

**Final Report Assignment 8**

**Question 1:**

In order to create a blog-term matrix, I first needed to create a python script to extract 98 unique links since 2 links were already provided for us. So, I created the python script A8Q1.py which constantly get a new blog url and outputs the blog name to Blogs.txt in Figure 1. Then, I store the html in a variable and find the RSS link in the html and output that RSS link into the file RSS.txt in Figure 2. The process is shown in Figure 3 of the extraction of the urls to get the RSS url.

```
http://pithytithere.blogspot.com/  
http://ihatethe90s.blogspot.com/  
http://mondaywakeup.blogspot.com/  
http://karldrinkwater.blogspot.com/
```

Figure 1

```
http://pithytithere.blogspot.com/feeds/posts/default?alt=rss  
http://ihatethe90s.blogspot.com/feeds/posts/default?alt=rss  
http://mondaywakeup.blogspot.com/feeds/posts/default?alt=rss  
http://karldrinkwater.blogspot.com/feeds/posts/default?alt=rss  
http://markeortega.blogspot.com/feeds/posts/default?alt=rss  
http://ps-music.blogspot.com/feeds/posts/default?alt=rss
```

Figure 2

```
count = 1  
link = r"http://www.blogger.com/next-blog?navBar=true&blogID=3471633091411211117"  
while count < 100:  
    print(count)  
    response = urllib.request.urlopen(link)  
    print(response.geturl())  
    soup = BeautifulSoup(response, 'html.parser')  
    #print(tag)  
    filename1 = r"C:\Users\Ryan\Documents\WebScience\Assignment8\Blogs.txt"  
    outfile = open(filename1, 'a')  
    temp = response.geturl()  
    temp1 = temp[0:len(temp)-17]  
    outfile.write(str(temp1))  
    outfile.write("\n")  
    outfile.close()  
  
    for tag in soup.findAll('link'):  
        filename2 = r"C:\Users\Ryan\Documents\WebScience\Assignment8\Response.txt"  
        outfile = open(filename2, 'w')  
        outfile.write(str(tag.encode('utf-8')))  
        outfile.write("\n")  
        outfile.close()  
  
    for line in open(filename2):
```

```

        if "application/rss+xml" in line:
            filename3 =
r"C:\Users\Ryan\Documents\WebScience\Assignment8\RSS.txt"
            outfile = open(filename3, 'a')
            outfile.write(str(temp1)+"feeds/posts/default?alt=rss")
            outfile.write("\n")
            outfile.close()

count+= 1

```

Figure 3

Next, since we were able to get the RSS urls, we have the information to make the blog-term matrix which is written in the python script A8Q1.1.py. To simplify this process, the Programming Collective Intelligence had several functions that I used and updated to python 3.3 to accomplish the task. The first two function I used was `getwordcounts()` and `getwords`, which passes this summary to `getwords`, which strips out all of the HTML and splits the words by nonalphabetical characters, returning them as a list as shown Figure 4.

```

# Returns title and dictionary of word counts for an RSS feed
def getwordcounts(url):
    # Parse the feed
    d=feedparser.parse(url)
    wc={}

    # Loop over all the entries
    for e in d.entries:
        if 'summary' in e: summary=e.summary
        else: summary=e.description

    # Extract a list of words
    words=getwords(e.title+' '+summary)
    for word in words:
        wc.setdefault(word,0)
        wc[word]+=1
    return d.feed.title,wc

def getwords(html):
    # Remove all the HTML tags
    txt=re.compile(r'<[^>]+>').sub("",html)

    # Split words by all non-alpha characters
    words=re.compile(r'[^A-Za-z]+').split(txt)

    # Convert to lowercase
    return [word.lower() for word in words if word!=""]

