

Eos491Assignment03

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EOS 491/526 Assignment #3

Daniel Scanks V00788200

Question #1

```
In [2]: import numpy as np
import matplotlib.pyplot as plt
import matplotlib.mlab as mlab
%matplotlib inline
import numpy.linalg as ag

print('solving overdetermined problem from Assignment 2, Question 1:')

#sensitivity matrix
A = np.matrix([[1.,1.,1.,1.,1.],[1.,1.,1.,1.,0.5],[1.,1.,1.,0.5,0],[1.,1.,0.5,0,0],[1.,0.5,0,0,0]])
A_T = A.transpose()

#true model
m_t = np.matrix([1,2,3,4,5])
m_t = m_t.transpose()

#true data
d_t = np.matrix([15.,12.5,8.,4.5,2.,0.5])
d = d_t.transpose()

#calculating m with SVD
U,s,V_T = ag.svd(A) # SVD decomposition of A into components
one1 = np.dot(V_T.T,ag.inv(np.diag(s)))
U = np.delete(U,np.s_[-1:],1) #Making U NxM
pseudoinv_svd = np.dot(one1,U.T)
m= np.dot(pseudoinv_svd,d)
print('model solution using svd psuedoinverse:')
print m
print('Vs.')
print('least-squared-error solution from assignment 2:')
print(np.matrix([[1],[2],[3],[4],[5]]))
print('The SVD pseudo-inverse method does produce the same result as the least-squared-error me

print()
print('solving under-determined problem from Assignment 2, Question 1:')
#sensitivity matrix
A = np.matrix([[1.,1.,1.],[1.,1.,0]])
```

```

A_T = A.transpose()

#true model
mt = np.matrix([1.,2.,3.])
m_t = mt.transpose()

#true data
d_t = np.matrix([6.,3.])
d = d_t.transpose()

U,s,V_T = ag.svd(A) # SVD decomposition of A into components (s = lamda)
s = np.matrix([[2.13577921,0],[0,0.66215345]]) #making s/Lamda into MxM diagonal matrix
invs = ag.inv(s)
invs = np.matrix([[ 0.46821319,0,0],[ 0, 1.51022395,0],[0,0,0]]) #Moore-Penrose
print('Moore-Penrose Inverse Lambda Matrix:')
print invs
one = np.dot(V_T.T,invs)
U = np.matrix([[ -0.78820544,-0.61541221,0],[ -0.61541221,0.78820544,0]]) #making U work for unde
pseudoinv_svd = np.dot(one,U.T)
m= np.dot(pseudoinv_svd,d)
print('model solution using svd psuedoinverse:')
print m
print('Vs.')
print('smallest model solution from assignment 2:')
print(np.matrix([[1.5],[1.5],[3]]))
print('The SVD pseudo-inverse method does produce the same result as the smallest method for an

solving overdetermined problem from Assignment 2, Question 1:
model solution using svd psuedoinverse:
[[ 1.]
 [ 2.]
 [ 3.]
 [ 4.]
 [ 5.]]
Vs.
least-squared-error solution from assignment 2:
[[1]
 [2]
 [3]
 [4]
 [5]]
The SVD pseudo-inverse method does produce the same result as the least-squared-error method for an over-
determined problem.
()
solving under-determined problem from Assignment 2, Question 1:
Moore-Penrose Inverse Lambda Matrix:
[[ 0.46821319  0.          0.          ]
 [ 0.          1.51022395  0.          ]
 [ 0.          0.          0.          ]]
model solution using svd psuedoinverse:
[[ 1.5          ]
 [ 1.5          ]
 [ 2.99999998]]
Vs.
smallest model solution from assignment 2:

```

```
[[ 1.5]
 [ 1.5]
 [ 3. ]]
```

The SVD pseudo-inverse method does produce the same result as the smallest method for an underdetermined

Question 2

```
In [3]: print('Question 2')
```

```
x = 500. #distance

# reciever depth values (m)
z = np.arange(10,110,10)

#noise (s)
n= np.random.normal(0,0.0001,10)
n = np.matrix(n)
noise = n.T
#Cd matrix
Cdin = (1/(0.0001**2))*np.ones(10)
Cdin = np.diag(Cdin)

#velocities (m/s)
v = np.matrix([1500.,1495.,1490.,1487.,1490.,1495.,1500.,1505.,1508.,1510.])
#slowness vector for source at 0m - rays pass through all layers
m0 = np.array([1/1500.,1/1495.,1/1490.,1/1487.,1/1490.,1/1495.,1/1500.,1/1505.,1/1508.,1/1510.])
m0 = np.matrix(m0)
m0 = m0.T
#slowness vector for source at 90m- ray passes through 10th layer twice(surface and through)
m90 = np.array([1/1495.,1/1490.,1/1487.,1/1490.,1/1495.,1/1500.,1/1505.,1/1508.,1/1510.,1/1510.])
m90 = np.matrix(m90)
m90 = m90.T
#slowness vector for source at 50m- ray passes through 6th layer twice(surface and through)
m50 = np.array([1/1495.,1/1490.,1/1487.,1/1490.,1/1495.,1/1500.,1/1500.,1/1505.,1/1508.,1/1510.])
m50 = np.matrix(m50)
m50 = m50.T

#a square, even determined
print('a) even determined')
#d = Am + n
#layer thicknesses
t = 10

# source at 0m
sin0 = np.zeros(10)
for i in range(0,10):
    sin0[i] = abs(z[i])/(np.sqrt(x**2+(z[i])**2))

#Asquare
A0 = np.zeros((10,10))
for i in range(0,10):
```

```

n= 0
while(n < i+1):
    A0[i,n] = t/sin0[i]
    n= n+1

#data
d0 = np.dot(A0,m0)
print('observed travelttime data for source at 0m')
d0_obs = d0 +noise
print d0_obs
#invert to find predicted model
A0inv = ag.inv(A0)
m0t = np.dot(A0inv,d0_obs)
print(' predicted slowness model for source at 0m')
print m0t

#i)
norm = np.max(abs(A0))
A = A0/(norm)
T = range(A.shape[1])
plt.figure(figsize=(6,3))
for i in range(A.shape[0]):
    base = A[i,]*0.
    base.fill(A.shape[1]-i)
    plt.fill_between(T, base, A[i,]+base)
plt.ylim(0,A.shape[1]+1)
plt.title('Rows of sensitivity matrix normalized by max')
plt.axis('off')
plt.show()

#ii)
U, s, V = np.linalg.svd(A0, full_matrices=True)
snorm = s/707.18515799
plt.plot(np.log10(snorm))
plt.title('Normalized Singular Values of A on Log Scale')
plt.grid(True)
plt.show()

#iii/iv)
depth = np.array((10,20,30,40,50,60,70,80,90,100))

one = np.dot(A0.T,A0)
two = ag.inv(one)
cm = np.dot(0.0001**2,two)
vals = np.sqrt(np.diag(cm))
vsq = np.array((1500.**2,1495.**2.,1490.**2,1487.**2,1490.**2,1495.**2,1500.**2,1505.**2,1508.**2,1510.**2))
#error values on velocities for each depth(layer)
unvel = np.zeros(10)
for i in range(0,10):
    unvel[i] = vals[i]*vsq[i]
x= np.squeeze(np.asarray(1/m0))
x1 = np.squeeze(np.asarray(1/m0t))
plt.figure(figsize=(6,3))

