, 'o')
```

```
>>> plt.plot(dom, 1./(1+np.exp(-b[0]-b[1]*dom)))
>>> plt.show()
```

Using this procedure, we obtain the plot in Figure 15.3. Note that the graph of  $\phi$ , known as a *sigmoidal curve*, gives the probability of  $y$  taking the value 1 at a particular value of  $x$ . Observe that as  $x$  increases, this probability approaches 1. This is reflected in the data.

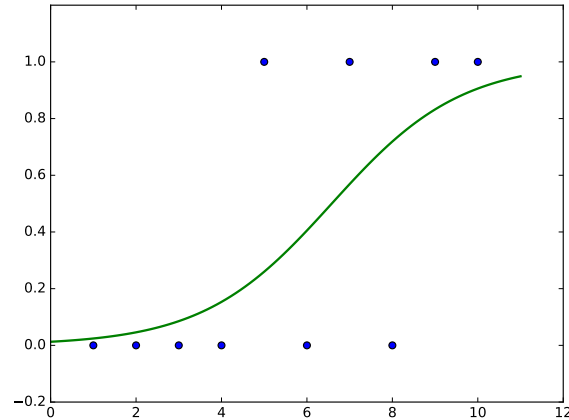


Figure 15.3: Data from the logistic regression example together with the calculated sigmoidal curve.

**Problem 4.** Following the example given above, find the maximum likelihood estimate of the parameters for the logistic regression data in the file `logregression.txt`. This is a whitespace-delimited text file formatted so that the  $i$ -th row consists of  $y_i, x_{i,1}, x_{i,2}, x_{i,3}$ . Since there are three predictor variables, there are four parameters in the model. Report the calculated values.

You should be able to use much of the code above unchanged. In particular, the function `objective()` does not need any changes. You simply need to set your variables `y` and `x` appropriately, and choose a new initial guess (an array of length four). Note that `x` should be an  $m \times 4$  array whose first column consists entirely of ones, whose second column contains the values in the second column of the data file, and so forth.

Logistic regression can become a bit more tricky when some of the predictor variables take on binary or categorical values. In such situations, the data requires a bit of pre-processing before running the minimization.

The values of the parameters that we obtain can be useful in analyzing relationships between the predictor variables and the  $y_i$  data points. They can also be used to classify or predict values of new data points.

## Lab 16

# SQL and Relational Databases

**Lab Objective:** *Understand concepts of a relational database and the fundamentals of the SQL language via SQLite.*

When working with large amounts of data, it is important to be able to quickly find and retrieve interesting information. Fortunately, there is a way to handle such massive amounts of data in a reasonably efficient way: a database. A database is simply a structured repository of data, and it allows us to store and retrieve information very quickly. It is managed by a *database management system*, or DBMS. The DBMS is software that allows users to interact directly with the database.

## Relational Databases

A *relational database* is a paradigm for organizing data inside of a database. In this paradigm, the data is broken down into tuples of information. These tuples are then grouped into tables, or *relations*, each of which is simply a set of tuples. Each table has a *schema* that defines the attributes of the tuples within the table. If we fix an order to the attributes in the schema, we can think of each attribute as a column of the table, and each tuple as a row of the table. See Figure 16.1 for an illustration of these ideas.

As an example, suppose we have demographic data for a large number of individuals. If we are interested in the gender and age of the individuals, we might make a table with schema (Name, Gender, Age). This table would consist of several 3-tuples, such as (Jane Doe, F, 20). Alternatively, we can view this table as having three columns and as many rows as there are individuals within our data set. We might also create a table with schema (Name, Employment Status, Income, Education).

In the relational paradigm, there must be at least one attribute in each schema that can act as a *primary key*. This can uniquely identify each tuple of the table. It is common to use an ID number or other such unique information for the primary key. In our example above, the “Name” attribute acted as a primary key. However, this attribute only works as a primary key provided no two individuals within the data set have the same name.

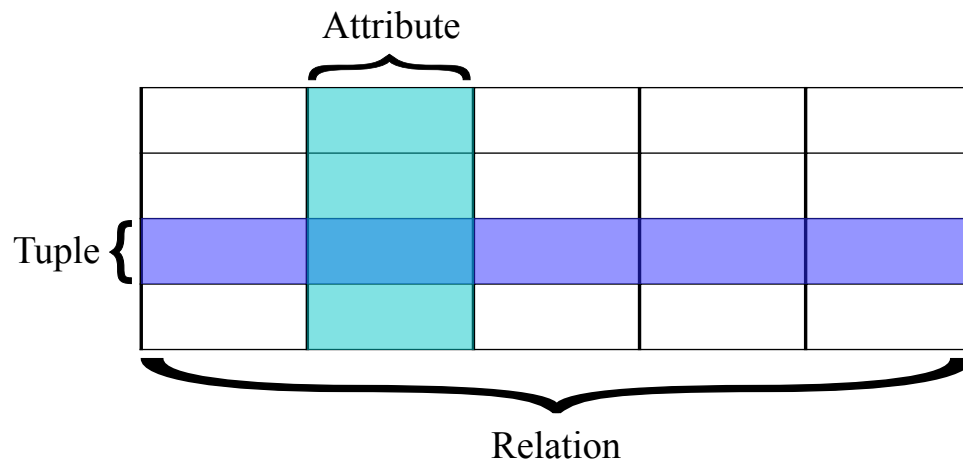


Figure 16.1: Elements of a relation.

One important feature of a database is the *transaction*, which is a conceptual protocol for interacting with the database. Most relational databases are transactional databases. The best way to conceptualize this is imagine that your database is like a bank. Your connection to the database is analogous to the bank teller. When you make one or more deposits and withdrawals, you are making a transaction. A database transaction should have certain properties to protect the integrity of the data. These properties are described in detail in [en.wikipedia.org/wiki/ACID](https://en.wikipedia.org/wiki/ACID)

## Introduction to SQL

Most common DBMSs use a variant of the SQL language to interact with the database. SQL is an acronym for *Structured Query Language*, and may be pronounced like the word “sequel” or by saying the letters “s”, “q”, and “l” separately. While SQL is not generally portable across different DBMSs, we will focus on the parts of SQL that are relatively common. In particular, we will base our discussion on the SQLite database management system, a very popular DBMS.

SQL consists of blocks of code called statements. Each statement is made up of clauses which may or may not require predicates. Predicates specify conditions that can limit the effect of a clause.

### NOTE

SQL commands are often written in all caps to help distinguish them from the other parts of the query. It is only a matter of style. SQLite, along with most other database managers, is case insensitive. In Python’s SQL interface, the semicolon is also not needed. However, most other database systems will require it, so it’s a good idea to conform in Python.

Let’s look at an example SQL statement:

Keyword	Syntax
CREATE TABLE	CREATE TABLE <table> (<col1> <type>, <col2> <type>, ...);
DROP TABLE	DROP TABLE <table>;
CREATE INDEX	CREATE INDEX <name> ON <table> (<col>);
DROP INDEX	DROP INDEX <name>;

Table 16.1: The SQL Schema commands

Keyword	Syntax
INSERT INTO	INSERT INTO <table> <attributes> VALUES (<value1>, <value2>, ...);
UPDATE	UPDATE <table> SET (<col1>=<val1>, <col2>=<val2>, ...) WHERE <condition>;
DELETE	DELETE FROM <table> WHERE <condition>;
SELECT	SELECT <attributes> FROM <table> WHERE <condition>;

Table 16.2: The SQL Data Manipulation commands

```
SELECT * FROM table WHERE id=3+1 AND name='Bob';
```

This statement includes a SELECT clause and a WHERE clause. The WHERE clause contains two predicates: `id=3+1` and `name='Bob'`. These two predicates limit the effect of the SELECT clause because any resulting tuples in the table must satisfy both conditions. This entire statement is classified as a query since it does not modify the database in any way.

SQL has several classes of statements. The two main classes we will cover in this lab are schema (Table 16.1) and data manipulation (Table 16.2). We will give you a simplified description of each command and its syntax. You are encouraged to look up the full syntax outside of this lab.

## SQL in Python

Python has built-in support for SQLite databases using the standard library. Let's open a database called `test1`.

```
import sqlite3 as sql
db = sql.connect("test1")
```

The `connect()` function is used to connect to a database. If it does not already exist, then a new database will be created using the string passed as the argument for the name. The new database was created as a file in the current working directory.

## Ending the SQL Session

Once we are finished performing SQL statements and interacting with the database, we need to commit our changes and safely close the connection to the database. This can be done by calling methods on the database connection object.

```
db.commit()      #save changes made in the transaction
```

Method	Description
<code>execute</code>	Execute a single SQL statement
<code>executemany</code>	Execute a single SQL statement over a sequence
<code>executescript</code>	Execute a SQL script (multiple SQL commands)
<code>close</code>	Closes the cursor object

Table 16.3: Cursor object methods

Python Type	SQLite Type
<code>None</code>	<code>NULL</code>
<code>int</code>	<code>INTEGER</code>
<code>long</code>	<code>INTEGER</code>
<code>float</code>	<code>REAL</code>
<code>str</code>	<code>TEXT</code>
<code>buffer</code>	<code>BLOB</code>

Table 16.4: Python and SQLite types mapping

```
db.close()      #safely close the database
```

A database connection is automatically closed in Python when the connection object is garbage-collected. However, it is nice to be safe and explicit in closing a database connection using the `close()` method.

## Cursor

To execute SQL commands, we need to get a cursor object from the database.

```
cur = db.cursor()
```

The cursor object has several useful methods (Table 16.3). Through the cursor, we will execute all of our SQL commands.

Before creating a table, we need to understand how SQLite stores information in a database. SQLite uses five native data types (a simplified system from other SQL database managers). Table 16.4, gives a mapping between Python and SQLite native types.

## Creating and Dropping Tables

Let's create a table.

```
cur.execute('CREATE TABLE StudentInformation (StudentID INTEGER NOT NULL, Name ←  
TEXT, MajorCode INTEGER);')
```

This will create the empty table in Table 16.5.

The arguments in parentheses are the column names followed by the data type that entries in that column will be, and together these form the schema of the table. The `INTEGER` data type in SQLite is a 1, 2, 3, 4, 6, or 8 byte integer depending on the



StudentID	Name	MajorCode
-----------	------	-----------

Table 16.5: StudentInformation

value. The `NOT NULL` command is a *constraint* on the StudentID column. It requires that all records in the table have a student ID.

#### NOTE

SQLite does not enforce types on columns. Just like Python, SQLite is dynamically typed. However, most other database systems strictly enforce column types. It is a good idea to conform to the column types specified in the schema.

Note that each command we execute returns the same cursor object. This object is equipped with a method that allows us to look at any results of the previous command. The result is formally known as the *result set*. If you use `cur.fetchall()`, you will see an empty list. That is because the create table command does not return a result set.

Now we want to build a relation between students, the courses they've had, and their grades in those courses.

```
cur.execute('CREATE TABLE StudentGrades (StudentID INT NOT NULL, CourseID INT, ←
Grade TEXT);')
```

**Problem 1.** In this problem, you will create two new tables in the database “sql1”. The first table will be called MajorInfo and have a column called MajorID and MajorName. MajorID is an integer and MajorName is a string.

The second table will be called CourseInfo and have columns called CourseID and CourseName, also integers and strings, respectively.

Hint: In order to view information about the columns of the table, run the following command:

```
cur.execute("PRAGMA table_info('table_name')")
for info in cur:
    print info
```

For each column, this command will output (ID, name, type, notnull, default value, primary key). Also, don't forget to commit and close your database.

We can also destroy tables using the `DROP TABLE` command.

```
cur.execute("CREATE TABLE test_table (id INT, name TEXT);")
```

We can delete the table by dropping it.

StudentID	Name	MajorCode
55	John Smith	2

Table 16.6: StudentInformation

```
cur.execute("DROP TABLE test_table;")
```

If a table doesn't exist, an exception will be raised. We can tell the database to drop the table only if it really exists by using `DROP TABLE IF EXISTS test_table;`.

## Inserting and Removing Data

Let's insert some data into our new tables. We can add rows to tables using the `INSERT INTO` command.

```
cur.execute("INSERT INTO StudentInformation VALUES(55, 'John Smith', 2);")
```

After running this statement, we will have the table in Table 16.6.

Note that SQLite will assume that values match sequentially with the schema of the table. We can also specify the schema of the table to use in the mapping of the values.

```
cur.execute("INSERT INTO StudentInformation(MajorCode, Name, StudentID) VALUES←  
(55, 'John Smith', 2);")
```

This will map the value 55 to MajorCode and the value 2 to StudentID. This may be useful sometimes.

It can quickly become tedious to insert large amounts of data into a table, one row at a time. We can automate the process somewhat by using the `executemany` method of the cursor object. To insert several rows into a table using a single command, we can do the following:

```
cur.executemany("INSERT INTO StudentInformation VALUES (?, ?, ?, ?);", rows)
```

In the code above, we assume that `rows` is a Python list of tuples, each tuple containing the data for one row.

We may remove rows from a table using the `DELETE FROM` command.

```
cur.execute("DELETE FROM StudentInformation WHERE MajorCode=55;")
```

### ACHTUNG!

*Never* use Python's string operations to construct a SQL query. It is extremely insecure and is an easy target for a well known type of database called a SQL injection attack.

Parameter substitution can be used to construct dynamic queries. In the simplest way, it involves using a '?' character whenever you want to use a

value and providing a sequence of values as a second argument to `execute()`.

```
statement = "INSERT INTO StudentInformation VALUES(?, ?, ?, ?);"
values = (55, 'John Smith', 372897382, 2)
cur.execute(statement, values)
```

**Problem 2.** The ICD is a large collection of codes used to classify any diagnosis that a doctor would make. When someone goes to the hospital or doctors office, their visit will be recorded using these codes. Insurance companies, the government, and researchers find this data useful. The data file provided to you, `icd9.csv`, has simulated health histories for one million persons. Each line has columns for identification number, gender, and age, followed by ICD-9 codes of various quantities. Note that the codes for each individual are written in a single string, each code separated by semicolons. Create a new database with a single table to store all the simulated data. Call the database “sql2” and the table “ICD.” Your table should have four columns, one each for id number, gender, age, and codes.

Because of the volume of data, it is highly recommended you use the `executemany()` method of the cursor. It will be about twice as fast as using an `execute()` for each line of the CSV file. Recall the `csv` package in Python. To read a CSV file into a list of tuples, where each tuple consists of the delimited values of a particular line in the file, one can use the following code as a guideline:

```
import csv
with open('filename', 'rb') as csvfile:
    rows = [row for row in csv.reader(csvfile, delimiter=',')]
```

Hint: Don’t forget to commit and close your database.

**Problem 3.** Create the following tables in the same database you created in Problem 1 (“sql1”). You may do so however you think is best.

StudentID	Name	MajorCode
401767594	Michelle Fernandez	1
678665086	Gilbert Chapman	1
553725811	Roberta Cook	2
886308195	Rene Cross	3
103066521	Cameron Kim	4
821568627	Mercedes Hall	3
206208438	Kristopher Tran	2
341324754	Cassandra Holland	1
262019426	Alfonso Phelps	3
622665098	Sammy Burke	2

Table 16.7: StudentInformation

ID	Name
1	Math
2	Science
3	Writing
4	Art

Table 16.8: MajorInfo

StudentID	ClassID	Grade
401767594	4	C
401767594	3	B-
678665086	4	A+
678665086	3	A+
553725811	2	C
678665086	1	B
886308195	1	A
103066521	2	C
103066521	3	C-
821568627	4	D
821568627	2	A+
821568627	1	B
206208438	2	A
206208438	1	C+
341324754	2	D-
341324754	1	A-
103066521	4	A
262019426	2	B
262019426	3	C
622665098	1	A
622665098	2	A-

Table 16.9: StudentGrades

ClassID	Name
1	Calculus
2	English
3	Pottery
4	History

Table 16.10: CourseInfo

## Updating Rows of a Table

We can modify records in a table by using the `UPDATE` command.

```
cur.execute("UPDATE StudentInformation SET MajorCode=2, StudentID=55, Name='←↵
Jonathan Smith' WHERE StudentID=2;")
```

### NOTE

When updating a table, having a sufficient `WHERE` clause is essential. Any record

StudentID	Name
401767594	Michelle Fernandez
678665086	Gilbert Chapman
341324754	Cassandra Holland

Table 16.11: Selected students who are math majors.

that matches the criteria will be modified. If we omitted the `WHERE` clause, every record in the table would be set to the values given in the example.

## Adding Columns to a Table

After you have created a table, you can add more columns to the table by using the `ALTER TABLE` command. For example, if we wanted to add the column "age" into our students table. We run this command.

```
cur.execute("ALTER TABLE StudentInformation ADD COLUMN age INTEGER;")
```

## Selecting Data From Tables

The process of retrieving data from a table in a database is accomplished by the `SELECT` statement. The `SELECT` statement can be thought of as a very high level set description. For example, to view the contents of an entire table, we simply need to unconditionally select its contents.

```
SELECT * FROM students;
```

This is equivalent to the following set (where  $x$  is a row).

$$\{x : x \in \text{classes}\}$$

We can also select specific columns.

```
SELECT StudentID, Name FROM students;
```

Or we can impose conditions on the selected rows.

```
SELECT StudentID, Name FROM students WHERE MajorCode=1;
```

This query results in the following table (Table 16.11) where the contents are all the students that are math majors.

You can also further refine which rows you select by using the `AND` or `OR` commands. These commands will connect expressions. For example, to get the math and science majors. One could run the command.

```
SELECT StudentID, Name FROM students WHERE MajorCode=1 OR MajorCode=2;
```

Method	Description
<code>fetchone()</code>	Return a single row from the result set
<code>fetchmany(n)</code>	Return the next $n$ rows from the result set
<code>fetchall()</code>	Return the entire result set

Table 16.12: Fetch methods of a cursor.

Select statements return a *result set*. This is an iterable object. Each row in the object is represented as a tuple of values.