```

Figure 4

The code that loops over every line RSS.txt and generates the word counts for each blog, as well as the number of blogs each word appeared in (apcount) as shown in Figure 5. After, we need to generate the list of words that will actually be used in the counts for each blog which is limited to 500 words for the assignment. We did not want every word so we limited the range to get rid of the common words as well as the rare words which describes the range of 10 percent to 50 percent which is shown in the process of Figure 6.

```
for feedurl in feedlist:
    try:
        title,wc=getwordcounts(feedurl)
        wordcounts[title]=wc
        for word,count in wc.items():
            apcount.setdefault(word,0)
            if count>1:
                apcount[word]+=1
    except:
        print('Failed to parse feed %s' % feedurl)
```

Figure 5

```
#get 500 words in the range
for w,bc in apcount.items():
    frac=float(bc)/len(feedlist)
    if len(wordlist) <= 500:
        if frac>0.1 and frac<0.5:
            wordlist.append(w)
print(len(wordlist))
```

Figure 6

The final step was to output the blog-term matrix to a file which I named blogdata.txt. I would output the words used from each blog as the top row and the first column represents the blog title. The file creation was successful, however, there were some abnormalities in the printing of the blog names where the encoding would not transition for some of the titles which was peculiar as I could not find a solution for that, and the tabs are not perfectly lined up with the numbers and the words that they were correlated since length was an issue and messes up the tabs.

## Question 2:

In order to accomplish the task of creating a dendrogram in ASCII and JPEG format from the blog-term matrix, I created the python script of A8Q2.py. In that script, I use again the functions described in Programming Collective Intelligence to help me create these dendograms. The first function I used was readfile which basically stores the words from top row, stores the blog names from the first column, and the data from blogdata.txt as shown in Figure 7.

```
def readfile(filename):
    #lines=[line for line in file(filename)]
    lines=[]
    for line in open(filename):
```

```

lines.append(line)

# First line is the column titles
colnames=lines[0].strip().split('\t')[1:]
rownames=[]
data=[]
for line in lines[1:]:
    p=line.strip().split('\t')
    # First column in each row is the rowname
    rownames.append(p[0])
    # The data for this row is the remainder of the row
    data.append([float(x) for x in p[1:]])
return rownames,colnames,data

```

Figure 7

Since, we were able to read the blog-term matrix and store the values into variables in the python script, we then created the functions pearson and hcluster to help create these hierarchical relationships. Pearson works by comparing relationships between blogs based of the number of words as shown in Figure 8, since some blogs contain more words than others. Hcluster, as shown in Figure 9, works by creating a group of clusters that are just the original items. The main loop searches for the best correlation between a pair which is then merged into a single cluster. The new cluster is the average of the pair of data. This process is repeated until only one cluster remains.

```

def pearson(v1,v2):
    # Simple sums
    sum1=sum(v1)
    sum2=sum(v2)

    # Sums of the squares
    sum1Sq=sum([pow(v,2) for v in v1])
    sum2Sq=sum([pow(v,2) for v in v2])

    # Sum of the products
    pSum=sum([v1[i]*v2[i] for i in range(len(v1))])

    # Calculate r (Pearson score)
    num=pSum-(sum1*sum2/len(v1))
    den=sqrt((sum1Sq-pow(sum1,2)/len(v1))*(sum2Sq-pow(sum2,2)/len(v1)))
    if den==0: return 0

    return 1.0-num/den

```

Figure 8

```

def hcluster(rows,distance=pearson):
    distances={}
    currentclustid=-1

    # Clusters are initially just the rows

```

```

clust=[bicluster(rows[i],id=i) for i in range(len(rows))]

while len(clust)>1:
    lowestpair=(0,1)
    closest=distance(clust[0].vec,clust[1].vec)

    # loop through every pair looking for the smallest distance
    for i in range(len(clust)):
        for j in range(i+1,len(clust)):
            # distances is the cache of distance calculations
            if (clust[i].id,clust[j].id) not in distances:
                distances[(clust[i].id,clust[j].id)]=distance(clust[i].vec,clust[j].vec)

            d=distances[(clust[i].id,clust[j].id)]

            if d<closest:
                closest=d
                lowestpair=(i,j)

    # calculate the average of the two clusters
    mergevec=[
        (clust[lowestpair[0]].vec[i]+clust[lowestpair[1]].vec[i])/2.0
        for i in range(len(clust[0].vec))]

    # create the new cluster
    newcluster=bicluster(mergevec,left=clust[lowestpair[0]],
                        right=clust[lowestpair[1]],
                        distance=closest,id=currentclustid)

    # cluster ids that weren't in the original set are negative
    currentclustid-=1
    del clust[lowestpair[1]]
    del clust[lowestpair[0]]
    clust.append(newcluster)

return clust[0]