```

```

plt.plot(x,depth, label = 'true model',color = 'b')
plt.plot(x1,depth, label = 'recovered model',color = 'k')
plt.title('Velocity Models as a Function of Depth With Standard Deviations(Green)')
plt.fill_betweenx(depth,x1-unvel,x1+unvel,facecolor = '#7EFF99',edgecolor='#3F7F4C')
plt.gca().invert_yaxis()
plt.ylabel('Depth(m)')
plt.xlabel('Velocity (m/s)')
plt.legend()
plt.show()
plt.figure(figsize=(6,3))
plt.plot(unvel,depth)
plt.title('Standard Deviation as a Function of Depth')
plt.gca().invert_yaxis()
plt.ylabel('Depth(m)')
plt.xlabel('Standard Deviation (m/s)')
plt.show()

#v)
#correlltion matrix
Rc = np.zeros((10,10))
for i in range (0,10):
    for j in range(0,10):
        Rc[i,j] = cm[i,j]/(np.sqrt(cm[i,i]*cm[j,j]))

norm = np.max(abs(Rc))
A = Rc/(norm)
T = range(A.shape[1])
plt.figure(figsize=(4,3))
for i in range(A.shape[0]):
    base = A[i,]*0.
    base.fill(A.shape[1]-i)
    plt.fill_between(T, base, A[i,]+base)
plt.ylim(0,A.shape[1]+1)
plt.title('Rows of Correlation matrix normalized by max')
plt.axis('off')
plt.show()

#vi)
#resolution matrix
Rm = np.zeros((10,10))
for i in range (0,10):
    Rm[i,i] = 1.

norm = np.max(abs(Rm))
A = Rm/(norm)
T = range(A.shape[1])
plt.figure(figsize=(4,3))
for i in range(A.shape[0]):
    base = A[i,]*0.
    base.fill(A.shape[1]-i)
    plt.fill_between(T, base, A[i,]+base)
plt.ylim(0,A.shape[1]+1)
plt.axis('off')

```

```

plt.title('Rows of Model Resolution Matrix normalized by max value' )
plt.show()
#vii)
print('For a source at 0m, each of the 10 layers will recieve from 1-10 rays through it. This m
print('for each layer. The first layer recieves all 10 rays, while the tenth recieves only one.
print('deviation increases with depth as seen in the model comparison. b/c of this the recovered
print(' increasing depth. The resolution matrix is equal to the identity matrix')

```

Question 2

a) even determined

observed traveltime data for source at 0m

```

[[ 0.33344808]
 [ 0.33427644]
 [ 0.33496996]
 [ 0.33595485]
 [ 0.33673544]
 [ 0.33725702]
 [ 0.33799631]
 [ 0.33864947]
 [ 0.33936283]
 [ 0.34060099]]

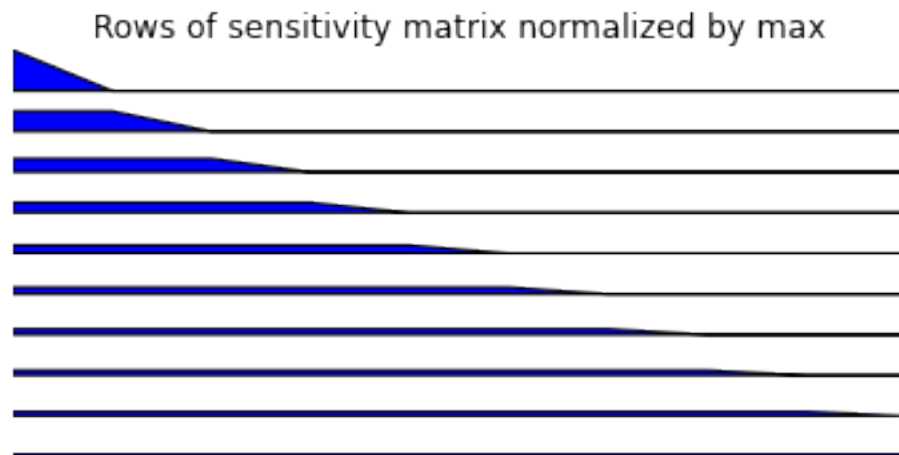
```

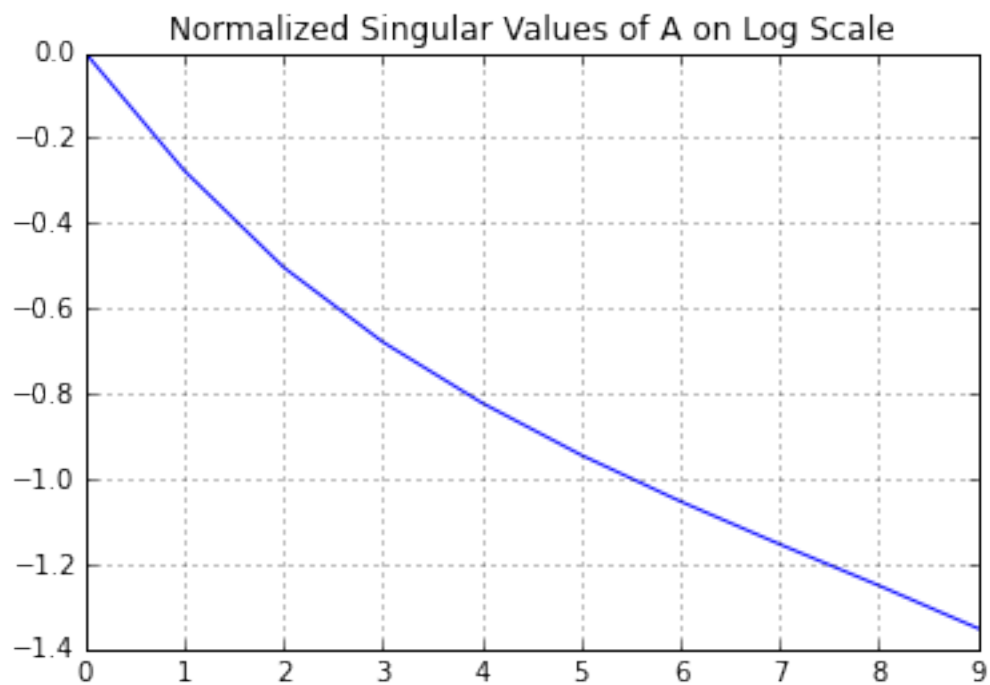
predicted slowness model for source at 0m

```

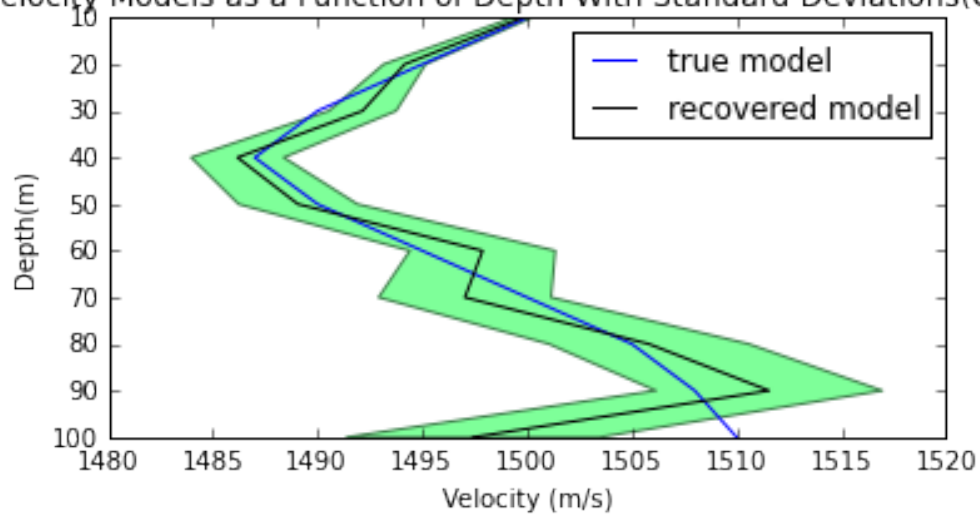
[[ 0.00066676]
 [ 0.00066927]
 [ 0.00067017]
 [ 0.00067287]
 [ 0.00067156]
 [ 0.00066761]
 [ 0.00066799]
 [ 0.00066409]
 [ 0.00066157]
 [ 0.00066782]]

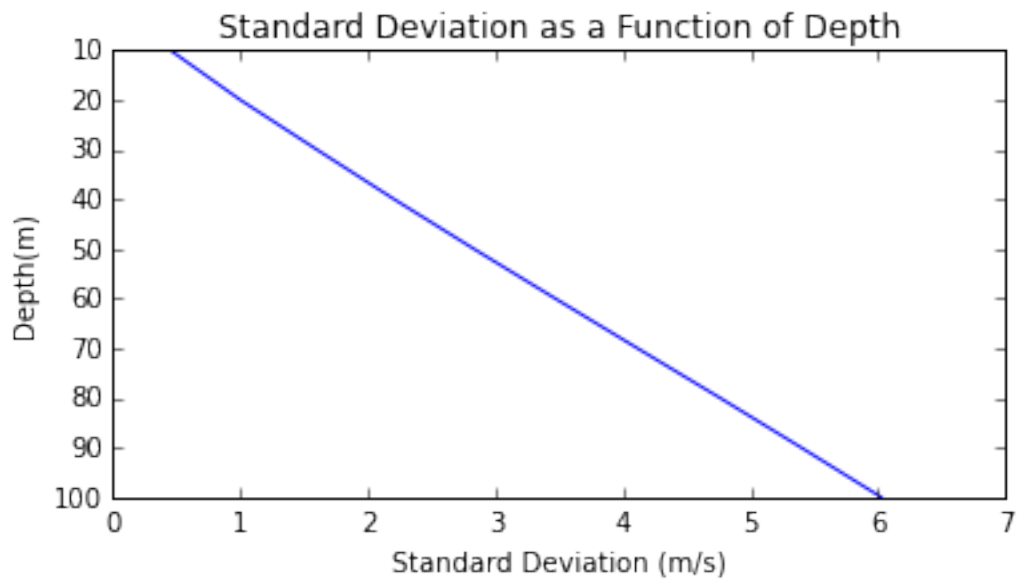
```