```
cur.execute('SELECT StudentID, Name FROM students WHERE MajorCode=1;')
for student in cur:
    print student
```

We can also use the fetch methods of the returned cursor to extract rows from the result set (Table 16.12).

**Problem 4.** From the ICD9 table you created in Problem 2, how many men between the ages of 25 and 35 are there? How many women between those same ages? Return your answers as a tuple.

## When an Error Occurs

It is important to be able to recover from errors gracefully, especially when working a database. Data integrity in a database is often a critical need. When an error occurs, we need to undo the changes that triggered the error. Fortunately, `sqlite3` reports a variety of errors. These errors and when they are raised is explained in PEP249 (<http://legacy.python.org/dev/peps/pep-0249/>).

**Error** The base class for errors thrown by `sqlite3`. All other errors inherit from this class. Catching this error will catch any error raised.

**InterfaceError** Raised when there is a problem with the interface to the database rather than the database itself.

**DatabaseError** Raised when there is an error with the database itself.

**DataError** Subclass of `DatabaseError`. Raised when there are errors in the processed data (division by zero, value out of range, etc.).

**OperationalError** Subclass of `DatabaseError`. Raised for errors related to the database that are not the fault of the programmer. For example, an unexpected disconnect, failure to process a transaction, a memory allocation error during a transaction, etc.

**IntegrityError** Subclass of `DatabaseError`. Raised when the relational integrity of the database is compromised.

**InternalError** Subclass of DatabaseError. Raised when there is an internal error such as an invalid cursor, out-of-sync transaction, etc.

**ProgrammingError** Subclass of DatabaseError. Raised for programming errors.

**NotSupportedError** Subclass of DatabaseError. Raised when a method is called that is not supported by the database.

The way to gracefully recover from errors is to catch them and handle them accordingly. For example, if any error occurs, with the interface or the database, we immediately rollback the transaction. If no error occurs, commit. We could use if-statements or we could use a try-except block.

```
try:
    <code>
    db.commit()
except sql.Error:
    db.rollback()
```

Note that rolling back is not needed if we are just performing queries. If we don't change any of the data in the database, there is no need to roll anything back. However, even with queries, there is the potential for errors. You must design your code to handle these errors gracefully.



## Lab 17

# SQL 2 (The SQL Sequel)

**Lab Objective:** *Learn more of the advanced and specialized features of SQL.*

## Database Normalization

Normalizing a database is the process of organizing tables and columns to minimize the amount of redundant information in the database. For example, a non-normalized database might have a table that stores customer contact information and a table that contains all of the products a company has sold. However, they might want to track who buys what products in case they need to contact them later. To do so, they store all the contact information of a particular buyer along with every item they purchased. Now, two tables store the customer contact information. If we needed to update a customer's phone number, we have to update two tables. While that may not be bad for small databases, larger databases would be near impossible to update correctly. The idea of normalizing a database allows us to store all customer contact information in one place in the database. All other tables that might need a customer's name, phone number, or address would reference the contact information table. When an update needs to be performed, we only need to update the contact information table. Then any table that references this information is also automatically up to date.

To properly normalize a database, we need to discuss the types of relations tables might have.

### One to One

This is the simplest relation to model. A single table can be used to express this relation. The relation is between one record and at most one other record. An example of this relationship is an employee and their organization. One employee works at one organization. Another example would be that a driver's license belongs to only one person.

StudentID	Name	MajorCode	MinorCode
401767594	Michelle Fernandez	1	NULL
678665086	Gilbert Chapman	NULL	NULL
553725811	Roberta Cook	2	1
886308195	Rene Cross	3	1
103066521	Cameron Kim	4	2
821568627	Mercedes Hall	NULL	3
206208438	Kristopher Tran	2	4
341324754	Cassandra Holland	1	NULL
262019426	Alfonso Phelps	NULL	NULL
622665098	Sammy Burke	2	3

Table 17.1: students

ID	Name
1	Math
2	Science
3	Writing
4	Art

Table 17.2: fields

## One to Many

This relationship and its inverse must be modeled with at least two tables. The general approach is to use a unique ID. Note that a relationship that appears one to one may actually be a one to many relationship. Many people will, therefore, use the same unique ID approach on one to one relationships too in the case it turns out to be a one to many relationship. An example of a one to many relationship would be between an department and its employees. The department would receive a unique ID and then each employee in that department would be tagged with that ID.

## Many to Many

This relationship requires at least three tables. A many to many relationship can be visualized as two, separate one to many relationships. The records in each of the two tables receive a unique ID. A third table then serves as a map between IDs of table to IDs of the other table. An example of a many to many relationship is doctors and patients. One doctor can have several patients and one patient can have several doctors.

For the rest of the lab, we will be using the following tables: 17.1, 17.2, 17.3, and 17.4.

**Problem 1.** Classify the relations between the various records in these tables: 17.1, 17.2, 17.3, and 17.4.

StudentID	ClassID	Grade
401767594	4	C
401767594	3	B-
678665086	4	NULL
678665086	3	A+
553725811	2	C
678665086	1	NULL
886308195	1	A
103066521	2	C
103066521	3	C-
821568627	4	D
821568627	2	NULL
821568627	1	B
206208438	2	A
206208438	1	C+
341324754	2	D-
341324754	1	NULL
103066521	4	A
262019426	2	B
262019426	3	NULL
622665098	1	A
622665098	2	A-

Table 17.3: grades

ClassID	Name
1	Calculus
2	English
3	Pottery
4	History

Table 17.4: classes

Classify each relation as either one to one, one to many, or many to many. Identify the tables used in each relationship.

#### NOTE

There are instances where you would not want a completely normalized database. Whether to normalize your database depends on your specific needs. Usually, though, the decision to denormalize a database is a last-resort attempt to improve performance.

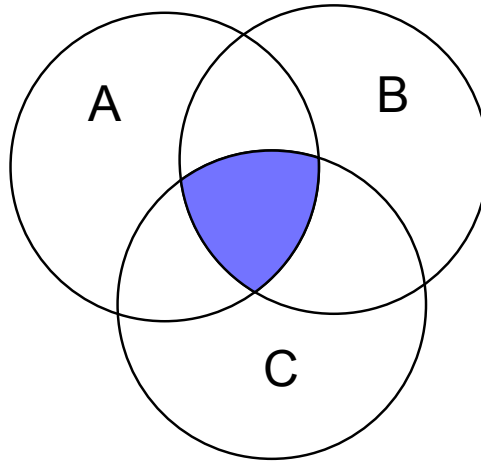


Figure 17.1: An inner joining of tables A, B, and C.

## Joining Tables

We can use SQL to join two or more tables together for a query. This is a very powerful tool. SQLite supports three types of standard table joins.

Joining tables is a common practice to collect data from different parts of the database into a single table. Joins are absolutely essential in a normalized database since data is split between multiple tables.

### Inner Join

This is often the default join operation in SQL. An inner join can be depicted as an intersection of two or more tables. When performing an inner join on tables, the result will only be those records that match across all tables. For example, this join will select all the students' names along with their major as long as the students.majorcode matches the majors.id. If the students.majorcode is missing or null, then they won't be selected.

```
SELECT students.name, majors.name FROM students JOIN majors ON students.majorcode↵
    =majors.id;
```

An inner join is equivalent to the following pseudo-loop in Python

```
for row_s in students:
    for row_m in majors:
        if predicates(row_s, row_m):
            yield columns(row_s, row_m)
```

### Left Outer Join

A left outer join will return all relations from the left table even if they don't match any relation on the joined tables. An illustration of a left outer join is given in figure 17.2.

students.name	majors.name
Michelle Fernandez	Math
Roberta Cook	Science
Rene Cross	Writing
Cameron Kim	Art
Kristopher Tran	Science
Cassandra Holland	Math
Sammy Burke	Science

Table 17.5: An inner join of students and majors

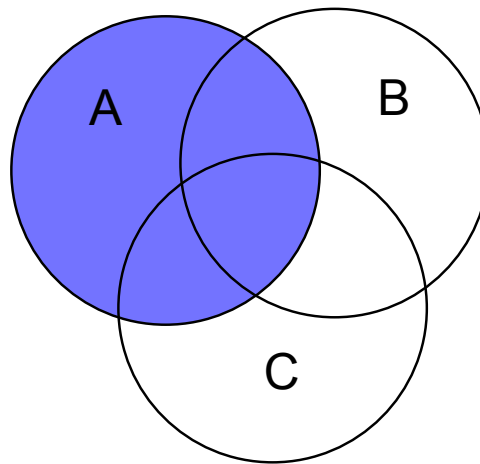


Figure 17.2: A left outer table join of A with tables B and C.

A Pythonesque loop that illustrates how to perform a left outer join is

```
for row_s in students:
    for row_m in majors:
        if predicates(row_s, row_m):
            yield columns(row_s, row_m)
        else:
            yield columns(row_s)
```

The following left outer join will result in the table shown in table 17.6.

```
SELECT students.name, majors.name FROM students LEFT OUTER JOIN majors ON ↵
students.majorcode=majors.id;
```

## Cross Join

Essentially a Cartesian product of tables. Care must be taken when using cross join because of the size of the joined table. A cross join should only be used on small tables. It matches each relation in one table with every other possible combination of relations in the joined tables. For example, if you were to run a cross join on the above join. You would get every student matched with every major. This doesn't really make much sense but can be useful for other applications. Use with caution.

students.name	majors.name
Michelle Fernandez	Math
Gilbert Chapman	None
Roberta Cook	Science
Rene Cross	Writing
Cameron Kim	Art
Mercedes Hall	None
Kristopher Tran	Science
Cassandra Holland	Math
Alfonso Phelps	None
Sammy Burke	Science

Table 17.6: A left outer join of students and majors

Function	Description
MIN()	Retrieve the smallest numeric value of a column
MAX()	Retrieve the largest numeric value of a column
SUM()	Sum the numeric values of a column
AVG()	Retrieve the average numeric value of the column
COUNT()	Retrieve the total number of matching records in a column

Table 17.7: SQL aggregation functions

## Advanced Selections

Aggregate functions are useful for summarizing the data in a column. The functions can be found in 17.7.

We can count the number of students by executing the following SQL statement.

```
SELECT COUNT(*) FROM students;
```

## Ordering and Grouping Relations

The **ORDER BY** keyword can be used to sort the result set by columns. We can sort in ascending order or descending order.

```
SELECT name FROM students ORDER BY name ASC;
SELECT name FROM students ORDER BY name DESC;
```

Another useful SQL keyword is the **GROUP BY** keyword. It is used along with an aggregating function to group the result set by columns.

```
SELECT grade, COUNT(studentid) FROM grades GROUP BY grade;
```

The result set is given in table 17.8.

grade	COUNT(studentid)
None	5
A	4
A+	1
A-	1
B	2
B-	1
C	3
C+	1
C-	1
D	1
D-	1

Table 17.8: Grouping of students by grade.

**Problem 2.** Create a database containing tables 17.1, 17.2, 17.3, and 17.4. Write a SQL query to count how many students belong to each major, including students that don't have a major. Sort your results in ascending order by name. Your result set should be table 17.9

None	3
Art	1
Math	2
Science	3
Writing	1

Table 17.9: Result set

Another important keyword is the **HAVING** keyword. This is necessary because the **WHERE** clause does not support aggregate functions. A **HAVING** clause requires a **GROUP BY** clause. The following will not work.

```
SELECT grade FROM grades GROUP BY grade WHERE COUNT(*)=1;
```

Since **COUNT** is an aggregating function, the following is required.

```
SELECT grade FROM grades GROUP BY grade HAVING COUNT(*)=1;
```

This SQL query returns all the grades that occur only once in the table. A simple way to remember the difference is *WHERE operates on individual records and HAVING operates on groups of records.*

**Problem 3.** Select all the students who have received grades (non-null grades) in more than two classes. How many grades did he receive?

## Case Expression

A case expression allows you to temporarily modify records from a select operation. There are two forms of the case expression; simple and searched. The simple form of the expression is a match and replace on a specified column. A simple case expression is demonstrated below. This code will return the name of the student along with their majorcode. But instead of integers, the names of the majors will be returned.

```
SELECT name,
CASE majorcode
  WHEN 1 THEN 'Math'
  WHEN 2 THEN 'Science'
  WHEN 3 THEN 'Writing'
  WHEN 4 THEN 'Art'
  ELSE 'Undeclared'
END AS major
FROM students;
```

A searched case expression using a boolean expression for the `WHEN` clauses.

```
SELECT name,
CASE
  WHEN majorcode IS NULL THEN 'Undeclared'
  ELSE majorcode
END AS major,
CASE
  WHEN minorcode IS NULL THEN 'Undeclared'
  ELSE minorcode
END AS minor
FROM students;
```

**Problem 4.** Find the overall GPA of all the students in the school. Use a regular 4.0 scale (A=4.0, B=3.0, C=2.0, D=1.0). Any pluses or minuses are dropped so an A- becomes an A.

Your result set should be one column and one row with average of all GPAs of all the students taking classes. Your solution should return a single floating point number.

Use the `ROUND()` function in SQL to round your result to the nearest hundredth.

## Like Command

The SQL keyword, `LIKE`, allows us to match patterns in a column. For example,



```
SELECT name, studentid FROM students WHERE studentid LIKE '%4';
```

will return all the students that have a student ID that ends with the digit 4. Use ‘\%’ before the ‘4’ to signify that there can be any number of characters before the ‘4.’ If you only want one character, you can use an underscore. For example, if you were to search a database of words in the english dictionary and you entered the following command:

```
SELECT word FROM englishDictionary WHERE word LIKE 'i_';
```

You would get words like ‘is,’ ‘it,’ or ‘in.’

**Problem 5.** Write a SQL statement that will find all students with a last name that begins with the letter ‘C’ and return their names and majors. Your returned records should be

Gilbert Chapman	None
Roberta Cook	Science
Rene Cross	Writing



## Lab 18

# Interior Point I

**Lab Objective:** *For decades after its invention, the Simplex algorithm was the only competitive method for linear programming. The past 30 years, however, have seen the discovery and widespread adoption of a new family of algorithms that rival—and in some cases outperform—the Simplex algorithm, collectively called Interior Point methods. One of the major shortcomings of the Simplex algorithm is that the number of steps required to solve the problem can grow exponentially with the size of the linear system. Thus, for certain large linear programs, the Simplex algorithm is simply not viable. Interior Point methods offer an alternative approach and enjoy much better theoretical convergence properties. In this lab we implement an Interior Point method for linear programs, and in the next lab we will turn to the problem of solving quadratic programs.*

## Introduction

Recall that a linear program is a constrained optimization problem with a linear objective function and linear constraints. The linear constraints define a set of allowable points called the *feasible region*, the boundary of which forms a geometric object known as a *polytope*. The theory of convex optimization ensures that the optimal point for the objective function can be found among the vertices of the feasible polytope. The Simplex Method tests a sequence of such vertices until it finds the optimal point. Provided the linear program is neither unbounded nor infeasible, the algorithm is certain to produce the correct answer after a finite number of steps, but it does not guarantee an efficient path along the polytope toward the minimizer. Interior point methods do away with the feasible polytope and instead generate a sequence of points that cut through the interior (or exterior) of the feasible region and converge iteratively to the optimal point. Although it is computationally more expensive to compute such interior points, each step results in significant progress toward the minimizer. See Figure 18.1. In general, the Simplex Method requires many more iterations (though each iteration is less expensive computationally).

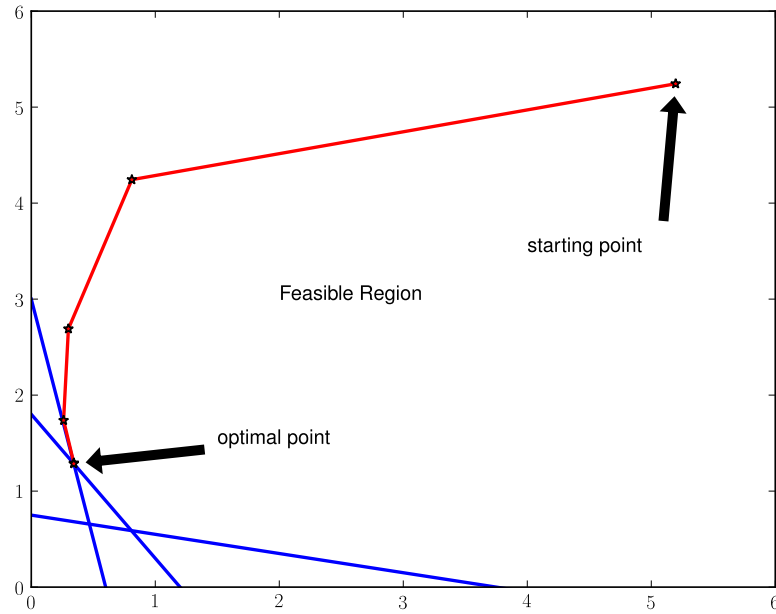


Figure 18.1: A path traced by an Interior Point algorithm.

## Primal-Dual Interior Point Methods

Some of the most popular and successful types of Interior Point methods are known as Primal-Dual Interior Point methods. Consider the following linear program:

$$\begin{aligned} & \text{minimize} && \mathbf{c}^T \mathbf{x} \\ & \text{subject to} && A\mathbf{x} = \mathbf{b} \\ & && \mathbf{x} \geq \mathbf{0}. \end{aligned}$$

Here,  $\mathbf{x}, \mathbf{c} \in \mathbb{R}^n$ ,  $\mathbf{b} \in \mathbb{R}^m$ , and  $A$  is an  $m \times n$  matrix with full row rank. This is the *primal* problem, and its *dual* takes the form:

$$\begin{aligned} & \text{maximize} && \mathbf{b}^T \boldsymbol{\lambda} \\ & \text{subject to} && A^T \boldsymbol{\lambda} + \boldsymbol{\mu} = \mathbf{c} \\ & && \boldsymbol{\mu}, \boldsymbol{\lambda} \geq \mathbf{0}, \end{aligned}$$

where  $\boldsymbol{\lambda} \in \mathbb{R}^m$  and  $\boldsymbol{\mu} \in \mathbb{R}^n$ .

## KKT Conditions

The theory of convex optimization gives us necessary and sufficient conditions for the solutions to the primal and dual problems via the Karush-Kuhn-Tucker (KKT) conditions. The Lagrangian for the primal problem is as follows:

$$\mathcal{L}(\mathbf{x}, \boldsymbol{\lambda}, \boldsymbol{\mu}) = \mathbf{c}^T \mathbf{x} + \boldsymbol{\lambda}^T (\mathbf{b} - A\mathbf{x}) - \boldsymbol{\mu}^T \mathbf{x}$$

The KKT conditions are

$$\begin{aligned} A^T \boldsymbol{\lambda} + \boldsymbol{\mu} &= \mathbf{c} \\ A\mathbf{x} &= \mathbf{b} \\ x_i \mu_i &= 0, \quad i = 1, 2, \dots, n, \\ \mathbf{x}, \boldsymbol{\mu} &\geq 0. \end{aligned}$$

It is convenient to write these conditions in a more compact manner, by defining an almost-linear function  $F$  and setting it equal to zero:

$$F(\mathbf{x}, \boldsymbol{\lambda}, \boldsymbol{\mu}) := \begin{bmatrix} A^T \boldsymbol{\lambda} + \boldsymbol{\mu} - \mathbf{c} \\ A\mathbf{x} - \mathbf{b} \\ M\mathbf{x} \end{bmatrix} = \mathbf{0},$$

$$(\mathbf{x}, \boldsymbol{\mu}) \geq 0,$$

where  $M = \text{diag}(\mu_1, \mu_2, \dots, \mu_n)$ . Note that the first row of  $F$  is the KKT condition for dual feasibility, the second row of  $F$  is the KKT condition for the primal problem, and the last row of  $F$  accounts for complementary slackness.

**Problem 1.** Define a function `interiorPoint()` that will be used to solve the complete interior point problem. This function should accept  $A$ ,  $\mathbf{b}$ , and  $\mathbf{c}$  as parameters, along with the keyword arguments `niter=20` and `tol=1e-16`. The keyword arguments will be used in a later problem.

For this problem, within the `interiorPoint()` function, write a function for the vector-valued function  $F$  described above. This function should accept  $\mathbf{x}$ ,  $\boldsymbol{\lambda}$ , and  $\boldsymbol{\mu}$  as parameters and return a 1-dimensional NumPy array with  $2n + m$  entries.

## Search Direction

A Primal-Dual Interior Point method is a line search method that starts with an initial guess  $(\mathbf{x}_0^T, \boldsymbol{\lambda}_0^T, \boldsymbol{\mu}_0^T)$  and produces a sequence of points that converge to  $(\mathbf{x}^{*T}, \boldsymbol{\lambda}^{*T}, \boldsymbol{\mu}^{*T})$ , the solution to the KKT equations and hence the solution to the original linear program. The constraints on the problem make finding a search direction and step length a little more complicated than for the unconstrained line search we have studied previously.

In the spirit of Newton's Method, we can form a linear approximation of the system  $F(\mathbf{x}, \boldsymbol{\lambda}, \boldsymbol{\mu}) = \mathbf{0}$  centered around our current point  $(\mathbf{x}, \boldsymbol{\lambda}, \boldsymbol{\mu})$ , and calculate the direction  $(\Delta \mathbf{x}^T, \Delta \boldsymbol{\lambda}^T, \Delta \boldsymbol{\mu}^T)$  in which to step to set the linear approximation equal to  $\mathbf{0}$ . This equates to solving the linear system:

$$DF(\mathbf{x}, \boldsymbol{\lambda}, \boldsymbol{\mu}) \begin{bmatrix} \Delta \mathbf{x} \\ \Delta \boldsymbol{\lambda} \\ \Delta \boldsymbol{\mu} \end{bmatrix} = -F(\mathbf{x}, \boldsymbol{\lambda}, \boldsymbol{\mu}) \quad (18.1)$$

Here  $DF(\mathbf{x}, \boldsymbol{\lambda}, \boldsymbol{\mu})$  denotes the total derivative matrix of  $F$ . We can calculate this matrix block-wise by obtaining the partial derivatives of each block entry of

$F(\mathbf{x}, \boldsymbol{\lambda}, \boldsymbol{\mu})$  with respect to  $\mathbf{x}$ ,  $\boldsymbol{\lambda}$ , and  $\boldsymbol{\mu}$ , respectively. We thus obtain:

$$DF(\mathbf{x}, \boldsymbol{\lambda}, \boldsymbol{\mu}) = \begin{bmatrix} 0 & A^T & I \\ A & 0 & 0 \\ M & 0 & X \end{bmatrix}$$

where  $X = \text{diag}(x_1, x_2, \dots, x_n)$ .

Unfortunately, solving Equation 18.1 often leads to a search direction that is too greedy. Even small steps in this direction may lead the iteration out of the feasible region by violating one of the constraints. To remedy this, we define the *duality measure*  $\nu^1$  of the problem:

$$\nu = \frac{\mathbf{x}^T \boldsymbol{\mu}}{n}$$

The idea is to use Newton's method to identify a direction that strictly decreases  $\nu$ . Thus instead of solving Equation 18.1, we solve:

$$DF(\mathbf{x}, \boldsymbol{\lambda}, \boldsymbol{\mu}) \begin{bmatrix} \Delta \mathbf{x} \\ \Delta \boldsymbol{\lambda} \\ \Delta \boldsymbol{\mu} \end{bmatrix} = -F(\mathbf{x}, \boldsymbol{\lambda}, \boldsymbol{\mu}) + \begin{bmatrix} \mathbf{0} \\ \mathbf{0} \\ \sigma \nu \mathbf{e} \end{bmatrix} \quad (18.2)$$

where  $\mathbf{e} = (1, 1, \dots, 1)^T$  and  $\sigma \in [0, 1)$  is called the *centering parameter*. The closer  $\sigma$  is to 0, the more similar the resulting direction will be to the plain Newton direction. The closer  $\sigma$  is to 1, the more the direction points inward to the interior of the of the feasible region.

**Problem 2.** Within `interiorPoint()`, write a subroutine to compute the search direction  $(\Delta \mathbf{x}^T, \Delta \boldsymbol{\lambda}^T, \Delta \boldsymbol{\mu}^T)$  by solving Equation 18.2. Use  $\sigma = \frac{1}{10}$  for the centering parameter.

Note that only the last block row of  $DF$  will need to be changed at each iteration (since  $M$  and  $X$  depend on  $\boldsymbol{\mu}$  and  $\mathbf{x}$ , respectively). Consider using the functions `lu_factor()` and `lu_solve()` from the `scipy.linalg` module to solving the system of equations efficiently.

## Step Length

Now that we have our search direction, it remains to choose our step length. We wish to step nearly as far as possible without violating the problem's constraints, thus remaining in the interior of the feasible region. First, we calculate the maximum allowable step lengths for  $\mathbf{x}$  and  $\boldsymbol{\mu}$ , respectively:

$$\begin{aligned} \alpha_{\max} &= \min \{1, \min \{-\mu_i / \Delta \mu_i \mid \Delta \mu_i < 0\}\} \\ \delta_{\max} &= \min \{1, \min \{-x_i / \Delta x_i \mid \Delta x_i < 0\}\} \end{aligned}$$

Next, we back off from these maximum step lengths slightly:

$$\begin{aligned} \alpha &= \min(1, 0.95 \alpha_{\max}) \\ \delta &= \min(1, 0.95 \delta_{\max}). \end{aligned}$$

<sup>1</sup> $\nu$  is the Greek letter for  $n$ , pronounced “nu.”

These are our final step lengths. Thus, the next point in the iteration is given by:

$$\begin{aligned}\mathbf{x}_{k+1} &= \mathbf{x}_k + \delta \Delta \mathbf{x}_k \\ (\boldsymbol{\lambda}_{k+1}, \boldsymbol{\mu}_{k+1}) &= (\boldsymbol{\lambda}_k, \boldsymbol{\mu}_k) + \alpha(\Delta \boldsymbol{\lambda}_k, \Delta \boldsymbol{\mu}_k).\end{aligned}$$

**Problem 3.** Within `interiorPoint()`, write a subroutine to compute the step size after the search direction has been computed. Avoid using loops when computing  $\alpha_{\max}$  and  $\beta_{\max}$  (use masking and NumPy functions instead).

## Initial Point

Finally, the choice of initial point  $(\mathbf{x}_0, \boldsymbol{\lambda}_0, \boldsymbol{\mu}_0)$  is an important, nontrivial one. A naïvely or randomly chosen initial point may cause the algorithm to fail to converge. The following function will calculate an appropriate initial point.

```
def starting_point(A, b, c):
    """Calculate an initial guess to the solution of the linear program
    min c^T x, Ax = b, x>=0.
    Reference: Nocedal and Wright, p. 410.
    """
    # Calculate x, lam, mu of minimal norm satisfying both
    # the primal and dual constraints.
    B = la.inv(A.dot(A.T))
    x = A.T.dot(B.dot(b))
    lam = B.dot(A.dot(c))
    mu = c - A.T.dot(lam)

    # Perturb x and s so they are nonnegative.
    dx = max((-3./2)*x.min(), 0)
    dmu = max((-3./2)*mu.min(), 0)
    x += dx*np.ones_like(x)
    mu += dmu*np.ones_like(mu)

    # Perturb x and mu so they are not too small and not too dissimilar.
    dx = .5*(x*mu).sum()/mu.sum()
    dmu = .5*(x*mu).sum()/x.sum()
    x += dx*np.ones_like(x)
    mu += dmu*np.ones_like(mu)

    return x, lam, mu
```

**Problem 4.** Complete the implementation of `interiorPoint()`.

Use the function `starting_point()` provided above to select an initial point, then run the iteration `niter` times, or until the duality measure is less than `tol`. Return the optimal point  $\mathbf{x}^*$  and the optimal value  $\mathbf{c}^T \mathbf{x}^*$ .

The duality measure  $\nu$  tells us in some sense how close our current point is to the minimizer. The closer  $\nu$  is to 0, the closer we are to the optimal point. Thus, by printing the value of  $\nu$  at each iteration, you can track how

your algorithm is progressing and detect when you have converged.

To test your implementation, use the following code to generate a random linear program, along with the optimal solution.

```
"""Generate a linear program min c^T x s.t. Ax = b, x>=0.
First generate m feasible constraints, then add
slack variables to convert it into the above form.
Inputs:
    m (int >= n): number of desired constraints.
    n (int): dimension of space in which to optimize.
Outputs:
    A ((m,n+m) ndarray): Constraint matrix.
    b ((m,) ndarray): Constraint vector.
    c ((n+m,) ndarray): Objective function with m trailing 0s.
    x ((n,) ndarray): The first 'n' terms of the solution to the LP.
"""
A = np.random.random((m,n))*20 - 10
A[A[:,-1]<0] *= -1
x = np.random.random(n)*10
b = np.zeros(m)
b[:n] = A[:n,:].dot(x)
b[n:] = A[n:,:].dot(x) + np.random.random(m-n)*10
c = np.zeros(n+m)
c[:n] = A[:n,:].sum(axis=0)/n
A = np.hstack((A, np.eye(m)))
return A, b, -c, x
```

```
>>> m, n = 7, 5
>>> A, b, c, x = randomLP(m, n)
>>> point, value = interiorPoint(A, b, c)
>>> np.allclose(x, point[:n])
True
```

## Least Absolute Deviations (LAD)

We now return to the familiar problem of fitting a line (or hyperplane) to a set of data. We have previously approached this problem by minimizing the sum of the squares of the errors between the data points and the line, an approach known as *least squares*. The least squares solution can be obtained analytically when fitting a linear function, or through a number of optimization methods (such as Conjugate Gradient) when fitting a nonlinear function.

The method of *least absolute deviations* (LAD) also seeks to find a best fit line to a set of data, but the error between the data and the line is measured differently. In particular, suppose we have a set of data points  $(y_1, \mathbf{x}_1), (y_2, \mathbf{x}_2), \dots, (y_m, \mathbf{x}_m)$ , where  $y_i \in \mathbb{R}$ ,  $\mathbf{x}_i \in \mathbb{R}^n$  for  $i = 1, 2, \dots, m$ . Here, the  $\mathbf{x}_i$  vectors are the *explanatory variables* and the  $y_i$  values are the *response variables*, and we assume the following linear model:

$$y_i = \beta^T \mathbf{x}_i + b, \quad i = 1, 2, \dots, m,$$

where  $\beta \in \mathbb{R}^n$  and  $b \in \mathbb{R}$ . The error between the data and the proposed linear



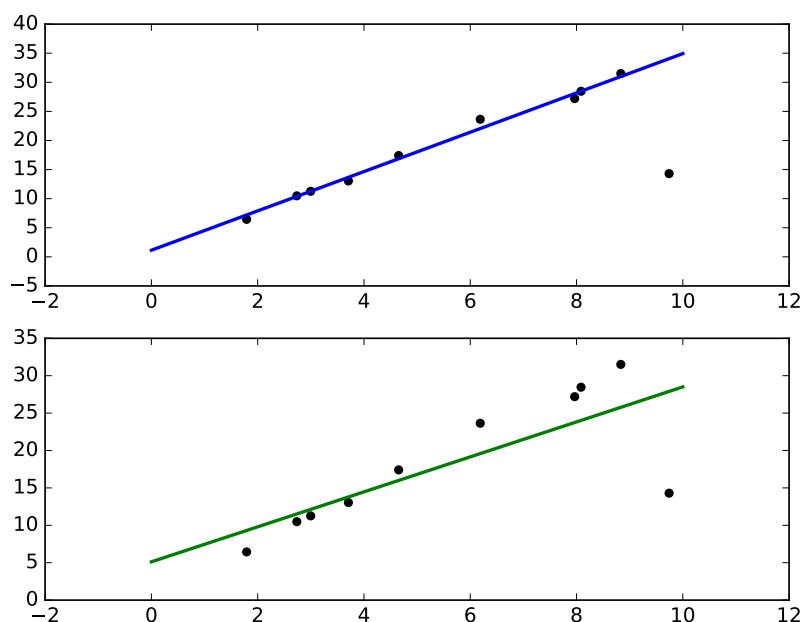


Figure 18.2: Fitted lines produced by least absolute deviations (top) and least squares (bottom). The presence of an outlier accounts for the stark difference between the two lines.

model is given by

$$\sum_{i=1}^n |\beta^T \mathbf{x}_i + b - y_i|,$$

and we seek to choose the parameters  $\beta, b$  so as to minimize this error.

## Advantages of LAD

The most prominent difference between this approach and least squares is how they respond to outliers in the data. Least absolute deviations is robust in the presence of outliers, meaning that one (or a few) errant data points won't severely affect the fitted line. Indeed, in most cases, the best fit line is guaranteed to pass through at least two of the data points. This is a desirable property when the outliers may be ignored (perhaps because they are due to measurement error or corrupted data). Least squares, on the other hand, is much more sensitive to outliers, and so is the better choice when outliers cannot be dismissed. See Figure 18.2.

While least absolute deviations is robust with respect to outliers, small horizontal perturbations of the data points can lead to very different fitted lines. Hence, the least absolute deviations solution is less stable than the least squares solution. In some cases there are even infinitely many lines that minimize the least absolute deviations error term. However, one can expect a unique solution in most cases.

The least absolute deviations solution arises naturally when we assume that the residual terms  $\beta^T \mathbf{x}_i + b - y_i$  have a particular statistical distribution (the Laplace distribution). Ultimately, however, the choice between least absolute deviations and least squares depends on the nature of the data at hand, as well as your own good judgment.

## LAD as a Linear Program

We can formulate the least absolute deviations problem as a linear program, and then solve it using our interior point method. For  $i = 1, 2, \dots, m$  we introduce the artificial variable  $u_i$  to take the place of the error term  $|\beta^T \mathbf{x}_i + b - y_i|$ , and we require this variable to satisfy  $u_i \geq |\beta^T \mathbf{x}_i + b - y_i|$ . This constraint is not yet linear, but we can split it into an equivalent set of two linear constraints:

$$\begin{aligned} u_i &\geq \beta^T \mathbf{x}_i + b - y_i, \\ u_i &\geq y_i - \beta^T \mathbf{x}_i - b. \end{aligned}$$

The  $u_i$  are implicitly constrained to be nonnegative.

Our linear program can now be stated as follows:

$$\begin{aligned} \text{minimize} \quad & \sum_{i=1}^m u_i \\ \text{subject to} \quad & u_i \geq \beta^T \mathbf{x}_i + b - y_i, \\ & u_i \geq y_i - \beta^T \mathbf{x}_i - b. \end{aligned}$$

Now for each inequality constraint, we bring all variables  $(u_i, \beta, b)$  to the left hand side and introduce a nonnegative slack variable to transform the constraint into an equality:

$$\begin{aligned} u_i - \beta^T \mathbf{x}_i - b - s_{2i-1} &= -y_i, \\ u_i + \beta^T \mathbf{x}_i + b - s_{2i} &= y_i, \\ s_{2i-1}, s_{2i} &\geq 0. \end{aligned}$$

Notice that the variables  $\beta, b$  are not assumed to be nonnegative, but in our interior point method, all variables are assumed to be nonnegative. We can fix this situation by writing these variables as the difference of nonnegative variables:

$$\begin{aligned} \beta &= \beta_1 - \beta_2, \\ b &= b_1 - b_2, \\ \beta_1, \beta_2, b_1, b_2 &\geq 0. \end{aligned}$$

Substituting these values into our constraints, we have the following system of constraints:

$$\begin{aligned} u_i - \beta_1^T \mathbf{x}_i + \beta_2^T \mathbf{x}_i - b_1 + b_2 - s_{2i-1} &= -y_i, \\ u_i + \beta_1^T \mathbf{x}_i - \beta_2^T \mathbf{x}_i + b_1 - b_2 - s_{2i} &= y_i, \\ u_i, \beta_1, \beta_2, b_1, b_2, s_{2i-1}, s_{2i} &\geq 0. \end{aligned}$$

Writing  $\mathbf{y} = (-y_1, y_1, -y_2, y_2, \dots, -y_m, y_m)^T$  and  $\beta_i = (\beta_{i,1}, \dots, \beta_{i,n})^T$  for  $i = \{1, 2\}$ , we can aggregate all of our variables into one vector as follows:

$$\mathbf{v} = (u_1, \dots, u_m, \beta_{1,1}, \dots, \beta_{1,n}, \beta_{2,1}, \dots, \beta_{2,n}, b_1, b_2, s_1, \dots, s_{2m})^T.$$

Defining  $\mathbf{c} = (1, 1, \dots, 1, 0, \dots, 0)^T$  (where only the first  $m$  entries are equal to 1), we can write our objective function as

$$\sum_{i=1}^m u_i = \mathbf{c}^T \mathbf{v}.$$

Hence, the final form of our linear program is:

$$\begin{aligned} & \text{minimize} && \mathbf{c}^T \mathbf{v} \\ & \text{subject to} && A\mathbf{v} = \mathbf{y}, \\ & && \mathbf{v} \geq 0, \end{aligned}$$

where  $A$  is a matrix containing the coefficients of the constraints. Our constraints are now equalities, and the variables are all nonnegative, so we are ready to use our interior point method to obtain the solution.

## LAD Example

Consider the following example. We start with an array `data`, each row of which consists of the values  $y_i, x_{i,1}, \dots, x_{i,n}$ , where  $\mathbf{x}_i = (x_{i,1}, x_{i,2}, \dots, x_{i,n})^T$ . We will have  $3m + 2(n + 1)$  variables in our linear program. Below, we initialize the vectors `c` and `y`.