```

Figure 9

Lastly, we needed a way to output to dendrogram in ASCII and JPEG format. I created the two functions of `printclust`, Figure 10, for ASCII and `drawdendrogram`, Figure 11, for JPEG. `Printclust` traverses the cluster recursively and prints the tree to a txt file. `Drawdendrogram` function also works along the same lines but in a fancier way to make the dendrogram more appealing by drawing nodes with height, width, and depths. Figure 12 shows the result of the `drawdendrogram`.

```
def printclust(clust,labels=None,n=0):
```

```

    filename2 = r"C:\Users\Ryan\Documents\WebScience\Assignment8\blogAsciiDendogram.txt"
    out=open(filename2,'a')

```

```

# indent to make a hierarchy layout
for i in range(n):
    print(' '),
    out.write(' '),
    if clust.id<0:
        # negative id means that this is branch
        print('-')
        out.write('-\t')
    else:
        # positive id means that this is an endpoint
        if labels==None:
            print(clust.id)
            out.write(clust.id)
        else:
            print(labels[clust.id])
            out.write(labels[clust.id])
    out.write('\n')
# now print the right and left branches
if clust.left!=None:
    printclust(clust.left,labels=labels,n=n+1)
if clust.right!=None:
    printclust(clust.right,labels=labels,n=n+1)

out.close()

```

Figure 10

```

def drawdendrogram(clust,labels,jpeg='clusters.jpg'):
    # height and width
    h=getheight(clust)*20
    w=1200
    depth=getdepth(clust)

    # width is fixed, so scale distances accordingly
    scaling=float(w-150)/depth

    # Create a new image with a white background
    img=Image.new('RGB',(w,h),(255,255,255))
    draw=ImageDraw.Draw(img)

    draw.line((0,h/2,10,h/2),fill=(255,0,0))

    # Draw the first node
    drawnode(draw,clust,10,(h/2),scaling,labels)
    img.save(jpeg,'JPEG')