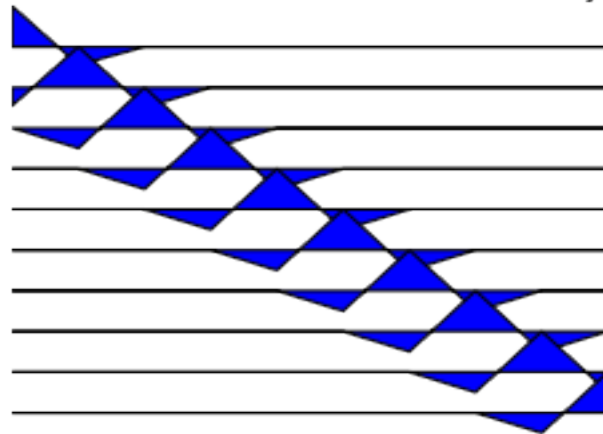


Velocity Models as a Function of Depth With Standard Deviations(Green)

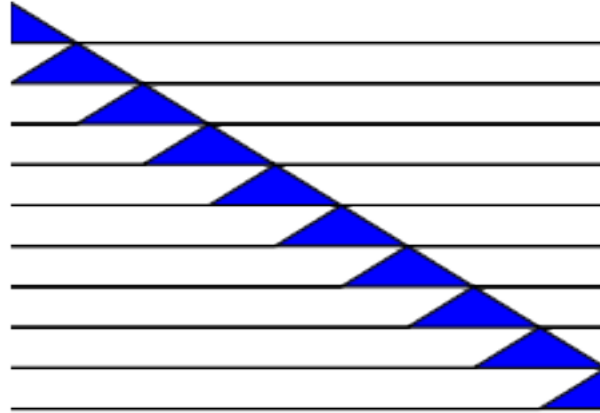




Rows of Correlation matrix normalized by max



Rows of Model Resolution Matrix normalized by max value



For a source at 0m, each of the 10 layers will receive from 1-10 rays through it. This means there are 10 rays for each layer. The first layer receives all 10 rays, while the tenth receives only one. As a result the deviation increases with depth as seen in the model comparison. b/c of this the recovered model is less accurate with increasing depth. The resolution matrix is equal to the identity matrix

```
In [4]: #-----part b
        z = np.arange(10,110,10)
        x= 500.
        print('b) over-determined')
        # source at 50m
        sin50 = np.zeros(10)
        for i in range(0,10):
            sin50[i] = abs(z[i]-50)/(np.sqrt(x**2+(z[i]-50)**2))

        A50 = np.zeros((10,10))
        for i in range(0,10):
            if i == 4:
                A50[i,5] = x
            elif i < 4:
                n=4
                while(n > i):
                    A50[i,n] = t/sin50[i]
                    n = n-1
            else:
                n= 5
                while(n < i+1):
                    A50[i,n] = t/sin50[i]
                    n = n+1

        # source at 90m
        sin90 = np.zeros(10)
        for i in range(0,10):
```

```

sin90[i] = abs(z[i]-90)/(np.sqrt(x**2+(z[i]-90)**2))

A90 = np.zeros((10,10))
for i in range(0,10):
    if i == 8:
        A90[i,9] = x
    elif i == 9:
        A90[i,9] = np.abs(z[9]-z[8])/sin90[9]
    else:
        n= 8
        while(n > i):
            A90[i,n] = t/sin90[i]
            n = n-1

#noise
n= np.random.normal(0,0.0001,30)
n = np.matrix(n)
noise = n.T

#new A
Ab = np.concatenate((A0, A50, A90), axis=0)
#data
db = np.dot(Ab,m0)
db_obs = db +noise
#invert to find predicted model
one = np.dot(Ab.T,Ab)
invone = ag.inv(one)
two = np.dot(invone,Ab.T)
mb = np.dot(two,db_obs)
print(' predicted slowness model for sources at 0,50,90m')
print mb

#i)
norm = np.max(abs(A0))
A = A0/(norm)
T = range(A.shape[1])
plt.figure(figsize=(6,2))
for i in range(A.shape[0]):
    base = A[i,]*0.
    base.fill(A.shape[1]-i)
    plt.fill_between(T, base, A[i,]+base)
plt.ylim(1,A.shape[1]+1)
plt.title('Rows 1-30 of sensitivity matrix normalized by max')
plt.ylabel('Rows 1-10')
plt.gca().xaxis.set_major_locator(plt.NullLocator())
plt.gca().yaxis.set_major_locator(plt.NullLocator())
plt.show()
norm = np.max(abs(A50))
A = A50/(norm)
T = range(A.shape[1])
plt.figure(figsize=(6,2))
for i in range(A.shape[0]):
    base = A[i,]*0.
    base.fill(A.shape[1]-i)
    plt.fill_between(T, base, A[i,]+base)