```
>>> m = data.shape[0]
>>> n = data.shape[1] - 1
>>> c = np.zeros(3*m + 2*(n + 1))
>>> c[:m] = 1
>>> y = np.empty(2*m)
>>> y[:2] = -data[:, 0]
>>> y[1:2] = data[:, 0]
>>> x = data[:, 1:]
```

The hardest part is initializing the constraint matrix correctly. It has  $2m$  rows and  $3m + 2(n + 1)$  columns. Try writing out the constraint matrix by hand for small  $m, n$ , and make sure you understand why the code below is correct.

```
>>> A = np.ones((2*m, 3*m + 2*(n + 1)))
>>> A[:2, :m] = np.eye(m)
>>> A[1:2, :m] = np.eye(m)
>>> A[:2, m:m+n] = -x
>>> A[1:2, m:m+n] = x
>>> A[:2, m+n:m+2*n] = x
>>> A[1:2, m+n:m+2*n] = -x
>>> A[:2, m+2*n] = -1
>>> A[1:2, m+2*n+1] = -1
>>> A[:, m+2*n+2:] = -np.eye(2*m, 2*m)
```

Now we can calculate the solution by calling our interior point function.

```
>>> sol = interiorPoint(A, y, c, niter=10)[0]
```

The variable `sol`, however, holds the value for the vector

$$\mathbf{v} = (u_1, \dots, u_m, \beta_{1,1}, \dots, \beta_{1,n}, \beta_{2,1}, \dots, \beta_{2,n}, b_1, b_2, s_1, \dots, s_{2m+1})^T.$$

We extract values of  $\beta = \beta_1 - \beta_2$  and  $b = b_1 - b_2$  with the following code:

```
>>> beta = sol[m:m+n] - sol[m+n:m+2*n]
>>> b = sol[m+2*n] - sol[m+2*n+1]
```

**Problem 5.** The file `simdata.txt` contains two columns of data. The first gives the values of the response variables ( $y_i$ ), and the second column gives the values of the explanatory variables ( $x_i$ ). Find the least absolute deviations line for this data set, and plot it together with the data. Plot the least squares solution as well to compare the results.

```
>>> from scipy.stats import linregress
>>> slope, intercept = linregress(data[:,1], data[:,0])[:2]
>>> domain = np.linspace(0,10,200)
>>> plt.plot(domain, domain*slope + intercept)
```

## Lab 19

# Interior Point II

**Lab Objective:** *Interior point methods originated as an alternative to the Simplex method for solving linear optimization problems. However, they can also be adapted to treat convex optimization problems in general. In this lab, we implement a primal-dual Interior Point method for convex quadratic constrained optimization and explore applications in elastic membrane theory and finance.*

## Quadratic Optimization Problems

A *quadratic constrained optimization problem* differs from a linear constrained optimization problem only in that the objective function is quadratic rather than linear. We can pose such a problem as follows:

$$\begin{array}{ll}\text{minimize} & \frac{1}{2}\mathbf{x}^T Q \mathbf{x} + \mathbf{c}^T \mathbf{x} \\ \text{subject to} & A\mathbf{x} \succeq \mathbf{b}, \\ & G\mathbf{x} = \mathbf{h}.\end{array}$$

We will restrict our attention to quadratic programs involving positive semidefinite quadratic terms (in general, indefinite quadratic objective functions admit many local minima, complicating matters considerably). Such problems are called *convex*, since the objective function is convex. To simplify the exposition, we will also only allow inequality constraints (generalizing to include equality constraints is not difficult). Thus, we have the problem

$$\begin{array}{ll}\text{minimize} & \frac{1}{2}\mathbf{x}^T Q \mathbf{x} + \mathbf{c}^T \mathbf{x} \\ \text{subject to} & A\mathbf{x} \succeq \mathbf{b}\end{array}$$

where  $Q$  is an  $n \times n$  positive semidefinite matrix,  $\mathbf{x}, \mathbf{c} \in \mathbb{R}^n$ ,  $A$  is an  $m \times n$  matrix, and  $\mathbf{b} \in \mathbb{R}^m$ .

The Lagrangian function for this problem is:

$$\mathcal{L}(\mathbf{x}, \boldsymbol{\mu}) = \frac{1}{2} \mathbf{x}^T Q \mathbf{x} + \mathbf{c}^T \mathbf{x} - \boldsymbol{\mu}^T (A \mathbf{x} - \mathbf{b}), \quad (19.1)$$

where  $\boldsymbol{\mu} \in \mathbb{R}^m$  is the (as of yet unknown) Lagrange multiplier.

We also introduce a nonnegative slack vector  $\mathbf{y} \in \mathbb{R}^m$  to change the inequality

$$A \mathbf{x} - \mathbf{b} \succeq \mathbf{0}$$

into the equality

$$A \mathbf{x} - \mathbf{b} - \mathbf{y} = \mathbf{0} \quad \implies \quad \mathbf{y} = A \mathbf{x} - \mathbf{b} \quad (19.2)$$

Equations 19.1 and 19.2, together with complementary slackness, gives us our complete set of KKT conditions:

$$\begin{aligned} Q \mathbf{x} - A^T \boldsymbol{\mu} + \mathbf{c} &= \mathbf{0}, \\ A \mathbf{x} - \mathbf{y} - \mathbf{b} &= \mathbf{0}, \\ y_i \mu_i &= 0, \quad i = 1, 2, \dots, m, \\ \mathbf{y}, \boldsymbol{\mu} &\succeq \mathbf{0}. \end{aligned}$$

## Quadratic Interior Point Method

The Interior Point method we describe here is an adaptation of the method we used with linear programming. Define  $Y = \text{diag}(y_1, y_2, \dots, y_m)$ ,  $M = \text{diag}(\mu_1, \mu_2, \dots, \mu_m)$ , and let  $\mathbf{e} \in \mathbb{R}^m$  be a vector of all ones. Then the roots of the function

$$F(\mathbf{x}, \mathbf{y}, \boldsymbol{\mu}) = \begin{bmatrix} Q \mathbf{x} - A^T \boldsymbol{\mu} + \mathbf{c} \\ A \mathbf{x} - \mathbf{y} - \mathbf{b} \\ Y M \mathbf{e} \end{bmatrix} = \mathbf{0}, \quad (\mathbf{y}, \boldsymbol{\mu}) \succeq \mathbf{0}$$

satisfy the KKT conditions. The derivative matrix of this function is given by

$$DF(\mathbf{x}, \mathbf{y}, \boldsymbol{\mu}) = \begin{bmatrix} Q & 0 & -A^T \\ A & -I & 0 \\ 0 & M & Y \end{bmatrix},$$

and the duality measure  $\nu$  for this problem is

$$\nu = \frac{\mathbf{y}^T \boldsymbol{\mu}}{m}.$$

## Search Direction

We calculate the search direction for this algorithm the same way that we did in the linear programming case. That is, we solve the system:

$$DF(\mathbf{x}, \mathbf{y}, \boldsymbol{\mu}) \begin{bmatrix} \Delta \mathbf{x} \\ \Delta \mathbf{y} \\ \Delta \boldsymbol{\mu} \end{bmatrix} = -F(\mathbf{x}, \mathbf{y}, \boldsymbol{\mu}) + \begin{bmatrix} \mathbf{0} \\ \mathbf{0} \\ \sigma \nu \mathbf{e} \end{bmatrix}, \quad (19.3)$$

where  $\sigma \in [0, 1)$  is the centering parameter.

**Problem 1.** Copy your `interiorPoint()` function from the previous lab into your solutions file for this lab, renaming it `qInteriorPoint()`. This new function should accept the arrays  $Q, \mathbf{c}, A$ , and  $\mathbf{b}$ , a tuple of arrays `guess` giving initial estimates for  $\mathbf{x}, \mathbf{y}$ , and  $\boldsymbol{\mu}$  (this will be explained later), along with the keyword arguments `niter=20` and `tol=1e-16`.

Modify your code to match the  $F$  and  $DF$  described above, and calculate the search direction  $(\Delta \mathbf{x}^T, \Delta \mathbf{y}^T, \Delta \boldsymbol{\mu}^T)$  by solving Equation 19.3. Use  $\sigma = \frac{1}{10}$  for the centering parameter.

Hint: What are the dimensions of  $F$  and  $DF$ ?

## Step Length

Now that we have our search direction, we select a step length. We want to step nearly as far as possible without violating the nonnegativity constraints. We back off slightly from the maximum allowed step length, however, because an overly greedy step at one iteration may prevent a decent step at the next iteration. Thus, we choose our step size

$$\alpha = \max\{a \in (0, 1] \mid \tau(\mathbf{y}, \boldsymbol{\mu}) + a(\Delta \mathbf{y}, \Delta \boldsymbol{\mu}) \succeq \mathbf{0}\},$$

where  $\tau \in (0, 1)$  controls how much we back off from the maximal step length. For now, choose  $\tau = 0.95$ . In general,  $\tau$  can be made to approach 1 at each successive iteration, and this may speed up convergence in some cases.

This is equivalent to the method of choosing a step direction used in the previous lab. In this case, however, we will use a single step length for all three of the parameters.

$$\beta_{\max} = \min\{1, \min\{-\mu_i / \Delta \mu_i \mid \Delta \mu_i < 0\}\}$$

$$\delta_{\max} = \min\{1, \min\{-y_i / \Delta y_i \mid \Delta y_i < 0\}\}$$

Since  $\boldsymbol{\mu}, \mathbf{y} \geq \mathbf{0}$ . If all of the entries of  $\Delta \boldsymbol{\mu}$  are positive, we let  $\beta_{\max} = 1$ , and likewise for  $\delta_{\max}$ . Next, we back off from these maximum step lengths slightly:

$$\beta = \min(1, \tau \beta_{\max})$$

$$\delta = \min(1, \tau \delta_{\max})$$

$$\alpha = \min(\beta, \delta)$$

This  $\alpha$  is our final step length. Thus, the next point in the iteration is given by:

$$(\mathbf{x}_{k+1}, \mathbf{y}_{k+1}, \boldsymbol{\mu}_{k+1}) = (\mathbf{x}_k, \mathbf{y}_k, \boldsymbol{\mu}_k) + \alpha(\Delta \mathbf{x}_k, \Delta \mathbf{y}_k, \Delta \boldsymbol{\mu}_k).$$

This completes one iteration of the algorithm.

## Initial Point

As usual, the starting point  $(\mathbf{x}_0, \mathbf{y}_0, \boldsymbol{\mu}_0)$  has an important effect on the convergence of the algorithm. The code listed below will calculate an appropriate starting point:

```

def startingPoint(G, c, A, b, guess):
    """
    Obtain an appropriate initial point for solving the QP
    .5 x^T Gx + x^T c s.t. Ax >= b.
    Inputs:
        G -- symmetric positive semidefinite matrix shape (n,n)
        c -- array of length n
        A -- constraint matrix shape (m,n)
        b -- array of length m
        guess -- a tuple of arrays (x, y, l) of lengths n, m, and m, resp.
    Returns:
        a tuple of arrays (x0, y0, l0) of lengths n, m, and m, resp.
    """
    m,n = A.shape
    x0, y0, l0 = guess

    # initialize linear system
    N = np.zeros((n+m+m, n+m+m))
    N[:n,:n] = G
    N[:n, n+m:] = -A.T
    N[n:n+m, :n] = A
    N[n:n+m, n:n+m] = -np.eye(m)
    N[n+m:, n:n+m] = np.diag(l0)
    N[n+m:, n+m:] = np.diag(y0)
    rhs = np.empty(n+m+m)
    rhs[:n] = -(G.dot(x0) - A.T.dot(l0)+c)
    rhs[n:n+m] = -(A.dot(x0) - y0 - b)
    rhs[n+m:] = -(y0*l0)

    sol = la.solve(N, rhs)
    dx = sol[:n]
    dy = sol[n:n+m]
    dl = sol[n+m:]

    y0 = np.maximum(1, np.abs(y0 + dy))
    l0 = np.maximum(1, np.abs(l0+dl))

    return x0, y0, l0

```

Notice that we still need to provide a tuple of arrays `guess` as an argument. Do your best to provide a reasonable guess for the array  $\mathbf{x}$ , and we suggest setting  $\mathbf{y}$  and  $\boldsymbol{\mu}$  equal to arrays of ones. We summarize the entire algorithm below.

- 
- 1: **procedure** INTERIOR POINT METHOD FOR QP
  - 2:     Choose initial point  $(\mathbf{x}_0, \mathbf{y}_0, \boldsymbol{\mu}_0)$ .
  - 3:     **while**  $k < \text{niters}$  and  $\nu < \text{tol}$ : **do**
  - 4:         Calculate the duality measure  $\nu$ .
  - 5:         Solve 19.3 for the search direction  $(\Delta \mathbf{x}_k, \Delta \mathbf{y}_k, \Delta \boldsymbol{\mu}_k)$ .
  - 6:         Calculate the step length  $\alpha$ .
  - 7:          $(\mathbf{x}_{k+1}, \mathbf{y}_{k+1}, \boldsymbol{\mu}_{k+1}) = (\mathbf{x}_k, \mathbf{y}_k, \boldsymbol{\mu}_k) + \alpha(\Delta \mathbf{x}_k, \Delta \mathbf{y}_k, \Delta \boldsymbol{\mu}_k)$ .
-



**Problem 2.** Complete the implementation of `qInteriorPoint()`. Return the optimal point  $\mathbf{x}$  as well as the final objective function value. You may want to print out the duality measure  $\nu$  to check the progress of the iteration.

Test your algorithm on the simple problem

$$\begin{aligned} \text{minimize} \quad & \frac{1}{2}x_1^2 + x_2^2 - x_1x_2 - 2x_1 - 6x_2 \\ \text{subject to} \quad & -x_1 - x_2 \geq -2, \\ & x_1 - 2x_2 \geq -2, \\ & -2x_1 - x_2 \geq -3, \\ & x_1, x_2 \geq 0. \end{aligned}$$

In this case, we have for the objective function matrix  $Q$  and vector  $\mathbf{c}$ ,

$$Q = \begin{bmatrix} 1 & -1 \\ -1 & 2 \end{bmatrix}, \quad \mathbf{c} = \begin{bmatrix} -2 \\ -6 \end{bmatrix}.$$

The constraint matrix  $A$  and vector  $\mathbf{b}$  are given by:

$$A = \begin{bmatrix} -1 & -1 \\ 1 & -2 \\ -2 & -1 \\ 1 & 0 \\ 0 & 1 \end{bmatrix}, \quad \mathbf{b} = \begin{bmatrix} -2 \\ -2 \\ -3 \\ 0 \\ 0 \end{bmatrix}.$$

Use  $\mathbf{x} = [.5, .5]$  as the initial guess. The correct minimizer is  $\left[\frac{2}{3}, \frac{4}{3}\right]$ .

#### NOTE

The Interior Point methods presented in this and the preceding labs are only special cases of the more general Interior Point algorithm. The general version can be used to solve many convex optimization problems, provided that one can derive the corresponding KKT conditions and duality measure  $\nu$ .

## Application: Optimal Elastic Membranes

The properties of elastic membranes (stretchy materials like a thin rubber sheet) are of interest in certain fields of mathematics and various sciences. A mathematical model for such materials can be used by biologists to study interfaces in cellular regions in an organism, or by engineers to design tensile structures. Often we can describe configurations of elastic membranes as a solution to an optimization problem. As a simple example, we will find the shape of a large circus tent by solving a quadratic constrained optimization problem using our Interior Point method.

Imagine a large circus tent held up by a few poles. We can model the tent

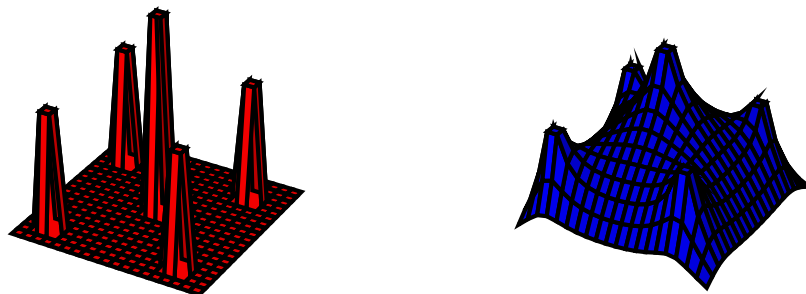


Figure 19.1: Tent pole configuration (left) and optimal elastic tent (right).

by a square two-dimensional grid, where each grid point has an associated number that gives the height of the tent at that point. At each grid point containing a tent pole, the tent height is constrained to be at least as large as the height of the tent pole. At all other grid points, the tent height is simply constrained to be greater than zero (ground height). In Python, we can store a two-dimensional grid of values as a simple two-dimensional array. We can then flatten this array to give a one-dimensional vector representation of the grid. If we let  $\mathbf{x}$  be a one-dimensional array giving the tent height at each grid point, and  $L$  be the one-dimensional array giving the underlying tent pole structure (consisting mainly of zeros, except at the grid points that contain a tent pole), we have the linear constraints:

$$\mathbf{x} \succeq L.$$

The theory of elastic membranes claims that such materials tend to naturally minimize a quantity known as the *Dirichlet energy*. This quantity can be expressed as a quadratic function of the membrane. Then since we have modeled our tent with a discrete grid of values, this energy function has the form

$$\frac{1}{2}\mathbf{x}^T H \mathbf{x} + \mathbf{c}^T \mathbf{x},$$

where  $H$  is a particular positive semidefinite matrix closely related to Laplace's Equation,  $\mathbf{c}$  is a vector whose entries are all equal to  $-(n-1)^{-2}$ , and  $n$  is the side length of the grid. Our circus tent is therefore given by the solution to the quadratic constrained optimization problem:

$$\begin{aligned} &\text{minimize} && \frac{1}{2}\mathbf{x}^T H \mathbf{x} + \mathbf{c}^T \mathbf{x} \\ &\text{subject to} && \mathbf{x} \succeq L. \end{aligned}$$

See Figure 19.1 for an example of a tent pole configuration and the corresponding tent.

We provide the following function for producing the Dirichlet energy matrix  $H$ .