```

Figure 11

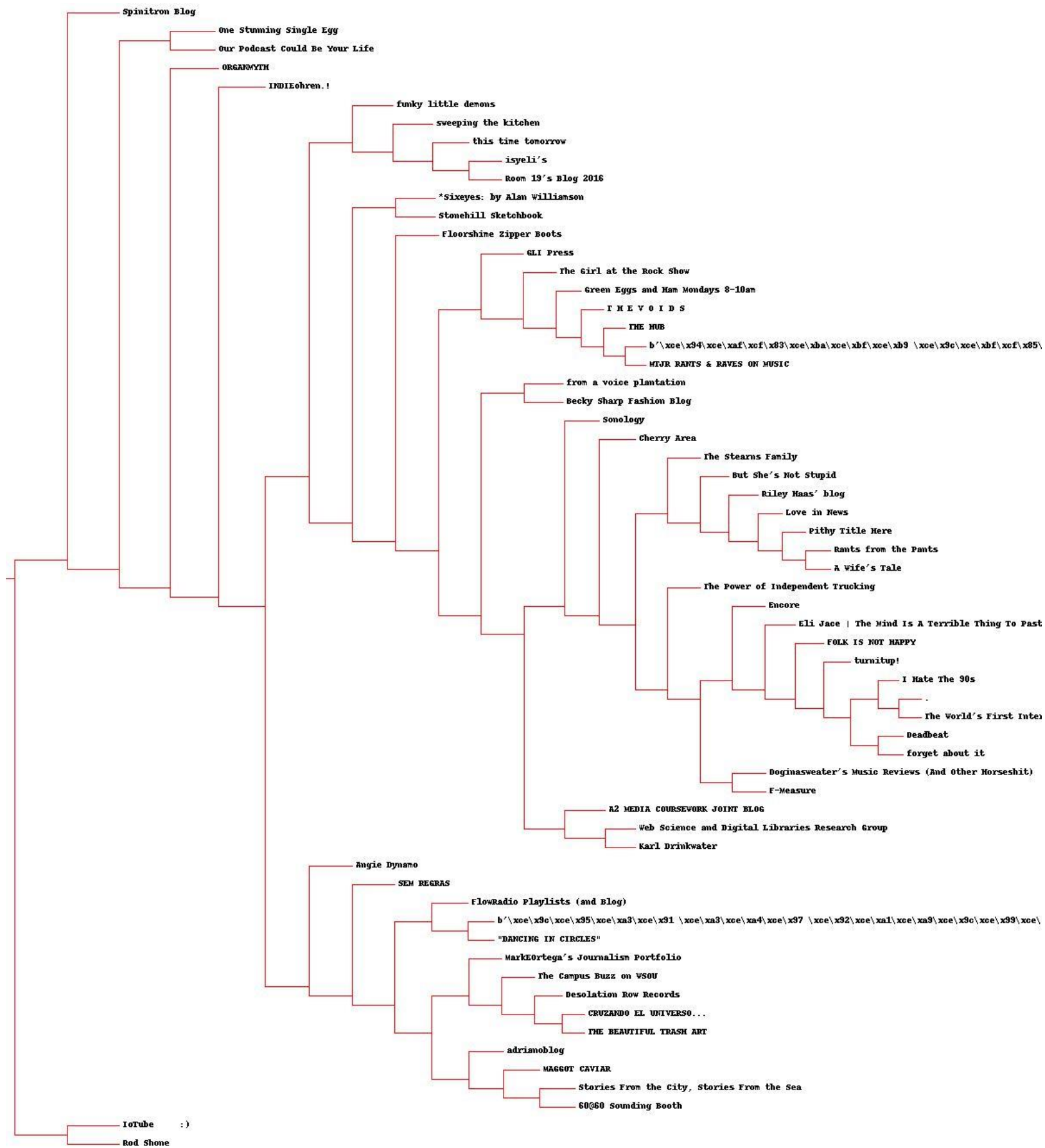


Figure 12

### Question 3:

In order to accomplish the task of clustering the blogs using K-means, I created the file of A8Q3.py. I used the PCI function of kcluster(). This function takes the same data rows as input as does the hierarchical clustering algorithm, along with the number of clusters (k) that the caller would like returned as shown in Figure 13.

```
def kcluster(rows,distance=pearson,k=4):
    # Determine the minimum and maximum values for each point
    ranges=[(min([row[i] for row in rows]),max([row[i] for row in rows]))
    for i in range(len(rows[0]))]

    # Create k randomly placed centroids
    clusters=[[random.random()*(ranges[i][1]-ranges[i][0])+ranges[i][0]
    for i in range(len(rows[0]))] for j in range(k)]

    lastmatches=None
    for t in range(100):
        print('Iteration %d' % t)
        bestmatches=[] for i in range(k)]

        # Find which centroid is the closest for each row
        for j in range(len(rows)):
            row=rows[j]
            bestmatch=0
            for i in range(k):
                d=distance(clusters[i],row)
                if d<distance(clusters[bestmatch],row): bestmatch=i
            bestmatches[bestmatch].append(j)

        # If the results are the same as last time, this is complete
        if bestmatches==lastmatches: break
        lastmatches=bestmatches

        # Move the centroids to the average of their members
        for i in range(k):
            avgs=[0.0]*len(rows[0])
            if len(bestmatches[i])>0:
                for rowid in bestmatches[i]:
                    for m in range(len(rows[rowid])):
                        avgs[m]+=rows[rowid][m]
                for j in range(len(avgs)):
                    avgs[j]/=len(bestmatches[i])
            clusters[i]=avgs

    return bestmatches, t
```