```

```

plt.ylim(1,A.shape[1]+1)
plt.ylabel('Rows 11-20')
plt.gca().xaxis.set_major_locator(plt.NullLocator())
plt.gca().yaxis.set_major_locator(plt.NullLocator())
plt.show()
norm = np.max(abs(A90))
A = A90/(norm)
T = range(A.shape[1])
plt.figure(figsize=(6,2))
for i in range(A.shape[0]):
    base = A[i,]*0.
    base.fill(A.shape[1]-i)
    plt.fill_between(T, base, A[i,]+base)
plt.ylim(1,A.shape[1]+1)
plt.ylabel('Rows 21-30')
plt.gca().xaxis.set_major_locator(plt.NullLocator())
plt.gca().yaxis.set_major_locator(plt.NullLocator())
plt.show()
#ii)
U, s, V = np.linalg.svd(Ab, full_matrices=True)
snorm = s/np.max(s)
plt.figure(figsize=(6,3))
plt.plot(np.log10(snorm))
plt.title('Normalized Singular Values of A on Log Scale')
plt.grid(True)
plt.show()
#iii/iv)
depth = np.array((10,20,30,40,50,60,70,80,90,100))
one = np.dot(Ab.T,Ab)
two = np.linalg.pinv(one)
cm = np.dot(0.0001**2,two)
vals = np.sqrt(np.diag(cm))
vsq = np.array((1500.**2,1495.**2,1490.**2,1487.**2,1490.**2,1495.**2,1500.**2,1505.**2,1508.**2,1510.**2))
#error values on velocities for each depth(layer)
unvel = np.zeros(10)
for i in range(0,10):
    unvel[i] = vals[i]*vsq[i]
x= np.squeeze(np.asarray(1/m0))
x1 = np.squeeze(np.asarray(1/m1))
plt.figure(figsize=(6,3))
plt.plot(x,depth, label = 'true model',color='b')
plt.plot(x1,depth, label = 'recovered model',color='k')
plt.title('Velocity Models as a Function of Depth With Standard Deviations(Green)')
plt.fill_betweenx(depth,x1-unvel,x1+unvel,facecolor = '#7EFF99',edgecolor='#3F7F4C')
plt.gca().invert_yaxis()
plt.ylabel('Depth(m)')
plt.xlabel('Velocity (m/s)')
plt.legend()
plt.show()
plt.figure(figsize=(6,3))
plt.plot(unvel,depth)
plt.title('Standard Deviation as a Function of Depth')
plt.gca().invert_yaxis()
plt.ylabel('Depth(m)')

```

```

plt.xlabel('Standard Deviation (m/s)')
plt.show()
#v)
#correlltion matrix
Rc = np.zeros((10,10))
for i in range (0,10):
    for j in range(0,10):
        Rc[i,j] = cm[i,j]/(np.sqrt(cm[i,i]*cm[j,j]))

norm = np.max(abs(Rc))
A = Rc/(norm)
T = range(A.shape[1])
plt.figure(figsize=(4,3))
for i in range(A.shape[0]):
    base = A[i,]*0.
    base.fill(A.shape[1]-i)
    plt.fill_between(T, base, A[i,]+base)
plt.ylim(0,A.shape[1]+1)
plt.title('Rows of Correlation matrix normalized by max')
plt.axis('off')
plt.show()

```

```

#vi)
#resolution matrix
Rm = np.zeros((10,10))
for i in range (0,10):
    Rm[i,i] = 1.

norm = np.max(abs(Rm))
A = Rm/(norm)
T = range(A.shape[1])
plt.figure(figsize=(4,3))
for i in range(A.shape[0]):
    base = A[i,]*0.
    base.fill(A.shape[1]-i)
    plt.fill_between(T, base, A[i,]+base)
plt.ylim(0,A.shape[1]+1)
plt.title('Rows of Model Resolution matrix normalized by max')
plt.axis('off')
plt.show()

```

#vii)

```

print('for this overdetermined case, we see that all layers except the first see multiple rays,
print('standard deviation is much lower as the recovered model is more accurate. The resolution
print('identity matrix for this overdetermined case.')

```

b) over-determined

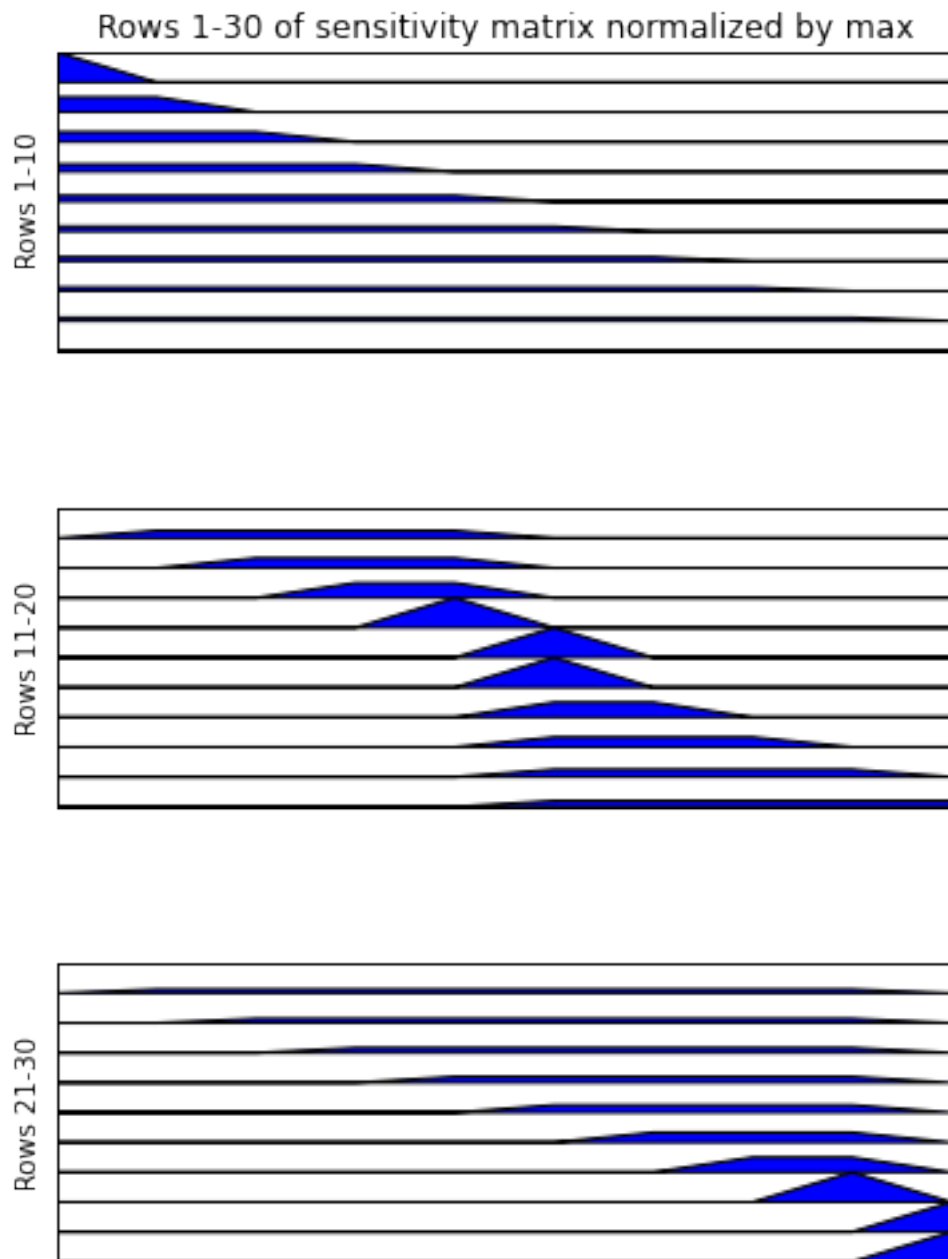
predicted slowness model for sources at 0,50,90m