```

from scipy.sparse import spdiags
def laplacian(n):
    """Construct the discrete Dirichlet energy matrix H for an n x n grid."""
    data = -1*np.ones((5, n**2))
    data[2,:] = 4
    data[1, n-1:n] = 0
    data[3, :n] = 0
    diags = np.array([-n, -1, 0, 1, n])
    return spdiags(data, diags, n**2, n**2).toarray()

```

Now we initialize the tent pole configuration for a grid of side length  $n$ , as well as initial guesses for  $\mathbf{x}$ ,  $\mathbf{y}$ , and  $\mu$ .

```

# Create the tent pole configuration.
>>> L = np.zeros((n,n))
>>> L[n//2-1:n//2+1,n//2-1:n//2+1] = .5
>>> m = [n//6-1, n//6, int(5*(n/6.))-1, int(5*(n/6.))]
>>> mask1, mask2 = np.meshgrid(m, m)
>>> L[mask1, mask2] = .3
>>> L = L.ravel()

# Set initial guesses.
>>> x = np.ones((n,n)).ravel()
>>> y = np.ones(n**2)
>>> mu = np.ones(n**2)

```

We leave it to you to initialize the vector  $\mathbf{c}$ , the constraint matrix  $A$ , and to initialize the matrix  $H$  with the `laplacian()` function. We can solve and plot the tent with the following code:

```

>>> from matplotlib import pyplot as plt
>>> from mpl_toolkits.mplot3d import axes3d

# Calculate the solution.
>>> z = qInteriorPoint(H, c, A, L, (x,y,mu))[0].reshape((n,n))

# Plot the solution.
>>> domain = np.arange(n)
>>> X, Y = np.meshgrid(domain, domain)
>>> fig = plt.figure()
>>> ax1 = fig.add_subplot(111, projection='3d')
>>> ax1.plot_surface(X, Y, z, rstride=1, cstride=1, color='r')
>>> plt.show()

```

**Problem 3.** Solve the circus tent problem with the tent pole configuration given above, for grid side length  $n = 15$ . Plot your solution.

## Application: Markowitz Portfolio Optimization

Suppose you have a certain amount of money saved up, with no intention of consuming it any time soon. What will you do with this money? If you hide it somewhere

in your living quarters or on your person, it will lose value over time due to inflation, not to mention you run the risk of burglary or accidental loss. A safer choice might be to put the money into a bank account. That way, there is less risk of losing the money, plus you may even add to your savings through interest payments from the bank. You could also consider purchasing bonds from the government or stocks from various companies, which come with their own sets of risks and returns. Given all of these possibilities, how can you invest your money in such a way that maximizes the return (i.e. the wealth that you gain over the course of the investment) while still exercising caution and avoiding excessive risk? Economist and Nobel laureate Harry Markowitz developed the mathematical underpinnings of an answer to this question in his work on modern portfolio theory.

A *portfolio* is a set of investments over a period of time. Each investment is characterized by a financial asset (such as a stock or bond) together with the proportion of wealth allocated to the asset. An asset is a random variable, and can be described as a sequence of values over time. The variance or spread of these values is associated with the risk of the asset, and the percent change of the values over each time period is related to the return of the asset. For our purposes, we will assume that each asset has a positive risk, i.e. there are no *riskless* assets available.

Stated more precisely, our portfolio consists of  $n$  risky assets together with an allocation vector  $\mathbf{x} = (x_1, \dots, x_n)^T$ , where  $x_i$  indicates the proportion of wealth we invest in asset  $i$ . By definition, the vector  $\mathbf{x}$  must satisfy

$$\sum_{i=1}^n x_i = 1.$$

Suppose the  $i^{th}$  asset has an expected rate of return  $\mu_i$  and a standard deviation  $\sigma_i$ . The total return on our portfolio, i.e. the expected percent change in our invested wealth over the investment period, is given by

$$\sum_{i=1}^n \mu_i x_i.$$

We define the risk of this portfolio in terms of the covariance matrix  $Q$  of the  $n$  assets:

$$\sqrt{\mathbf{x}^T Q \mathbf{x}}.$$

The covariance matrix  $Q$  is always positive semidefinite, and captures the variance and correlations of the assets.

Given that we want our portfolio to have a prescribed return  $R$ , there are in general many possible allocation vectors  $\mathbf{x}$  that make this possible. It would be wise to choose the vector minimizing the risk. We can state this as a quadratic program:

$$\begin{aligned} & \text{minimize} && \frac{1}{2} \mathbf{x}^T Q \mathbf{x} \\ & \text{subject to} && \sum_{i=1}^n x_i = 1 \\ & && \sum_{i=1}^n \mu_i x_i = R. \end{aligned}$$

Note that we have slightly altered our objective function for convenience, as minimizing  $\frac{1}{2}\mathbf{x}^T Q \mathbf{x}$  is equivalent to minimizing  $\sqrt{\mathbf{x}^T Q \mathbf{x}}$ . The solution to this problem will give the portfolio with least risk having a return  $R$ . Because the components of  $\mathbf{x}$  are not constrained to be nonnegative, the solution may have some negative entries. This indicates short selling those particular assets. If we want to disallow short selling, we simply include nonnegativity constraints, stated in the following problem:

$$\begin{aligned} & \text{minimize} && \frac{1}{2}\mathbf{x}^T Q \mathbf{x} \\ & \text{subject to} && \sum_{i=1}^n x_i = 1 \\ & && \sum_{i=1}^n \mu_i x_i = R \\ & && \mathbf{x} \succeq \mathbf{0}. \end{aligned}$$

Each return value  $R$  can be paired with its corresponding minimal risk  $\sigma$ . If we plot these risk-return pairs on the risk-return plane, we obtain a hyperbola. In general, the risk-return pair of any portfolio, optimal or not, will be found in the region bounded on the left by the hyperbola. The positively-sloped portion of the hyperbola is known as the *efficient frontier*, since the points there correspond to optimal portfolios. Portfolios with risk-return pairs that lie to the right of the efficient frontier are inefficient portfolios, since we could either increase the return while keeping the risk constant, or we could decrease the risk while keeping the return constant. See Figure 19.2.

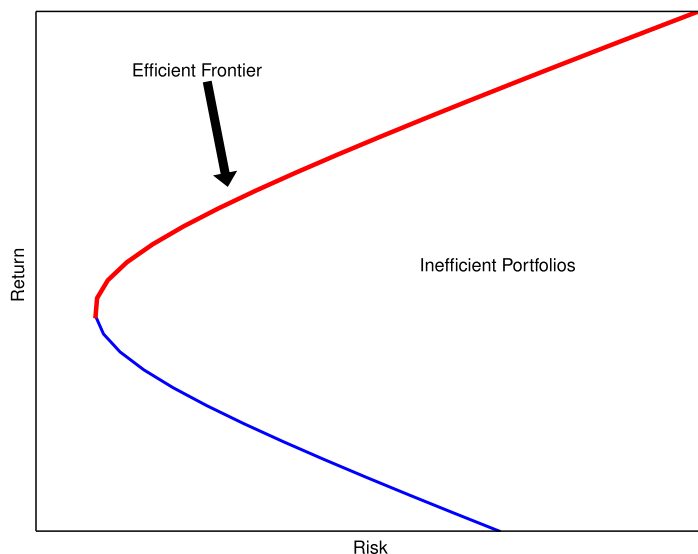


Figure 19.2: Efficient frontier on the risk-return plane.

One difficulty of this model is that the risk and return of each asset is in general unknown. After all, no one can predict the stock market with complete certainty.

There are various ways of estimating these values given past stock prices, and we take a very straightforward approach. Suppose for each asset we have  $k$  previous return values of the asset. That is, for asset  $i$ , we have the data vector

$$y^i = [y_1^i, \dots, y_k^i]^T.$$

We estimate the expected rate of return for asset  $i$  by simply taking the average of  $y_1, \dots, y_k$ , and we estimate the variance of asset  $i$  by taking the variance of the data. We can estimate the covariance matrix for all assets by taking the covariance matrix of the vectors  $y^1, \dots, y^n$ . In this way, we obtain estimated values for  $Q$  and each  $\mu_i$ .

**Problem 4.** The text file `portfolio.txt` contains historical stock data for several assets (U.S. bonds, gold, S&P 500, etc). In particular, the first column gives the years corresponding to the data, and the remaining eight columns give the historical returns of eight assets over the course of these years. Use this data to estimate the covariance matrix  $Q$  as well as the expected rates of return  $\mu_i$  for each asset. Assuming that we want to guarantee an expected return of  $R = 1.13$  for our portfolio, find the optimal portfolio both with and without short selling.

Since the problem contains both equality and inequality constraints, use the QP solver in CVXOPT rather than your `qInteriorPoint()` function.

Hint: Use `numpy.cov()` to compute  $Q$ .

## Lab 20

# Value Function Iteration

**Lab Objective:** *This section teaches the fundamentals of Dynamic Programming using value function iteration.*

Previously we have optimized a single decision or question. In this lab we will optimize a sequence of decisions. The techniques to solve these problems are called dynamic optimization.

Dynamic optimization provides different answers than optimization techniques we have studied previously. For example, an oil company might want to know how much oil to excavate in one day in order to maximize profit. If we only consider today, then the answer is to excavate and sell as much as possible. If each day is considered in isolation, then the strategy to optimize profit is to maximize excavation in order to maximize profits. However, in reality oil prices change from day to day and as supply increases or decreases, and so maximizing excavation may in fact lead to less profit. On the other hand, if the oil company considers how production on one day will affect subsequent decisions, they may be able to maximize their profits. In this lab we will explore techniques for solving such a problem.

## The Cake Eating Problem

Rather than maximizing oil profits, we will focus on solving a general problem that can be applied in many areas called the cake eating problem. Given a cake of a certain size, how do we eat it to maximize our enjoyment (in other words, our utility) over time? Some people may prefer to eat all of their cake at once, and not save any for later. Others may prefer to only eat a little bit at a time. These preferences will be expressed precisely using a utility function. Our task is to find an optimal strategy given an increasing utility function,  $u$ . Precisely, given a cake of size  $W_0$  and some amount of consumption  $c_0 \in [0, W_0]$ , the utility gained is given by

$$u(c_0).$$

If we want to maximize utility over one time period, we will consume the entire cake. How do we maximize utility over several days?

## Discount Factors

A person or firm will typically have a preference for saving or consuming. For example, a dollar today can be invested and yield interest, whereas a dollar received next year will not include the accrued interest. In this lab, cake now will yield more utility than cake in the future. We can model this by multiplying future utility by a discount factor  $\beta \in (0, 1)$ . For example, if we were to consume  $c_0$  cake at time 0 and  $c_1$  cake at time 1, then the total utility gained will be

$$u(c_0) + \beta u(c_1).$$

## The Optimization Problem

If we are to consume a cake of size  $W_0$  over  $T$  time periods, then we can represent our consumption at each step as a vector

$$(c_0, c_1, \dots, c_T)$$

where

$$\sum_{i=1}^T c_i = W_0.$$

We will call such a vector a policy. Thus, our optimization problem is to

$$\begin{aligned} &\text{maximize } \sum_{t=0}^T \beta^t u(c_t) \\ &\text{subject to } \sum_{t=0}^T c_t = 1, c_t \geq 0. \end{aligned}$$

**Problem 1.** It might seem obvious what sort of policy will yield the most utility, but the truth may surprise you. See Figure 20.1 for some examples. Write a function called `graph_policy` will accepts

- a policy,
- a utility function, and
- a discount factor;

and returns the total utility gained with the policy input. Also display a plot of the total utility gained over time. Ensure that the policy that the user passes in sums to 1. Otherwise, raise an `InputError`.



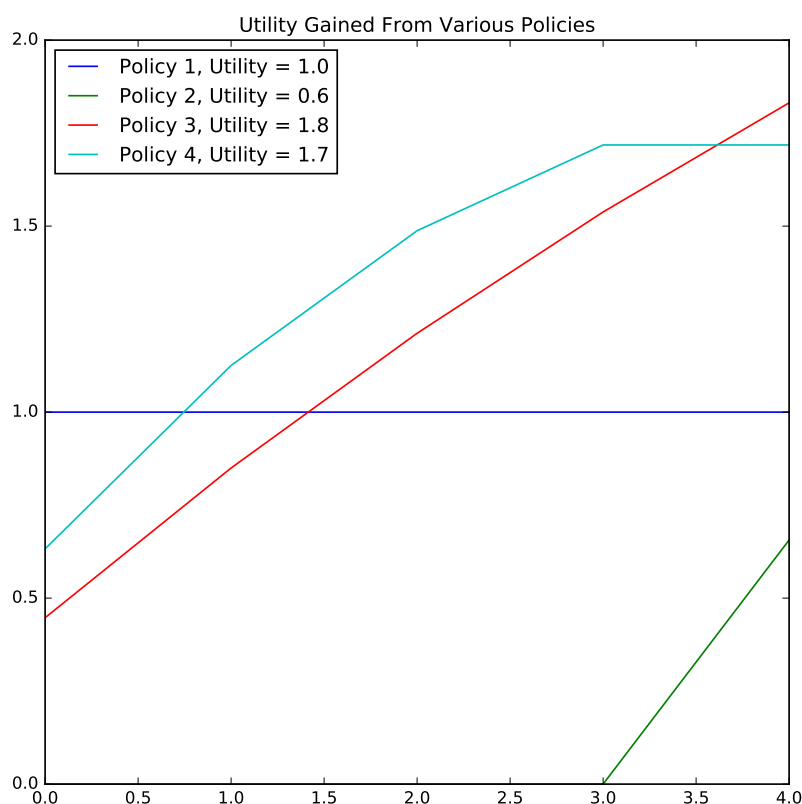


Figure 20.1: Plots for various policies with a square root utility function. Policy 1 eats all the cake in the first step while policy 2 eats all the cake in the last step. Their difference in utility demonstrate the effect of the discount factor on waiting to eat. Policy 3 eats the same amount of cake at each step, while policy 4 starts eating a lot of cake but eats less and less as time goes on and the cake runs out.

## The Value Function

We have posed the cake eating problem as an optimization problem, but we do not have a good way to solve it yet. To that end, we introduce the value function. The value function  $V(a, b, W)$  is the maximal value of

$$\begin{aligned} & \text{maximize} \quad \sum_{t=a}^b \beta^t u(c_t) \\ & \text{subject to} \quad \sum_{t=a}^b c_t = W, c_t \geq 0 \end{aligned}$$

for  $t = a, a + 1, \dots, b$ . In other words, it gives the utility gained from following an optimal policy from time  $a$  to time  $b$ . So if we start with a cake of size  $W_0$  at time 0 and have half the cake left at time  $t$ , then  $V(t, T, \frac{W_0}{2})$  gives how much utility we will gain by proceeding optimally from  $t$ .

Thus, if we know what the optimal policy in the future is, we can figure out the optimal policy for the present, since

$$V(t, T, W_t) = \max_{W_{t+1}} u(W_t - W_{t+1}) + \beta V(t + 1, T, W_{t+1}).$$

Recall that we know what the utility function  $u$  is, as well as  $\beta$ . Also, note that our consumption at time  $t$  is given by the amount of cake at the beginning of time  $t$  minus the amount of cake at the beginning of time  $t + 1$ , or  $W_t - W_{t+1}$ .

In other words, if we know how to maximize utility in the future, we only need to maximize utility in the now in order to maintain optimality. So if we know what  $V(t + 1, T, W_{t+1})$  yields for all possible  $W_{t+1}$ , then we choose the best  $W_{t+1}$  to figure out what the value function yields in the present. Thus, if we can evaluate the value function, we can also determine the optimal policy.

## Solving the Optimization Problem

**Problem 2.** In this problem we will write a helper function that will help us choose the optimal policy. We will assume our discretized cake has volume 1 and an integer  $N$  equally-sized pieces. Write a method that accepts  $N$  and a utility function. Create a vector whose entries correspond to possible amounts of cake given the discretization. For example, if we wanted to consider a cake split into 4 pieces, the vector should be

$$w = (0, 0.25, 0.5, 0.75, 1.0)$$

Return a matrix whose  $ij^{th}$  entry is the amount of utility gained by starting with  $i$  cake pieces and ending with  $j$  pieces. In other words, the  $ij^{th}$  entry should be  $u(w_i - w_j)$ . Let the default utility function be the square root function. Set impossible situations to 0 (i.e., eating more than you have). We call the resulting matrix the consumption matrix.

How can we find the value function if we do not know the optimal policy? So far in our problem, we do not know how to start eating in order to maximize utility. However, we know that we do not want to have any cake left over when time runs out. Thus, the amount of utility we gain from having  $W_{T-1}$  cake at time  $T - 1$  is given by  $u(W_{T-1})$ , and so we know  $V(T - 1, T, W_{T-1})$  given a choice of  $W_{T-1}$ . For example, if we had a cake split into 4 pieces and wanted to eat it in  $T = 4$  time intervals, we could express what we know about the value function from time  $T$  to  $T + 1$  as

$$\begin{bmatrix} * & * & * & * & u(1) & 0 \\ * & * & * & * & u(0.75) & 0 \\ * & * & * & * & u(0.5) & 0 \\ * & * & * & * & u(0.25) & 0 \\ * & * & * & * & :wu(0) & 0 \end{bmatrix}$$

where the  $ij^{th}$  entry gives the value of having  $w_j$  cake at time  $j$  and  $*$  represents unknown values. This is called the value function matrix, and note that it is dimension  $N \times T + 2$ , since we want columns for  $t = 0$  and  $t = T + 1$ . The last column is there to show that after time 4, there is no value in having any cake.

**Problem 3.** Write a function that accepts

- $T$  (the number of time steps),
- $N$  (the number of pieces into which we split our cake),
- a discount factor  $\beta$ , and
- a utility function;

and returns the value function matrix with the last two columns filled in. Let the default utility function be the square root function.

As we mentioned in the previous section, if we know what the value function evaluates to in the future, we can evaluate the value function in the present. If we are at time  $t$ , and we know what the value function evaluates to at time  $t + 1$  (given by the appropriate column of the value function matrix we have built), then we can calculate

$$V_t(W_t) = u(W_t - W_{t+1}) + \beta V_{t+1}(W_{t+1})$$

for all possible values of  $W_t$  and  $W_{t+1}$ . This will produce an  $N \times N$  matrix giving the value of all possible values of starting with a cake of size  $W_t$  and finishing with size  $W_{t+1}$ . We call this matrix the current value matrix. The largest entry of each row then is the optimal value that the value function can attain at this step, given that we start with the amount of cake that corresponds to the row. Thus, the maximal values of each row become the column of the value function matrix at time  $t$  and if we know one column of the value matrix, we may iterate backwards to fill the rest of it in. Note that we can start this process with just the column of zeros that we know occupies the last column of the value function matrix.

**Problem 4.** Modify the solution to the previous problem to determine the entire value function matrix. Initialize the matrix as zeros, and starting from the next to last column

- calculate the current value matrix,

- find the largest value in each row, and
- fill in the column with these values.

Now that the value function matrix is filled in we could say that the optimization problem is solved in some sense. However, it is not immediately apparent how to make decisions given the value function matrix only. What we really want is the optimal policy. It turns out that we already calculated it in the previous problem - we just didn't keep track of it. Recall that we calculated a current value matrix for each column of the value matrix, and that the  $ij^{th}$  entry of that matrix was the value of starting with  $i$  pieces of cake and finishing with  $j$  pieces of cake. Thus, the policy for starting a time step with  $i$  pieces of cake is  $w_i - w_j$  (the vector  $w = (w_1, \dots, w_N)$  is the equal partition of the cake), where  $j$  is the index of  $w$  that corresponds to the maximum value of row  $i$  in the current value matrix. We can use this information to fill out an  $N \times T + 1$  policy matrix at the same time that we fill out the value matrix ( $T+1$  because we include  $t = 0$ ). The  $ij^{th}$  entry of the policy matrix tells us how much cake to eat if we start with  $w_i$  cake at time  $j$ .

**Problem 5.** Modify the solution to the previous problem to determine the policy matrix. Initialize the matrix as zeros and fill it in starting from the last column at the same time that you determining the value function matrix.

**Problem 6.** The  $ij^{th}$  entry of the policy matrix tells us how much cake to eat at time  $j$  if we start with  $i$  pieces. Use this information to find the optimal policy for starting with a cake of size 1 split into  $N$  pieces, and then plot the policy.

A summary of the arrays generated in this lab is given below, in the order that they were generated in the lab:

Consumption matrix: Equal to  $u(u_i - w_j)$ , the utility gained when you start with  $i$  pieces and end with  $j$  pieces.

Value Function matrix: How valuable is it to have  $w_i$  pieces at time  $j$ .

Current Value matrix: How valuable is each possible decision at time  $t$ .

Policy matrix: The amount of cake we decide to eat at time  $t$ .

## Lab 21

# Policy Function Iteration

**Lab Objective:** *This section teaches how to improve dynamic programming convergence using policy function iteration.*

Now that we have covered how to solve simple dynamic programming problems by value function iteration, we consider the convergence of the algorithm. We demonstrate two additional methods known as policy function iteration, or Howard's Improvement, and modified policy function iteration.

## Policy Function Iteration

For infinite horizon dynamic programming problems, it can be shown that value function iteration converges at the rate  $\beta$ , where  $\beta$  is the discount factor. In practice,  $\beta$  is usually close to one, which means this algorithm often converges slowly.

In order to examine the value function iteration algorithm, it is helpful to see which functions take the most runtime. We can perform this analysis using the profiling tools in IPython.

**Problem 1.** Import your function `eatCake` from the Value Function Iteration lab into an IPython environment. Profile this function with arguments  $\beta = .9$ ,  $N = 100$ , `finite=False`, `plot=False`. Now change the arguments  $\beta = .95$  and  $N = 1000$ . How does your runtime change? What parts of the code take up the most time?

Recall that we can access the profiling tool in IPython as follows:

```
>>> %prun function_call
```

where `function_call` is a placeholder for whatever function you wish to profile.

In Problem 1 you should have noticed that runtime was significantly longer to run for larger  $N$  or  $\beta$  closer to 1. The profiler gives more detailed information than just the overall runtime, however. The results of Problem 1 should look something

like the following (we have removed a few columns and several rows from the full output):

```
503 function calls in 2.101 seconds

Ordered by: internal time

ncalls  tottime  filename:lineno(function)
      1    1.759  <ipython-input-4-1487b3d35ebf>:1(eatCake)
      59    0.244  {method 'argmax' of 'numpy.ndarray' objects}
      1    0.033  twodim_base.py:427(triu)
      1    0.018  {numpy.core.multiarray.where}
      1    0.009  method 'repeat' of 'numpy.ndarray' objects}
      1    0.009  {method 'outer' of 'numpy.ufunc' objects}
      1    0.005  twodim_base.py:349(tri)
      1    0.004  twodim_base.py:657(mask_indices)
      1    0.004  {method 'astype' of 'numpy.ndarray' objects}
      59    0.004  {method 'reduce' of 'numpy.ufunc' objects}
```

We notice that the most time was spent in the maximization step (method `'argmax'`).

Recall that the value function iteration method for the infinite horizon problem approximates the value function  $V$  iteratively, producing a sequence of approximations  $V_1, V_2, V_3, \dots$  that converge to  $V$ . At each step, the algorithm also determines the policy function  $\psi_k$  corresponding to the approximated value function  $V_k$ . This process can also be viewed as applying the approximate policy function  $\psi_k$  once to obtain the approximate value function  $V_k$ . Unfortunately, this gives us a rather crude approximation to the value function, resulting in slow convergence.

What if instead of iteratively approximating the value function in this manner, we instead iteratively approximate the policy function, and calculate the exact value function associated with each new policy function? This is the idea behind the policy function iteration algorithm. In this way we iterate on the policy functions rather than the value functions. The algorithm for the policy function iteration can be summarized as follows:

1. Set an initial policy rule  $W' = \psi_0(W)$  and a tolerance  $\delta$ .
2. Compute the value function assuming this rule is used forever:

$$V_k(W) = \sum_{t=0}^{\infty} \beta^t u(W_t - \psi_k(W_t)).$$

3. Determine a new policy  $\psi_{k+1}$  so that

$$\psi_{k+1}(W) = \operatorname{argmax}_{W'} \{u(W - W') + \beta V_k(W')\}.$$

4. If  $\delta_k = \|\psi_{k+1} - \psi_k\| < \delta$ , stop, otherwise go back to step 2 with subscript  $k + 1$ .

In order to compute the value function,  $V_k$  corresponding to a given policy  $\psi_k$ , we must solve

$$V_k(W) = u(W - W') + \beta V_k(W') \quad (21.1)$$

for  $V_k$ .

As always, we take a discrete approximation to  $W$ , obtaining a length  $N$  vector

$$w = (w_1, w_2, \dots, w_N)$$

giving the possible cake quantities. The variable  $W'$  becomes  $w' = \psi_k(w)$ . Once we have done this, equation (21.1) is a linear system which we can rewrite as

$$V_k(w) = u(w - w') + \beta Q V_k(w)$$

where  $Q$  is the  $N \times N$  matrix

$$Q_{ij} = \begin{cases} 1 & \text{if } w'_i = w_j \\ 0 & \text{otherwise.} \end{cases}$$

Solving this system of equations, we have  $V_k(w) = (I - \beta Q)^{-1} u(w - w')$ . Although  $Q$  may be large, we can take advantage of the fact that it is sparse, containing only  $N$  nonzero entries out of  $N^2$  total entries.

**Problem 2.** Solve the infinite horizon cake eating problem from the Value Function Iteration lab again, this time using policy function iteration. Write a function `policyIter` that takes arguments  $\beta$  (discount factor),  $N$  (size of discrete approximation), and  $W_{max}$  (size of original cake, set to default value of 1). Take the function  $u$  to be the square root function, as before. Return the converged value function and policy function, both of which should be arrays of length  $N$ .

As in the value function iteration, first create your discrete approximation of the  $W$  values:

```
>>> import numpy as np
>>> w = np.linspace(0, Wmax, N)
```

You will still need to pre-compute all values of  $u(W - W')$ , storing these in an  $N \times N$  array. Make sure, as before, that the upper triangular entries are set to large negative values, so that we don't choose to consume more cake than is available. In the code snippets below, we will refer to this array as `u`.

You may also find it convenient to not track the approximated policy function  $\psi_k$  directly during the iteration, but rather to have a length  $N$  array `psi_ind`, whose  $i$ -th entry gives the index of  $w'_i$  relative to the discrete approximation  $w$ . Thus, rather than initializing a policy function  $\psi_0$  directly, you can initialize it indirectly by setting, for example,

```
>>> psi_ind = np.arange(N)
```

which corresponds to an initial policy  $\psi_0(W) = W$ . The policy function vector can be obtained from `psi_ind` by simply slicing `w` as follows:

```
>>> psi = w[psi_ind]
```

In order to take advantage of the sparse matrices  $I$  and  $Q$ , use the following imports from the SciPy `sparse` library.

```
>>> from scipy import sparse
>>> from scipy.sparse import linalg
```

and the following code to initialize  $I$  (outside the loop)

```
>>> I = sparse.identity(N, format='csr')
>>> rows = np.arange(0, N)
```

and  $Q$  (inside the loop)

```
>>> columns = psi_ind
>>> data = np.ones(N)
>>> Q = sparse.coo_matrix((data, (rows, columns)), shape=(N,N))
>>> Q = Q.tocsr()
```

Rather than compute  $(I - \beta Q)^{-1}$  directly, use SciPy's sparse solver

```
V = linalg.spsolve(I-beta*Q, u(w-w[psi_ind]))
```

where `u` is the square root function.

In each iteration, we update `psi_indices` much as we did in the value function iteration algorithm:

```
>>> psi_ind = np.argmax(U + beta*V, axis=1)
```

where we assume `v` has shape  $(1, N)$ .

Use the 2-norm when computing  $\|\psi_{k+1} - \psi_k\|$ , and set the tolerance to  $\delta = 1e - 9$ .

Take  $N = 1000$  and  $\beta = .95$ . Plot the policy function and compare with your policy function from the Value Function Iteration Lab, using the same inputs. You should obtain the same answer, but in less runtime.

## Modified Policy Function Iteration

While policy function iteration converges in fewer iterations, solving the linear system can be slow, especially for problems with a large state space. There is an alternative to this called modified policy function iteration.

In modified policy function iteration, we don't compute the exact value function corresponding to a policy. Instead, at step 2 of the policy iteration algorithm we iterate  $m$  times on the value function equation (21.1) to get an approximation of the new value function. This is faster than solving for the exact value function for large state spaces. There is no strict rule on the value of  $m$ , the number of value function iterations. In practice values such as  $m = 10$  or  $m = 15$  often work well.

Note that our methods for solving dynamic programs boil down to some combination of two things: iterating on the value function and iterating on the policy function. Modified policy function does a combination of the two, taking advan-



tage of the advantages of both methods. Because modified policy iteration takes only slightly more work to code than value function iteration, it is often preferred in practice. Whether policy or modified policy iteration will perform better may depend on the problem.

**Problem 3.** Solve the infinite horizon cake eating problem again, this time using the modified policy function iteration method.

Write a function `modPolicyIter` that takes the same arguments as your `policyIter` function, along with an additional keyword argument `m` (set to default value  $m = 15$ ), which gives the number of iterations used to approximate the value function at each step. Return the converged value function and policy function.

Much of the code in your `policyIter` will be unchanged when implementing this function. The key differences are as follows. First, you do not need to initialize the sparse arrays  $I$  and  $Q$  in the modified policy function iteration. Secondly, rather than solving a linear system of equations to obtain the value function, you will loop the equation