Figure 13



Since we are able to define the number of clusters, I had to create a way of printing out the centroid values. So, I created a new file which the name would be the value for k and have the number of iterations in it, as well as, blognames for each centroid. This format is shown in Figure 15.

```
filename2 = r"C:\Users\Ryan\Documents\WebScience\Assignment8\k_5.txt"
out=open(filename2,'a')
out.write("Iterations: "+ str(t)+"\n")
k = 0
while k < 5:
    out.write("[")
    for r in kclust[k]:
        out.write(blognames[r]+ ", ")
    out.write("]\n")
    k+=1
out.close()
```

Figure 14

Iterations: 4

[., Deadbeat, Eli Jace | The Mind Is A Terrible Thing To Paste, from a voice plantation, GLI Press, Doginasweater's Music Reviews (And Other Horseshit), MAGGOT CAVIAR, forget about it, The World's First Internet Baby, Encore, Floorshime Zipper Boots, Cherry Area, Rod Shone, Sonology, turnitup!, Riley Haas' blog, I Hate The 90s, Angie Dynamo, FOLK IS NOT HAPPY ]

Figure 15- Format k = 5

After performing the cluster for blogs using k =5, 10, and 20, I stored the results in text files of k\_5.txt, k\_10.txt, and k\_20.txt. These files contained the centroids with the blog names inside as well as the number of iterations that happened from the kcluster function. For k =5, the number of iterations were 4. For k=10, the number of iterations were 4, as well. For k = 20, the number of iterations was 5. It seems like the right number for centroids is between 5 and 10 while 20 contains centroids that do not have any blog names in them. This is also true for k = 10, however, the number of centroids with 0 blogs is significantly less for 10 than it is for 20 which makes me think that the ideal value is between 5 and 10.

#### Question 4:

In order to accomplish the goal of using Use MDS to create a JPEG of the blogs similar to that in the slides, I created the python file A8Q4.py which takes two function of scaledown and draw2d from the PCI textbook. The Scaledown function takes the difference between every pair of items and tries to make a chart in which the distances between the items match those differences. The process of the function is shown in Figure 16. The draw2d function works in a way to generate an image with all the labels of all the different items plotted at the new coordinates of that blog names.

```
def scaledown(data,distance=pearson,rate=0.01):
    n=len(data)

    # The real distances between every pair of items
    realdist=[[distance(data[i],data[j]) for j in range(n)]
               for i in range(0,n)]
```

```

# Randomly initialize the starting points of the locations in 2D
loc=[[random.random(),random.random()] for i in range(n)]
fakedist=[[0.0 for j in range(n)] for i in range(n)]

lasterror=None
for m in range(0,1000):
    # Find projected distances
    for i in range(n):
        for j in range(n):
            fakedist[i][j]=sqrt(sum([pow(loc[i][x]-loc[j][x],2)
                                     for x in range(len(loc[i]))]))

    # Move points
    grad=[[0.0,0.0] for i in range(n)]

    totalerror=0
    for k in range(n):
        for j in range(n):
            if j==k: continue
            # The error is percent difference between the distances
            errorterm=(fakedist[j][k]-realdist[j][k])/realdist[j][k]

            # Each point needs to be moved away from or towards the other
            # point in proportion to how much error it has
            grad[k][0]+=((loc[k][0]-loc[j][0])/fakedist[j][k])*errorterm
            grad[k][1]+=((loc[k][1]-loc[j][1])/fakedist[j][k])*errorterm

            # Keep track of the total error
            totalerror+=abs(errorterm)
    print(totalerror)

    # If the answer got worse by moving the points, we are done
    if lasterror and lasterror<totalerror: break
    lasterror=totalerror

    # Move each of the points by the learning rate times the gradient
    for k in range(n):
        loc[k][0]-=rate*grad[k][0]
        loc[k][1]-=rate*grad[k][1]

return loc

```

Figure 16

After performing the test, the jpeg created is named blog2d.jpeg and is shown in Figure 17. The number of iterations that were performed were 62. I ran this a couple of times and the final value was about the lowest number of iterations while the other runs were closer to 150 or even 228 in one case which was peculiar to me.