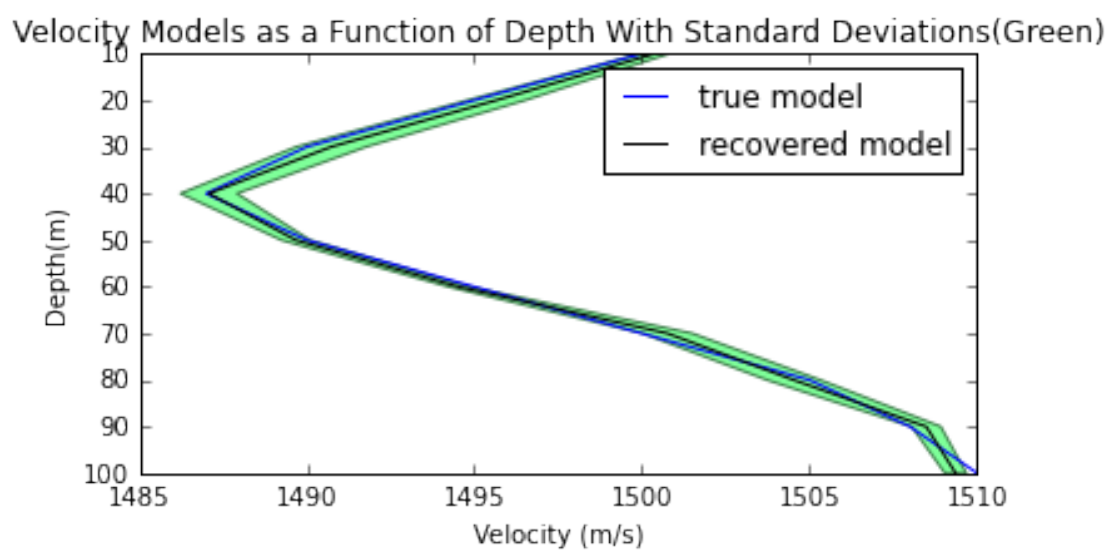
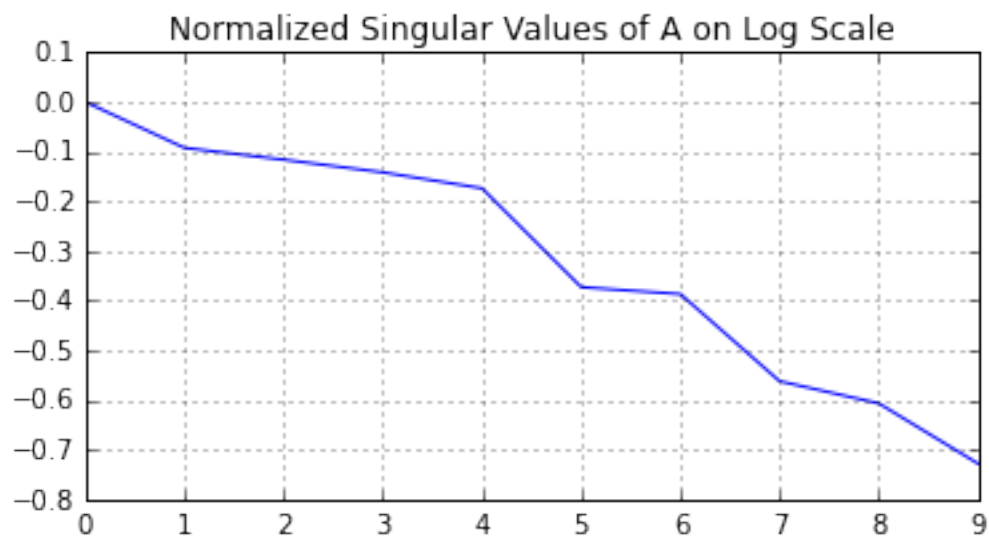
```

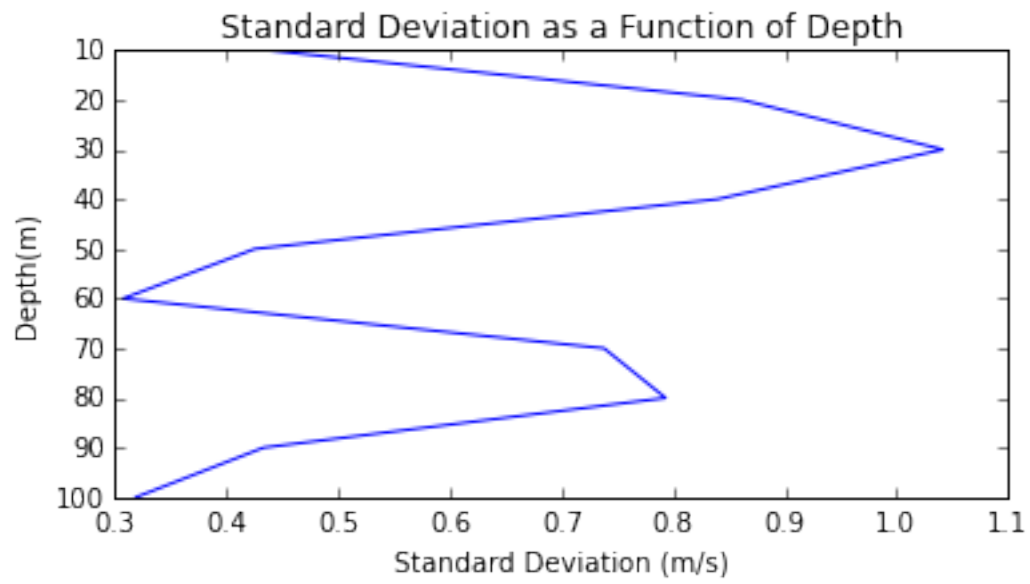
[[ 0.00066649]
 [ 0.0006686 ]
 [ 0.00067081]
 [ 0.00067246]
 [ 0.00067129]

```

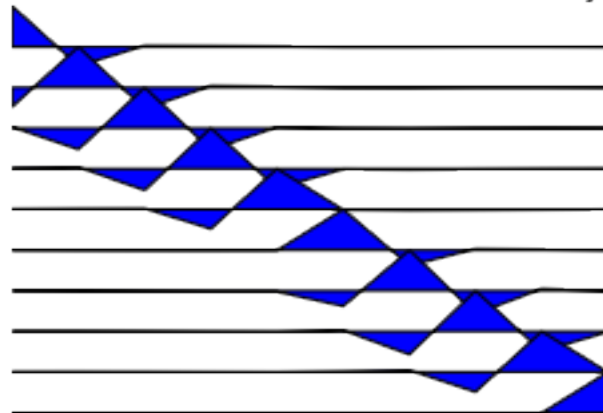
```
[ 0.0006691 ]  
[ 0.00066633]  
[ 0.00066466]  
[ 0.00066292]  
[ 0.00066253]
```