```
>>> V = u(w - w[psi_ind]) + beta*V[psi_ind]
```

$m$  times in each iteration. Notice how this line of code corresponds with Equation (21.1), where  $\mathbf{w}$  represents  $W$ ,  $\mathbf{w}[\text{psi\_ind}]$  represents  $W'$ , and  $\mathbf{V}[\text{psi\_ind}]$  represents  $V(W')$ .

The remainder of the code should be unchanged.

**Problem 4.** Solve the cake eating problem with each of the three methods and report how many iterations each takes. Use  $N = 1000$  as the number of grid points for  $W$  and  $\beta = 0.95$ . It is important that you use the same initial guess in each case in order to make the results comparable. The accuracy of the initial guess greatly affects the number of iterations to convergence. Take your initial guess as  $V = 0$ , which corresponds to an initial guess of the policy function with indices  $[0, 1, 2, \dots, N - 1]$  (meaning  $\psi(W) = W$ , i.e. we eat no cake, leaving it all for the next period).

In general we should see that value function iteration takes more iterations than modified policy function iteration which in turn takes more iterations than policy function iteration. It is important to note that this does not directly say anything about runtime. Each iteration of policy iteration may take longer than an iteration of value function iteration.

## Discrete Choice (Threshold) Problems

One powerful application of dynamic programming is that we can make models that have both continuous and discrete state variables. These models are sometimes referred to as discrete choice problems or optimal stopping problems. Examples include models of employment that involve both the choice of whether to work and how much to work, models of firm entry and exit that involve the choice of both whether to produce and how much to produce, and models of marriage that involve the choice of whether to date (get married or keep dating) and how much to date. This application illustrates the versatility of dynamic programming as a dynamic solution method

In this lab, we follow a simple version of a standard job search model. Assume that workers live infinitely long. We will split a worker's life into discrete time periods, and in each period the worker is either employed or unemployed, and receives a job offer. The worker must make a choice between discrete actions (such as accepting or rejecting a job offer), with the goal of maximizing some utility function (hence, this is a *discrete choice* problem).

We can state this problem in terms of dynamic programming by defining an appropriate value function. Let the value of entering a period with most recent wage  $w$ , current job offer wage  $w'$ , and employment status  $s$  be given by the following value function,

$$V(w, w', s) = \begin{cases} V^E(w) & \text{if } s = E \\ V^U(w, w') & \text{if } s = U \end{cases} \quad (21.2)$$

where employment status is a binary variable  $s \in \{E, U\}$  ( $E$  indicates “employed” and  $U$  indicates “unemployed”); a person can be either employed or unemployed.

As in the cake eating problem, the value function is calculated as the sum of some reward (based on the current state) and the discounted value of entering the next period in some particular state. The reward function, denoted (as usual) by  $u$ , gives the utility of spending available funds. Assuming that a worker receives some wage  $x$  in a given period and spends all available money in the period, the utility of consumption is given by

$$u(x).$$

Calculating the value for the next period depends on the employment status in the current period, so we address this separately for each case.

Let us first consider the case where the individual is unemployed ( $s = U$ ). As is customary, let  $s'$  denote the employment status of the worker in the next period. In this unemployed state, the worker receives unemployment benefits equal to a fraction of her most recent wage, i.e.  $\alpha w$ , where  $\alpha \in (0, 1)$ . Hence, the utility of consumption in the current unemployed state is given by

$$u(\alpha w).$$

The worker also receives one wage offer ( $w'$ ) per period, and will obtain this wage in the next period provided that she chooses to accept employment, i.e. provided  $s' = E$ . The worker must decide whether to accept the current wage offer  $w'$  or to remain unemployed in the next period, i.e. she must decide on the value of  $s'$ .

How does she make this choice? She must weigh the value of entering the next period as an employed worker with wage  $w'$  (given by  $V^E(w')$ ) versus the value of entering the next period as an unemployed worker with previous wage  $w$  and unknown wage offer  $w''$  (given by  $V^U(w, w'')$ ). Because the worker cannot know what the future wage offer  $w''$  will be, it is treated as a random variable with a particular probability distribution. Hence, the worker must actually compute the *expected* value of entering the next period unemployed. This term is simply

$$\mathbb{E}_{w''} V^U(w, w''),$$

where  $\mathbb{E}_{w''}$  denotes the expectation operator with respect to the probability distribution of future wage offers  $w''$ . To sum up, the worker chooses to accept the wage offer  $w'$  or remain unemployed in the next period based on which option gives the greater expected value, and the value of this decision is given by

$$\max\{V^E(w'), \mathbb{E}_{w''} V^U(w, w'')\}.$$

The overall value of the current unemployed state with previous wage  $w$  and current wage offer  $w'$  is just the utility of consumption plus the discounted value of the next period, i.e.

$$V^U(w, w') = u(\alpha w) + \beta \max\{V^E(w'), \mathbb{E}_{w''} V^U(w, w'')\}, \quad (21.3)$$

where  $\beta$  is the discount factor.

Now we turn to the case where the job status is employed ( $s = E$ ). In this case, the worker receives a wage  $w$  in the current period, and so the utility of consumption is just

$$u(w).$$

In the next period, the worker will have most recent wage  $w$ , she will receive wage offer  $w''$ , and will have employment status  $s'$ . As in the unemployed case,  $w''$  is unknown and treated as a random variable. Unlike the unemployed case, however, the worker's future employment status  $s'$  is not under her control, but rather is also a random variable. The reason for this is that the worker will remain employed until she loses the job, a random event that occurs with some fixed probability in each time period. Hence, we must calculate the expected value of the next period with respect to both  $w''$  and  $s'$ . We may write the entire value function for the employed case as

$$V^E(w) = u(w) + \beta \mathbb{E}_{w'', s'} V(w, w'', s'). \quad (21.4)$$

To calculate the expectation term, we need to know the joint probability distribution over  $w''$  and  $s'$ . This can be characterized in the following way. We assume that  $s'$  and  $w''$  are independent. Hence, we can split the joint expectation operator into the composition of the two individual expectation operators:

$$\mathbb{E}_{w'', s'} = \mathbb{E}_{w''} \mathbb{E}_{s'}.$$

Let  $\gamma$  represent the probability that an employed worker becomes unemployed in the next period, so that  $1 - \gamma$  is the probability of remaining employed in the next

period. If the worker stays employed in the next period ( $s' = E$ ), then next period's wage equals the current period's wage, and the term inside the expectation is

$$V(w, w'', E) = V^E(w).$$

We then have

$$\begin{aligned}\mathbb{E}_{s'} V(w, w'', s') &= (1 - \gamma)V(w, w'', E) + \gamma V(w, w'', U) \\ &= (1 - \gamma)V^E(w) + \gamma V^U(w, w'').\end{aligned}$$

Notice that the term  $(1 - \gamma)V^E(w)$  is constant with respect to  $w''$ . Then

$$\begin{aligned}\mathbb{E}_{w''} \mathbb{E}_{s'} V(w, w'', s') &= \mathbb{E}_{w''} [(1 - \gamma)V^E(w) + \gamma V^U(w, w'')] \\ &= \mathbb{E}_{w''} (1 - \gamma)V^E(w) + \mathbb{E}_{w''} \gamma V^U(w, w'') \\ &= (1 - \gamma)V^E(w) + \gamma \mathbb{E}_{w''} V^U(w, w'').\end{aligned}$$

Hence, we can rewrite (21.4) as follows:

$$V^E(w) = u(w) + \beta \left[ (1 - \gamma)V^E(w) + \gamma \mathbb{E}_{w''} V^U(w, w'') \right]. \quad (21.5)$$

We have now completely described the value function. What about the policy function? The policy function for the unemployed worker gives her decision on whether to accept the job  $s' = E$  or to reject the job  $s' = U$ . This will be a function of both the most recent wage  $w$  and the current wage offer  $w'$ . The employment status  $s'$  in the next period is determined by the policy function  $\psi$ :

$$s' = \psi(w, w').$$

These discrete choice problems are often called threshold problems because the policy choice depends on whether the state variable is greater than or less than some threshold level. That is, an unemployed worker will accept a job if and only if the offer wage is above some set amount that depends on the most recent wage  $w$ . In the labor search model, the threshold level is called the “reservation wage”  $w'_R$ . The reservation wage  $w'_R$  is defined as the wage offer such that the worker is indifferent between accepting the job  $s' = E$  and staying unemployed  $s' = U$ . Hence, this reservation wage satisfies the equation

$$V^E(w'_R) = \mathbb{E}_{w''} [V^U(w, w'')]. \quad (21.6)$$

The policy function will then take the form of accepting the job if  $w' \geq w'_R$  or rejecting the job offer and remaining unemployed if  $w' < w'_R$ :

$$s' = \psi(w, w') = \begin{cases} E & \text{if } w' \geq w'_R \\ U & \text{if } w' < w'_R. \end{cases} \quad (21.7)$$

Figure 21.1 shows an example of the discrete policy function.

In summary, the labor search discrete choice problem is characterized by the value functions (21.2), (21.3), and (21.5), the reservation wage (21.6), and the policy function (21.7). Because wage offers are distributed according to some given

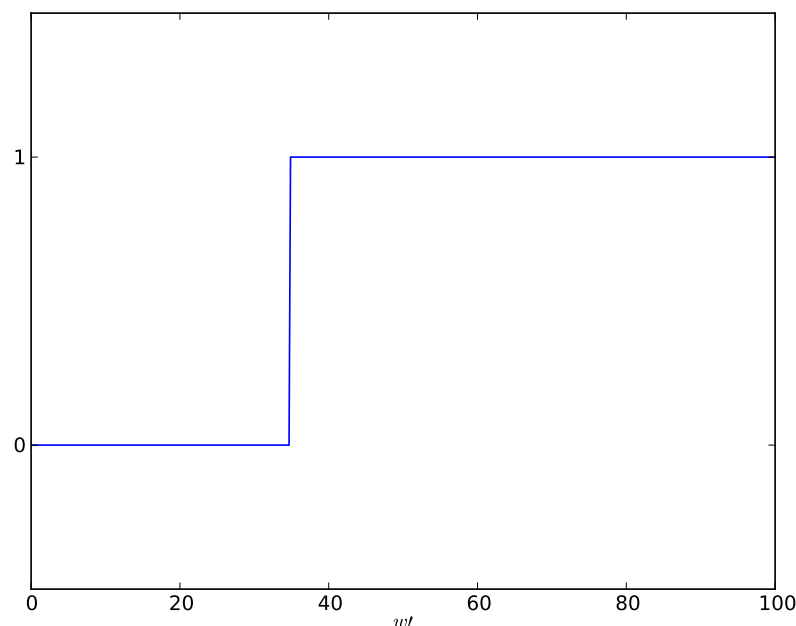


Figure 21.1: Here is the policy function for fixed  $w = 50$ . Numerically we let 0 represent unemployment,  $U$ , and 1 represent employment,  $E$ . Thus we see that an individual will choose to take a new job, given their old wage was 50, at a wage of roughly 35. Thus for a previous wage of 50, we say the reservation wage is 35.

probability distribution (denote the cdf by  $F(w')$ ), and because the policy function takes the form of (21.7), the probability that the unemployed worker receives a wage offer that she will reject is  $F(w'_R)$  and the probability that she receives a wage offer that she will accept is  $1 - F(w'_R)$ . Just like the continuous-choice cake eating problems, this problem can be solved by value function, policy function, or modified policy function iteration.

The value function iteration solution method for the equilibrium in the labor search problem is analogous to the value function iteration from the previous labs. The only difference is that two value functions ( $V^E$  and  $V^U$ ) must converge to a fixed point in this problem instead of just one value function converging in the previous problems. Although there are two value functions to consider, there is only one policy function, since decisions are only made in the unemployed state. Thus, there is only one policy function on which to iterate in the case of policy or modified policy iteration.

In the following problems, you will solve the job search problem using value function iteration and modified policy function iteration. Assume that the consumption utility function  $u$  is given by

$$u(w) = \sqrt{w}.$$

Assume that the probability of becoming unemployed in a given period is  $\gamma = 0.10$ ,

the fraction of wages paid in unemployment benefits is  $\alpha = 0.5$ , and the discount factor is  $\beta = 0.9$ .

Assume that the log of wage offers are distributed normally. We then say that offers are distributed lognormally and write

$$w' \sim \text{LogN}(\mu, \sigma).$$

This is a convenient choice for the distribution of wage offers. Among other things, it guarantees that wage offers will be positive. A mean of 20 and variance of 200 are typical parameters of such a wage distribution, and we will use these parameters in the following problems.

As usual when dealing with continuous variables, we form a discrete approximation of the possible wage values. In particular, approximate the wage values by a vector of length  $N = 500$  of equally-spaced values from  $w_{min} = 0$  to  $w_{max} = 100$ , inclusive. We then form a corresponding discrete approximation of the probability density function  $f(w')$  for the lognormal wage offers using code provided in the file `discretelognorm.py`, as follows, where `w` is the length- $N$  vector of wage values,  $m$  is the mean, and  $v$  is the variance as specified above:

```
>>> from discretelognorm import discretelognorm
>>> f = discretelognorm(w, m, v)
```

The function `discretelognorm` computes the discrete pdf of the specified lognormal distribution in much the same way that you calculate the discrete normal pdf when solving the stochastic cake eating problem.

**Problem 5.** Solve the job search problem using value function iteration. Return the converged value functions  $V^E$  and  $V^U$ , as well as the converged policy function  $\psi$ . The following steps provide detailed instructions. Note that there are multiple ways to proceed, and the following is simply one (fairly good) possibility.

1. As described above, represent the possible wage values by an array `w` of length  $N$ . Denote this array entrywise by

$$w = (w_1, w_2, \dots, w_N).$$

Calculate the corresponding discrete lognormal pdf `f`, exactly as shown above.

2. Note that  $u(w)$  and  $u(\alpha w)$  are needed when computing the value functions. Since these quantities do not change from one iteration to another, it is smart to compute them once at the outset. Denote  $u(w)$  by `uw` and  $u(\alpha w)$  by `uaw`. These are easily calculated as follows:

```
>>> uw = u(w)
>>> uaw = u(alpha*w).reshape((N,1))
```

where  $u$  is the square root function. We must reshape `uaw` because of array broadcasting issues that arise in the code snippets below.

3. Since  $V^E$  is a function of only  $w$ , it will be represented by a vector of length  $N$ , where the  $i$ -th entry gives  $V^E(w_i)$ . The unemployed value function  $V^U$ , however, is a function of both  $w$  and  $w'$ , so it will be represented by an  $N \times N$  array, where the  $(i, j)$ -th entry gives  $V^U(w_i, w_j)$ . Initialize the entries of these arrays to 0:

```
>>> VE = np.zeros(N)           #employed value function
>>> VU = np.zeros((N,N))      #unemployed value function
```

4. Note that  $\mathbb{E}_{w''} V^U(w, w'')$  is needed to calculate both  $V^E$  and  $V^U$ . This expectation depends on  $w$ , and so can be represented by a length  $N$  array, where the  $i$ -th entry is  $\mathbb{E}_{w''} V^U(w_i, w'')$ . It is convenient to assign a variable to this array to keep track of it throughout the iterations. We denote the expectation by `EVU`, and initialize it to zeros:

```
>>> EVU = np.zeros(N)
```

5. For reasons that will soon become apparent, we will need to create an  $N \times N$  helper array whose rows are equal to `VE` (call this array `MVE`), and a  $N \times N$  helper array whose columns are equal to `EVU` (call this array `MEVU`). At the outset, simply initialize these arrays to zeros.
6. Because job status is a binary variable, the policy function returns one of two possible values. It is convenient to represent “employed” by 1 and “unemployed” by 0. Now the policy function depends on  $w$  and  $w'$ , so it will also be represented by an  $N \times N$  array `PSI` of zeros and ones, where the  $(i, j)$ -th entry gives  $\psi(w_i, w_j)$ .
7. Now we are ready to begin the iteration. A single iteration involves computing the updated value functions  $V^E$  and  $V^U$  from equations (21.5) and (21.3) and then calculating the 2-norm distance between both pairs of old and updated value functions to test for convergence. If both of these 2-norm distances are less than  $10^{-9}$ , terminate the iteration.

Before calculating the updated value functions, we first update our helper arrays `MVE` and `MEVU`. The rows of `MVE` need to equal `VE`. We can use array broadcasting:

```
>>> MVE[:, :] = VE.reshape((1,N))
```

The columns of `MEVU` need to equal `EVU`, so use a similar technique:

```
>>> MEVU[:, :] = EVU.reshape((N,1))
```

Now let us address how to compute the updated  $V^U$ , which we denote by `VU1`. Equation (21.3) shows that it is the sum of two terms. The first,  $u(\alpha w)$ , we have already computed and stored in the variable `uaw`. The second term involves a maximization between two alternatives. One can imagine writing a double for loop ranging over the values of  $w'$  and  $w$  to compute each individual  $\max\{V^E(w'), \mathbb{E}_{w''} V^U(w, w'')\}$ , but we can take advantage of the helper arrays `MVE` and `MEVU` to do this computation in one efficient line of code. Note that the  $(i, j)$ -th entry of `MVE` is just  $V^E(w_j)$  and the  $(i, j)$ -th entry of `MEVU` is  $\mathbb{E}_{w''}(w_i, w'')$ , and

$$V^U(w_i, w_j) = u(\alpha w_i) + \beta \max\{V^E(w_j), \mathbb{E}_{w''} V^U(w_i, w'')\}.$$

Hence, taking the entrywise maximum of the arrays `MVE` and `MEVU` gives us the appropriate max term for  $V^U$ . To get the entrywise maximum of two arrays, stack the arrays along a new axis using `np.dstack`, and maximize along that axis. The computation for `VU`, then, is

```
>>> VU1 = uaw + beta*np.max(np.dstack([MEVU, MVE]), axis=2)
```

Calculating the updated  $V^E$ , denoted by `VE1`, is more straightforward. Equation (21.5) shows that it is just a particular linear combination of the arrays `uw`, `VE`, and `EVU`:

```
>>> VE1 = uw + beta*((1-gamma)*VE + gamma*EVU)
```

We can now calculate the 2-norm distances between old and updated value functions. It remains to update `VE`, `VU`, and `EVU`. The first two updates are trivial, and calculating `EVU` is equivalent to the matrix-vector multiplication of `VU` with `f`. This is similar to how we computed expectations in previous labs:

```
>>> EVU = np.dot(VU,f).ravel()
```

We use the `ravel` function to ensure that `EVU` is a flat array.

8. Notice that it is not necessary to iteratively update the policy function, as it is not needed to update the value functions. Thus, we need only compute the policy function once, after convergence of the value functions has been achieved. This is done in a manner similar to calculating  $\max\{V^E(w'), \mathbb{E}_{w''} V^U(w, w'')\}$  as described above, except we need to take the *argmax*:

```
>>> PSI = np.argmax(np.dstack([MEVU, MVE]), axis=2)
```

9. Compute the reservation wage  $w'_R$  as a function of the current wage  $w$ . It will be represented by a length  $N$  array called `wr`. The reservation wage is the value of  $w'$  where the policy function changes from zeros



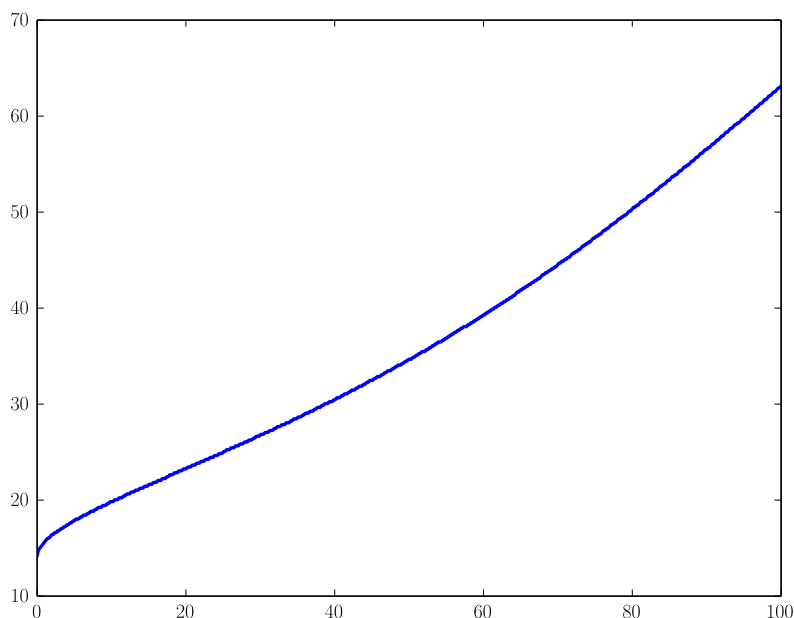


Figure 21.2: The reservation wage as a function of previous wage for the job search problem.

to ones (the optimal choice changes from remaining unemployed to accepting the job offer). We can calculate this as follows:

```
>>> wr_ind = np.argmax(np.diff(Psi), axis = 1)
>>> wr = w[wr_ind]
```

10. Plot the equilibrium reservation wage  $w'_R$  of the converged problem as a function of the current wage  $w$  with the current wage on the  $x$ -axis and the reservation wage  $w'_R$  on the  $y$ -axis. This is the most common way to plot discrete choice policy functions. The reservation wage represents the wage that makes the unemployed worker indifferent between taking a job offer and rejecting it. So any wage above the reservation wage line represents  $s' = E$  and any wage below the reservation wage line represents  $s' = U$ . Your plot should resemble that in Figure 21.2.

In the previous problem, it was necessary to iterate on two value functions. Consequently the convergence is relatively slow. We can improve upon this situation by using modified policy function iteration.

**Problem 6.** Solve the same problem, this time using modified policy function iteration with 15 value function iterations within each policy iteration. You should be able to re-use much of your code from the previous problem.

Start off by initializing all of the same variables. Additionally, initialize your policy function array `PSI`, say

```
>>> PSI = 2*np.ones((N,N))
```

Next comes the iteration. Essentially, the iteration will consist of an outer while-loop (which terminates once the 2-norm distance between successive policy functions passes below  $10^{-9}$ ), and an inner for loop (with 15 loops).

The first step in the while-loop is to calculate the new policy function `PSI1`, just as in the previous problem. Next, perform the inner for-loop, which consists simply of the value function iteration, but this time using the current policy function. This means the line of code

```
>>> VU = uaw + beta*np.max(np.dstack([MEVU, MVE]), axis=2)
```

is no longer valid, as it does not use the policy function. We must instead have

```
>>> VU = uaw + beta*(MVE*PSI1 + MEVU*(1 - PSI1))
```

Why is this code correct?

Finally, after exiting the for loop, calculate the 2-norm distance between the old and the new policy function, and then update your old policy function, i.e.