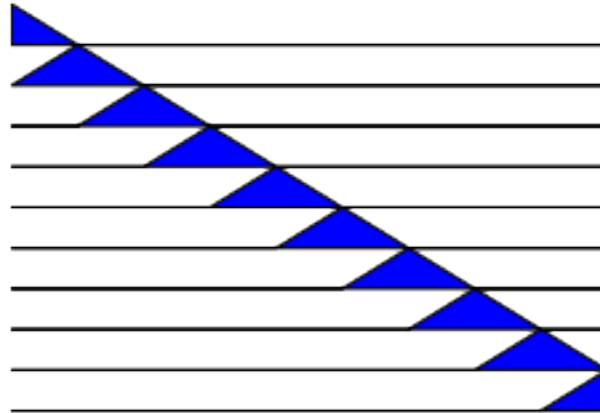




Rows of Correlation matrix normalized by max



Rows of Model Resolution matrix normalized by max



for this overdetermined case, we see that all layers except the first see multiple rays, and therefore standard deviation is much lower as the recovered model is more accurate. The resolution matrix is equal to identity matrix for this overdetermined case.

```
In [6]: #-----partc
print('c')
zmiss = np.array((10,20,40,50,60,70,80,90,100))
x = 500.
#new matrix (A0 minus row 3)
Ac = np.delete(A0, (2), axis=0)
#noise
n= np.random.normal(0,0.0001,9)
n = np.matrix(n)
noise = n.T
#data
dc = np.dot(Ac,m0)
dc_obs = dc +noise
#invert to find predicted model
one = np.dot(Ac,Ac.T)
oneinv = ag.inv(one)
two = np.dot(Ac.T,oneinv)
mc = np.dot(two,dc_obs)
print(' predicted slowness model for source at 0m with no 30m receiver')
print mc

#i)
norm = np.max(abs(Ac))
A = Ac/(norm)
T = range(A.shape[1])
plt.figure(figsize=(6,3))
for i in range(A.shape[0]):
    base = A[i,]*0.
    base.fill(A.shape[1]-i)
```



```

plt.fill_between(T, base, A[i,]+base)
plt.ylim(0,A.shape[1]+1)
plt.title('Rows of sensitivity matrix normalized by max')
plt.axis('off')
plt.show()
#ii)
U, s, V = np.linalg.svd(Ac, full_matrices=True)
snorm = s/np.max(s)
plt.figure(figsize=(6,3))
plt.plot(np.log10(snorm))
plt.title('Normalized Singular Values of A on Log Scale')
plt.grid(True)
plt.show()
#iii/iv)
depth = np.array((10,20,30,40,50,60,70,80,90,100))
one = np.dot(Ac,Ac.T)
oneinv = ag.inv(one)
two = np.dot(0.0001**2,Ac.T)
three = np.dot(oneinv,oneinv)
four = np.dot(two,three)
cm = np.dot(four,Ac)
vals = np.sqrt(np.diag(cm))
vsq = np.array((1500.**2,1495.**2.,1490.**2,1487.**2,1490.**2,1495.**2,1500.**2,1505.**2,1508.**2,1510.**2))
#error values on velocities for each depth(layer)

unvel = np.zeros(10)
for i in range(0,10):
    unvel[i] = vals[i]*vsq[i]
x= np.squeeze(np.asarray(1/m0))
x1 = np.squeeze(np.asarray(1/mc))
plt.figure(figsize=(6,3))
plt.plot(x,depth, label = 'true model',color='b')
plt.plot(x1,depth, label = 'recovered model',color='k')
plt.title('Velocity Models as a Function of Depth With Standard Deviations(Green)')
plt.fill_betweenx(depth,x1-unvel,x1+unvel,facecolor='#7EFF99',edgecolor='#3F7F4C')
plt.gca().invert_yaxis()
plt.ylabel('Depth(m)')
plt.xlabel('Velocity (m/s)')
plt.legend()
plt.show()
plt.figure(figsize=(6,3))
plt.plot(unvel,depth)
plt.title('Standard Deviation as a Function of Depth')
plt.gca().invert_yaxis()
plt.ylabel('Depth(m)')
plt.xlabel('Standard Deviation (m/s)')
plt.show()
#v)
#correltion matrix
Rc = np.zeros((10,10))
for i in range (0,10):
    for j in range(0,10):
        Rc[i,j] = cm[i,j]/(np.sqrt(cm[i,i]*cm[j,j]))

```

```

norm = np.max(abs(Rc))
A = Rc/(norm)
T = range(A.shape[1])
plt.figure(figsize=(4,3))
for i in range(A.shape[0]):
    base = A[i,]*0.
    base.fill(A.shape[1]-i)
    plt.fill_between(T, base, A[i,]+base)
plt.ylim(0,A.shape[1]+1)
plt.title('Rows of Correlation matrix normalized by max')
plt.axis('off')
plt.show()
#vi)
#resolution matrix
one1 = np.dot(Ac,Ac.T)
one1inv = ag.inv(one1)
Ag = np.dot(Ac.T,one1inv)
Rm = np.dot(Ag,Ac)

norm = np.max(abs(Rm))
A = Rm/(norm)
T = range(A.shape[1])
plt.figure(figsize=(4,3))
for i in range(A.shape[0]):
    base = A[i,]*0.
    base.fill(A.shape[1]-i)
    plt.fill_between(T, base, A[i,]+base)
plt.ylim(0,A.shape[1]+1)
plt.title('Rows of Model Resolution matrix normalized by max')
plt.axis('off')
plt.show()
#vi)
print('The missing reciever at 30m makes the the model resolution and correlation matrices skewed')
print('The correlation rows above and below the 3rd are somewhat skewed too. The standard deviation is')
print('the standard deviation for a). The deviation is pretty constained and increases with depth')

```

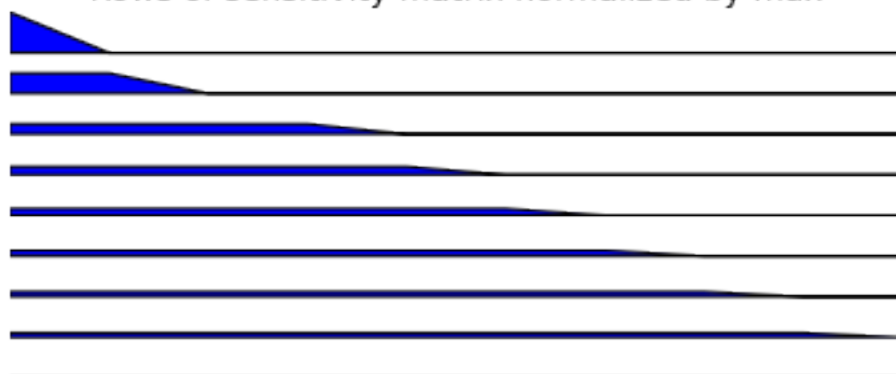
c)

```

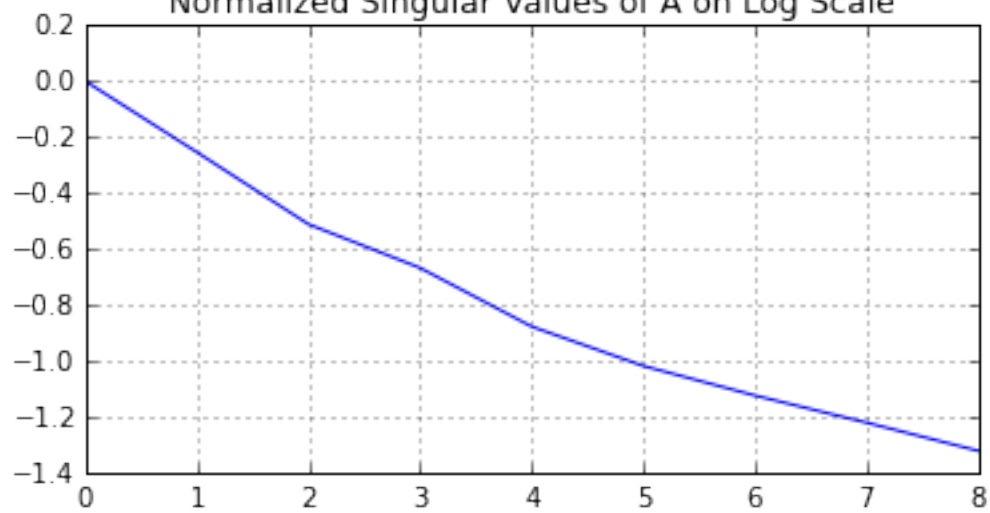
predicted slowness model for source at 0m with no 30m receiver
[[ 0.00066652]
 [ 0.0006695 ]
 [ 0.00067159]
 [ 0.00067159]
 [ 0.00067161]
 [ 0.0006675 ]
 [ 0.00066833]
 [ 0.00066274]
 [ 0.00066097]
 [ 0.00066209]]

```

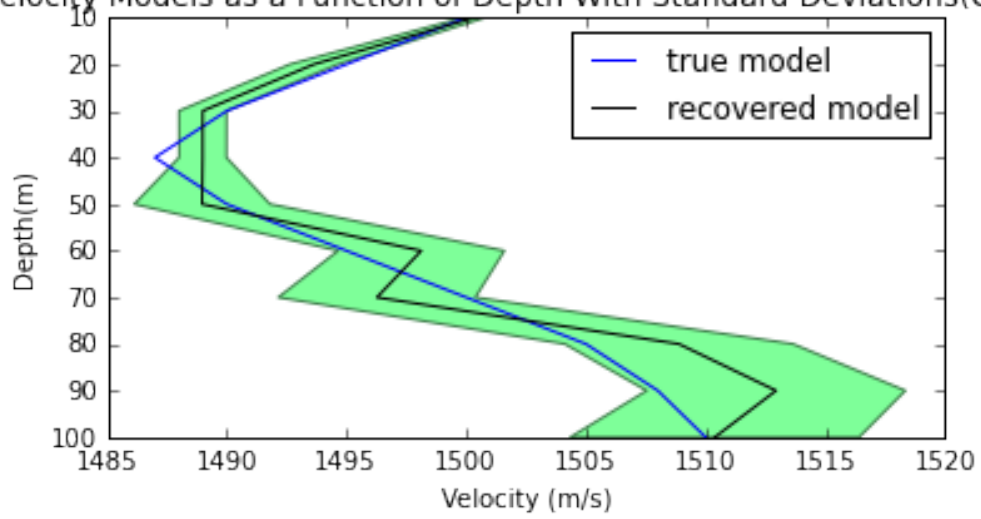
Rows of sensitivity matrix normalized by max



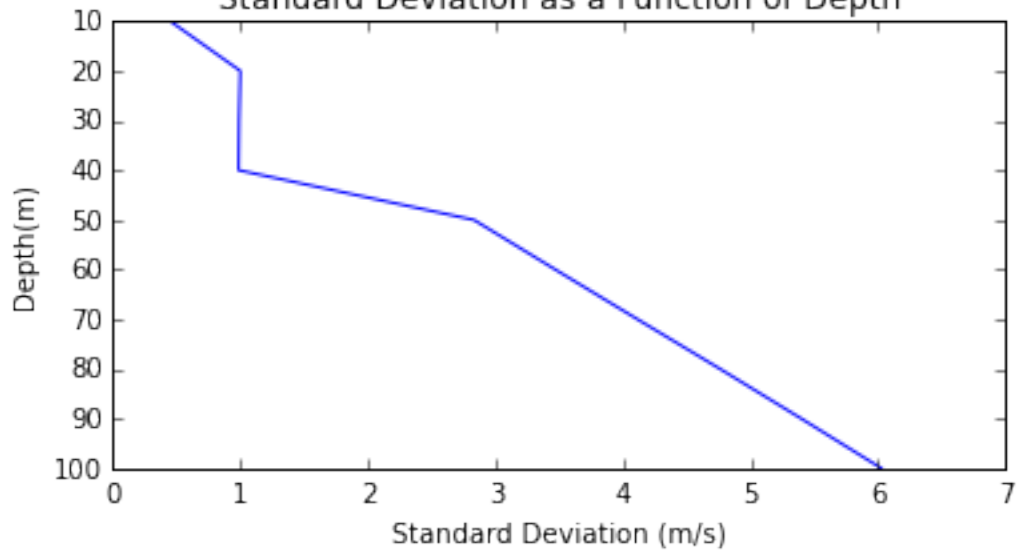
Normalized Singular Values of A on Log Scale



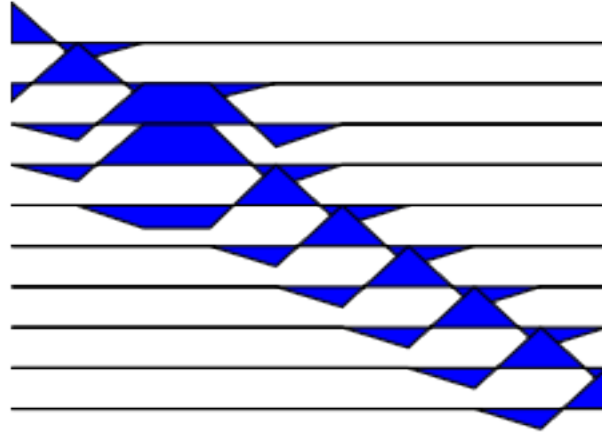
Velocity Models as a Function of Depth With Standard Deviations(Green)



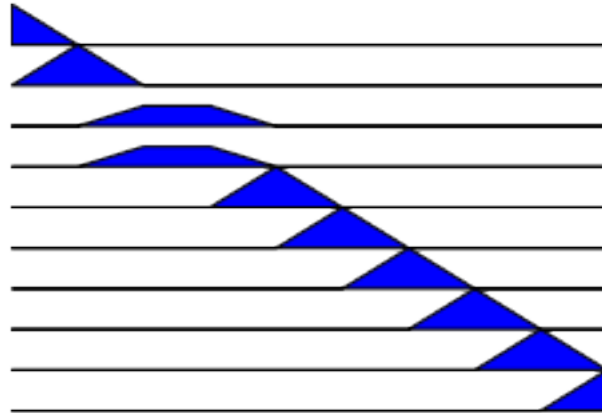
Standard Deviation as a Function of Depth



Rows of Correlation matrix normalized by max



Rows of Model Resolution matrix normalized by max



The missing receiver at 30m makes the the model resolution and correlation matrices skewed on the plots. The correlation rows above and below the 3rd are somewhat skewed too. The standard deviation is similar the standard deviation for a). The deviation is pretty constained and increases with depth for the most

```
In [7]: from scipy import linalg
print('d) mixed determined')
A0n = np.delete(A0, (2), axis=0)
A50n = np.delete(A50, (2), axis=0)
A90n = np.delete(A90, (2), axis=0)
#noise
n= np.random.normal(0,0.0001,27)
n = np.matrix(n)
```

```

noise = n.T
#new A
Ad = np.concatenate((A0n, A50n, A90n), axis=0)
#data
dd = np.dot(Ad,m0)
dd_obs = dd +noise
#invert to find predicted model
N,M = Ad.shape
U,s,V_T = ag.svd(Ad) # SVD decomposition of A into components (n = lamda)
s = linalg.diagsvd(s,M,M)
s = np.delete(s,(9),1)
s = np.delete(s,(9),0)
V= V_T.T
V = np.delete(V,(9),1)
Unew = np.delete(U, np.s_[9:27:], axis = 1)
s = ag.inv(s)
one = np.dot(V,s)
pseudoinv_svd = np.dot(one,Unew.T)
md= np.dot(pseudoinv_svd,dd_obs)
print(' predicted slowness model for sources at 0,50,90m without 30m reciever')
#md= np.array(md)
print md
#i
norm = np.max(abs(A0n))
A = A0n/(norm)
T = range(A.shape[1])
plt.figure(figsize=(6,2))
for i in range(A.shape[0]):
    base = A[i,]*0.
    base.fill(A.shape[1]-i)
    plt.fill_between(T, base, A[i,]+base)
plt.ylim(2,A.shape[1]+1)
plt.title('Rows 1-27 of sensitivity matrix normalized by max')
plt.ylabel('Rows 1-9')
plt.gca().xaxis.set_major_locator(plt.NullLocator())
plt.gca().yaxis.set_major_locator(plt.NullLocator())
plt.show()
norm = np.max(abs(A50n))
A = A50n/(norm)
T = range(A.shape[1])
plt.figure(figsize=(6,2))
for i in range(A.shape[0]):
    base = A[i,]*0.
    base.fill(A.shape[1]-i)
    plt.fill_between(T, base, A[i,]+base)
plt.ylim(2,A.shape[1]+1)
plt.ylabel('Rows 10-18')
plt.gca().xaxis.set_major_locator(plt.NullLocator())
plt.gca().yaxis.set_major_locator(plt.NullLocator())
plt.show()
norm = np.max(abs(A90n))
A = A90n/(norm)
T = range(A.shape[1])
plt.figure(figsize=(6,2))