```
>>> PSI = PSI1
```

After convergence is achieved, once again compute the reservation wage array, and plot it as in the previous problem. Then return the converged policy function.

**Problem 7.** How many iterations did the value function iteration method take? How many iterations did the modified policy function iteration method take? Which was faster?

## **Part II**

# **Appendices**



## Appendix A

# NumPy Visual Guide

### Lab Objective

*are straightforward  
arrays are used  
tions. Though  
can be extended*

## Data Access

The entries of a  
single entry, ent  
indexing begins

$$A[0] = \begin{bmatrix} \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times \end{bmatrix} \quad A[2,1] = \begin{bmatrix} \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times \end{bmatrix}$$

## Slicing

A lone colon extracts  
can be read as “the  
[a:] means “the  $a^{th}$  e  
including) the  $b^{th}$  ent

$$A[1] = A[1,:] = \begin{bmatrix} \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times \end{bmatrix} \quad A[:,2] = \begin{bmatrix} \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times \end{bmatrix}$$

$$A[1:, :2] = \begin{bmatrix} \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times \end{bmatrix} \quad A[1:-1, 1:-1] = \begin{bmatrix} \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times \end{bmatrix}$$

## Stacking

`np.hstack()` stacks sequence of arrays horizontally and `np.vstack()` stacks a sequence of arrays vertically.

$$A = \begin{bmatrix} \times & \times & \times \\ \times & \times & \times \\ \times & \times & \times \end{bmatrix} \quad B = \begin{bmatrix} * & * & * \\ * & * & * \\ * & * & * \end{bmatrix}$$

$$\text{np.hstack}((A, B, A)) = \begin{bmatrix} \times & \times & \times & * & * & * & \times & \times & \times \\ \times & \times & \times & * & * & * & \times & \times & \times \\ \times & \times & \times & * & * & * & \times & \times & \times \end{bmatrix}$$

$$\text{np.vstack}((A, B, A)) = \begin{bmatrix} \times & \times & \times \\ \times & \times & \times \\ \times & \times & \times \\ * & * & * \\ * & * & * \\ * & * & * \\ \times & \times & \times \\ \times & \times & \times \\ \times & \times & \times \end{bmatrix}$$

Because 1-D arrays are flat, `np.hstack()` concatenates 1-D arrays and `np.vstack()` stacks them vertically. To make several 1-D arrays into the columns of a 2-D array, use `np.column_stack()`.

$$x = [\times \quad \times \quad \times \quad \times] \quad y = [* \quad * \quad * \quad *]$$

$$\text{np.hstack}((x, y, x)) = [\times \quad \times \quad \times \quad \times \quad * \quad * \quad * \quad * \quad \times \quad \times \quad \times \quad \times]$$

$$\text{np.vstack}((x, y, x)) = \begin{bmatrix} \times & \times & \times & \times \\ * & * & * & * \\ \times & \times & \times & \times \end{bmatrix} \quad \text{np.column_stack}((x, y, x)) = \begin{bmatrix} \times & * & \times \\ \times & * & \times \\ \times & * & \times \\ \times & * & \times \end{bmatrix}$$

## Broadcasting

NumPy automatically aligns arrays for component-wise operations whenever possible. See <http://docs.scipy.org/doc/numpy/user/basics.broadcasting.html> for more in-depth examples and broadcasting rules.

$$A = \begin{bmatrix} 1 & 2 & 3 \\ 1 & 2 & 3 \\ 1 & 2 & 3 \end{bmatrix} \quad x = [10 \quad 20 \quad 30]$$

$$A + x = \begin{bmatrix} 1 & 2 & 3 \\ 1 & 2 & 3 \\ 1 & 2 & 3 \end{bmatrix} + \begin{bmatrix} 10 & 20 & 30 \end{bmatrix} = \begin{bmatrix} 11 & 22 & 33 \\ 11 & 22 & 33 \\ 11 & 22 & 33 \end{bmatrix}$$

$$A + \text{np.vstack}(x) = \begin{bmatrix} 1 & 2 & 3 \\ 1 & 2 & 3 \\ 1 & \end{bmatrix} + \begin{bmatrix} 10 \\ 20 \end{bmatrix} = \begin{bmatrix} 11 & 12 & 13 \\ 21 & 22 & 23 \end{bmatrix}$$

## Operations along an Axis

Most array methods have an `axis` parameter to specify the axis along which to operate. To compute the sum of each row, use `axis=1`.

$$A.\text{sum}(\text{axis}=0) = \begin{bmatrix} 1 & 2 & 3 & 4 \\ 1 & 2 & 3 & 4 \\ 1 & 2 & 3 & 4 \\ 1 & 2 & 3 & 4 \end{bmatrix} = [4 \quad 8 \quad 12 \quad 16]$$

$$A.\text{sum}(\text{axis}=1) = \begin{bmatrix} 1 & 2 & 3 & 4 \\ 1 & 2 & 3 & 4 \\ 1 & 2 & 3 & 4 \\ 1 & 2 & 3 & 4 \end{bmatrix} = [10 \quad 10 \quad 10 \quad 10]$$





## Appendix B

# Plot Customization and Matplotlib Syntax Guide

**Lab Objective:** *The documentation for Matplotlib can be a little difficult to maneuver and basic information is sometimes difficult to find. This appendix condenses and demonstrates some of the more applicable and useful information on plot customizations. For an introduction to Matplotlib, see lab ??.*

## Colors

By default, every plot is assigned a different color specified by the “color cycle”. It can be overwritten by specifying what color is desired in a few different ways.

- 

Matplotlib recognizes some basic built-in colors.

Code	Color
'b'	blue
'g'	green
'r'	red
'c'	cyan
'm'	magenta
'y'	yellow
'k'	black
'w'	white

The following displays how these colors can be implemented. The result is displayed in Figure B.1.

```
1 import numpy as np
2 from matplotlib import pyplot as plt

4 colors = np.array(["k", "g", "b", "r", "c", "m", "y", "w"])
  x = np.linspace(0, 5, 1000)
6  y = np.ones(1000)
```

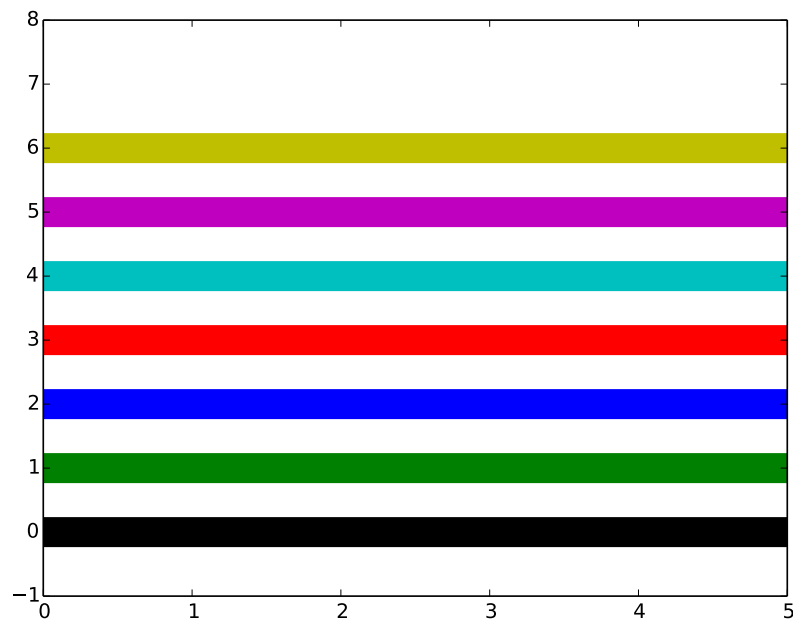


Figure B.1: A display of all the built-in colors.

```
8 for i in xrange(8):  
    plt.plot(x, i*y, colors[i], linewidth=18)  
10  
plt.ylim([-1, 8])  
12 plt.savefig("colors.pdf", format='pdf')  
plt.clf()
```

colors.py

There are many other ways to specific colors. A popular method to access colors that are not built-in is to use a `RGB` tuple. Colors can also be specified using an html hex string or its associated html color name like `"DarkOliveGreen"`, `"FireBrick"`, `"LemonChiffon"`, `"MidnightBlue"`, `"PapayaWhip"`, or `"SeaGreen"`.

## Window Limits

You may have noticed the use of `plt.ylim([ymin, ymax])` in the previous code. This explicitly sets the boundary of the y-axis. Similarly, `plt.xlim([xmin, xmax])` can be used to set the boundary of the x-axis. Doing both commands simultaneously is possible with the `plt.axis([xmin, xmax, ymin, ymax])`. Remember that these commands must be executed after the plot.

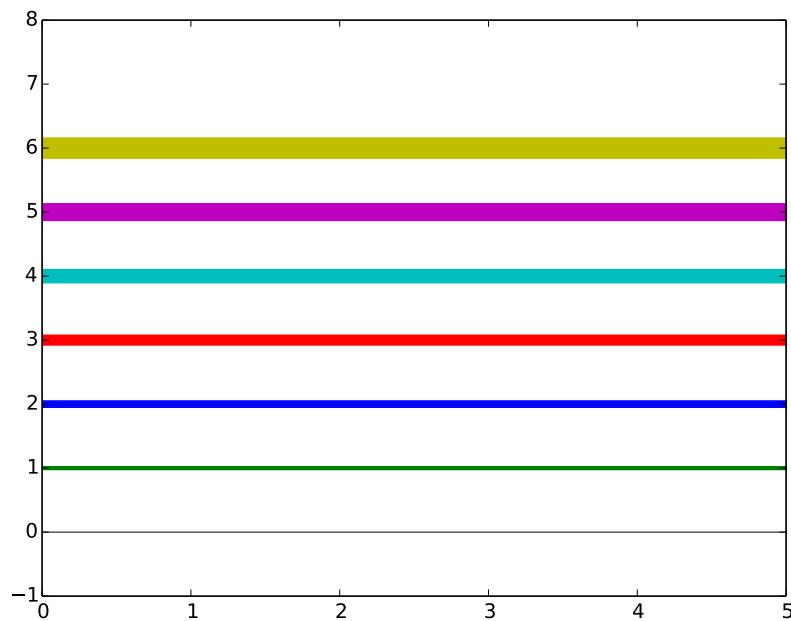


Figure B.2: plot of varying linewidths.

## Lines

### Thickness

You may have noticed that the width of the lines above seemed thin considering we wanted to inspect the line color. `linewidth` is a keyword argument that is defaulted to be `None` but can be given any real number to adjust the line width.

The following displays how `linewidth` is implemented. It is displayed in Figure B.2.

```
1 lw = np.linspace(.5, 15, 8)
2
3 for i in xrange(8):
4     plt.plot(x, i*y, colors[i], linewidth=lw[i])
5
6 plt.ylim([-1, 8])
7 plt.show()
```

linewidth.py

### Style

By default, plots are drawn with a solid line. The following are accepted format string characters to indicate line style.

character	description
-	solid line style
--	dashed line style
-.	dash-dot line style
:	dotted line style
.	point marker
,	pixel marker
o	circle marker
v	triangle_down marker
^	triangle_up marker
<	triangle_left marker
>	triangle_right marker
1	tri_down marker
2	tri_up marker
3	tri_left marker
4	tri_right marker
s	square marker
p	pentagon marker
*	star marker
h	hexagon1 marker
H	hexagon2 marker
+	plus marker
x	x marker
D	diamond marker
d	thin_diamond marker
	vline marker
-	hline marker

The following displays how `linestyle` can be implemented. It is displayed in Figure B.3.

```

1 x = np.linspace(0, 5, 10)
2 y = np.ones(10)
  ls = np.array(['-.', ':', 'o', 's', '*', 'H', 'x', 'D'])
4
  for i in xrange(8):
6     plt.plot(x, i*y, colors[i]+ls[i])
8
plt.axis([-1, 6, -1, 8])
plt.show()
```

linestyle.py

## Text

It is also possible to add text to your plots. To label your axes, the `plt.xlabel()` and the `plt.ylabel()` can both be used. The function `plt.title()` will add a title to a plot. If you are working with subplots, this command will add a title to the subplot you are currently modifying. To add a title above the entire figure, use `plt.suptitle()`.

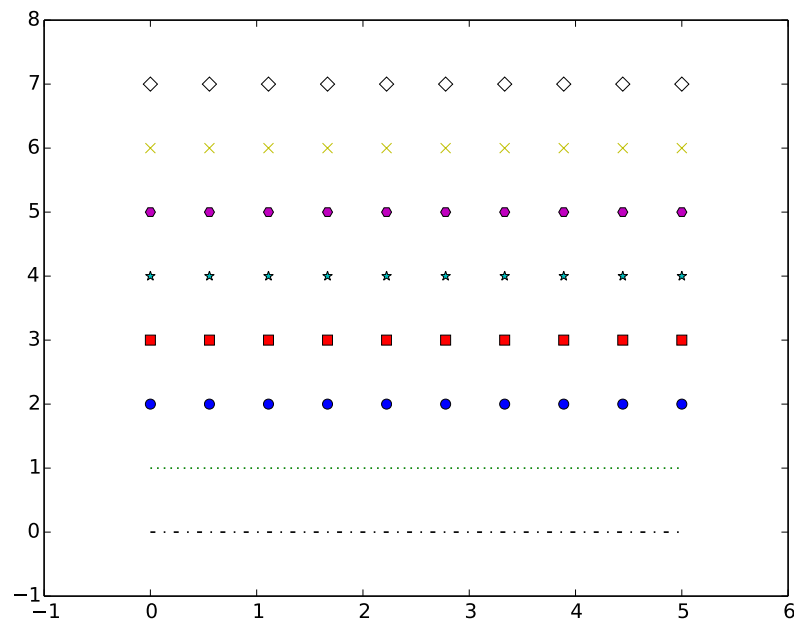


Figure B.3: plot of varying linestyles.

All of the `text()` commands can be customized with `fontsize` and `color` keyword arguments.

We can add these elements to our previous example. It is displayed in Figure B.4.

```

1 for i in xrange(8):
2     plt.plot(x, i*y, colors[i]+ls[i])

4 plt.title("My Plot of Varying Linestyles", fontsize = 20, color = "gold")
5 plt.xlabel("x-axis", fontsize = 10, color = "darkcyan")
6 plt.ylabel("y-axis", fontsize = 10, color = "darkcyan")

8 plt.axis([-1, 6, -1, 8])
9 plt.show()

```

text.py

See <http://matplotlib.org> for Matplotlib documentation.

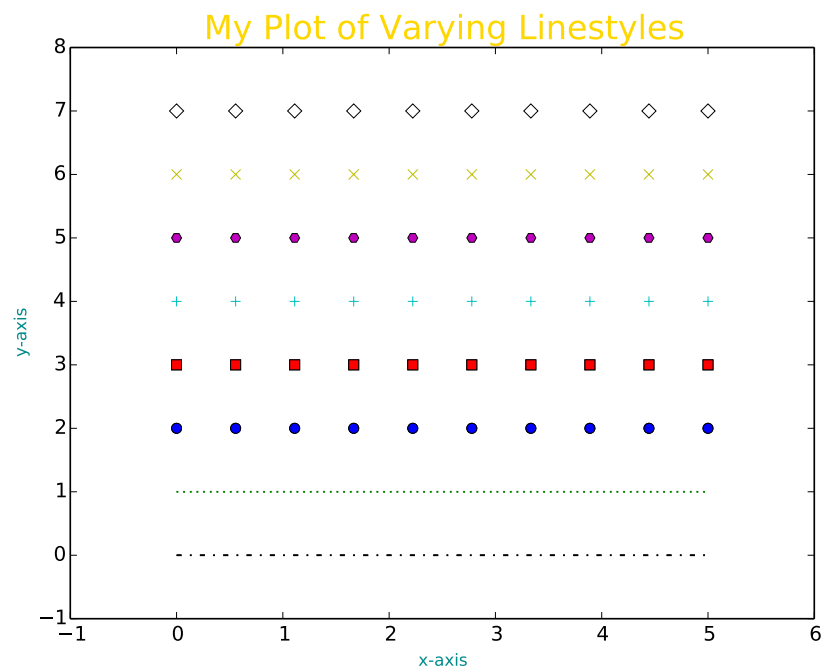


Figure B.4: plot of varying linestyles using text labels.