```

```

for i in range(A.shape[0]):
    base = A[i,]*0.
    base.fill(A.shape[1]-i)
    plt.fill_between(T, base, A[i,]+base)
plt.ylim(2,A.shape[1]+1)
plt.ylabel('Rows 19-27')
plt.gca().xaxis.set_major_locator(plt.NullLocator())
plt.gca().yaxis.set_major_locator(plt.NullLocator())
plt.show()
#ii)
s1 = ag.inv(s)
s1 = np.diag(s1)
snorm = s1/np.max(s1)
plt.figure(figsize=(6,3))
plt.plot(np.log10(snorm))
plt.title('Normalized Singular Values of A on Log Scale')
plt.grid(True)
plt.show()
#iii/iv)
depth = np.array((10,20,30,40,50,60,70,80,90,100))
one = np.dot(s,s)
two = np.dot(V,one)
cm = np.dot(two,V.T)
vals = np.diag(cm)
vsq = np.array((1500.**2,1495.**2.,1490.**2,1487.**2,1490.**2,1495.**2,1500.**2,1505.**2,1508.**2,1510.**2))
#error values on velocities for each depth(layer)
unvel = np.zeros(10)
for i in range(0,10):
    unvel[i] = vals[i]*vsq[i]
print unvel
x= np.squeeze(np.asarray(1/m0))
x1 = np.squeeze(np.asarray(1/md))
plt.figure(figsize=(6,3))
plt.plot(x,depth, label = 'true model',color='b')
plt.plot(x1,depth, label = 'recovered model',color='k')
plt.title('Velocity Models as a Function of Depth With Standard Deviations(Green)')
plt.fill_betweenx(depth,x1-unvel,x1+unvel,facecolor='#7EFF99',edgecolor='#3F7F4C')
plt.gca().invert_yaxis()
plt.ylabel('Depth(m)')
plt.xlabel('Velocity (m/s)')
plt.legend()
plt.show()
plt.figure(figsize=(6,3))
plt.plot(unvel,depth)
plt.title('Standard Deviation as a Function of Depth')
plt.gca().invert_yaxis()
plt.ylabel('Depth(m)')
plt.xlabel('Standard Deviation (m/s)')
plt.show()

#v)
#correltion matrix
Rc = np.zeros((10,10))
for i in range (0,10):

```

```

        for j in range(0,10):
            Rc[i,j] = cm[i,j]/(np.sqrt(cm[i,i]*cm[j,j]))

norm = np.max(abs(Rc))
A = Rc/(norm)
T = range(A.shape[1])
plt.figure(figsize=(4,3))
for i in range(A.shape[0]):
    base = A[i,]*0.
    base.fill(A.shape[1]-i)
    plt.fill_between(T, base, A[i,]+base)
plt.ylim(0,A.shape[1]+1)
plt.title('Rows of Correlation matrix normalized by max')
plt.axis('off')
plt.show()

#vi)
#resolution matrix)
Rm = np.dot(V,V.T)

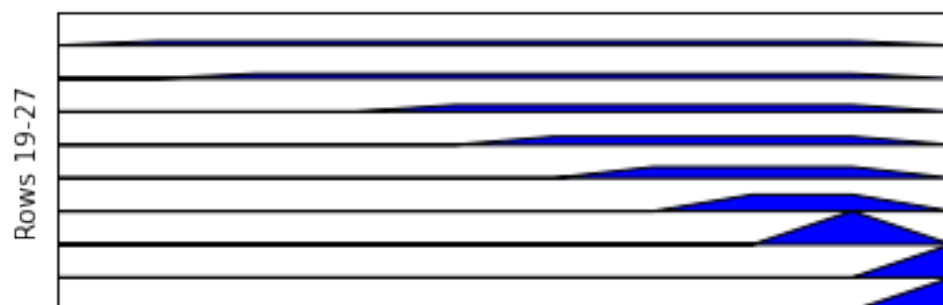
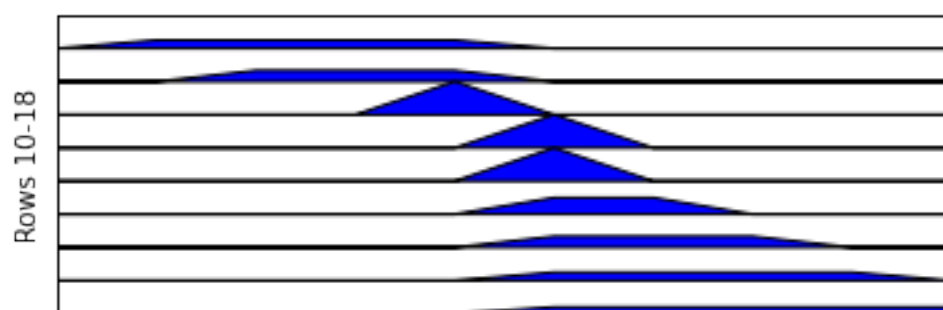
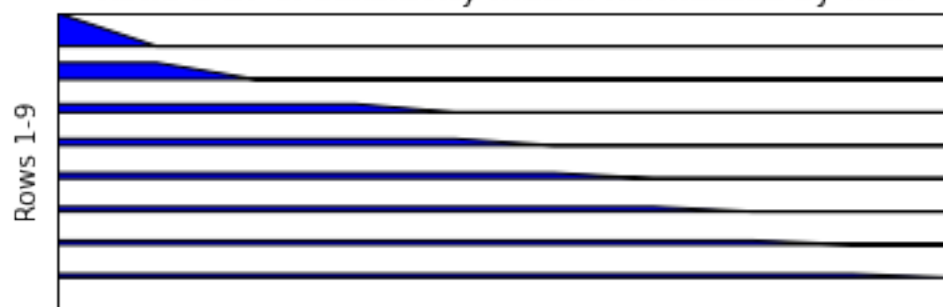
norm = np.max(abs(Rm))
A = Rm/(norm)
T = range(A.shape[1])
plt.figure(figsize=(4,3))
for i in range(A.shape[0]):
    base = A[i,]*0.
    base.fill(A.shape[1]-i)
    plt.fill_between(T, base, A[i,]+base)
plt.ylim(0,A.shape[1]+1)
plt.title('Rows of Model Resolution matrix normalized by max')
plt.axis('off')
plt.show()

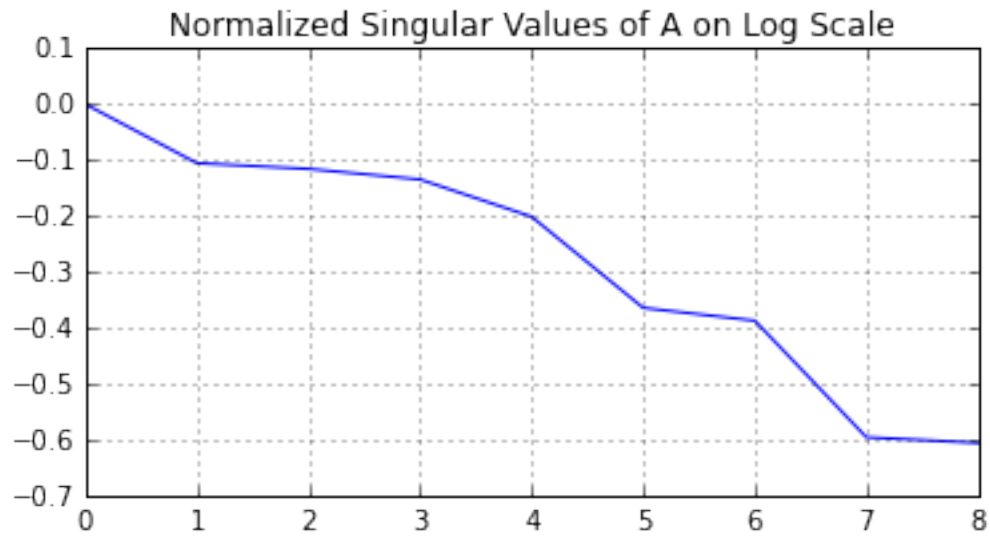
#vii)
print('the SVD pseudo inverse did a good job of reconstructing the true model. There was 9 singular values')
print(' the model correlation and resolution matrices resembled those in part c). The standard deviation was smallest at')
print('distance from the source, at 0m,50m,90m the deviation was smallest.')

d) mixed determined
predicted slowness model for sources at 0,50,90m without 30m receiver
[[ 0.00066695]
 [ 0.00066868]
 [ 0.00067193]
 [ 0.00067193]
 [ 0.00067114]
 [ 0.00066874]
 [ 0.00066675]
 [ 0.00066465]
 [ 0.00066299]
 [ 0.00066227]]

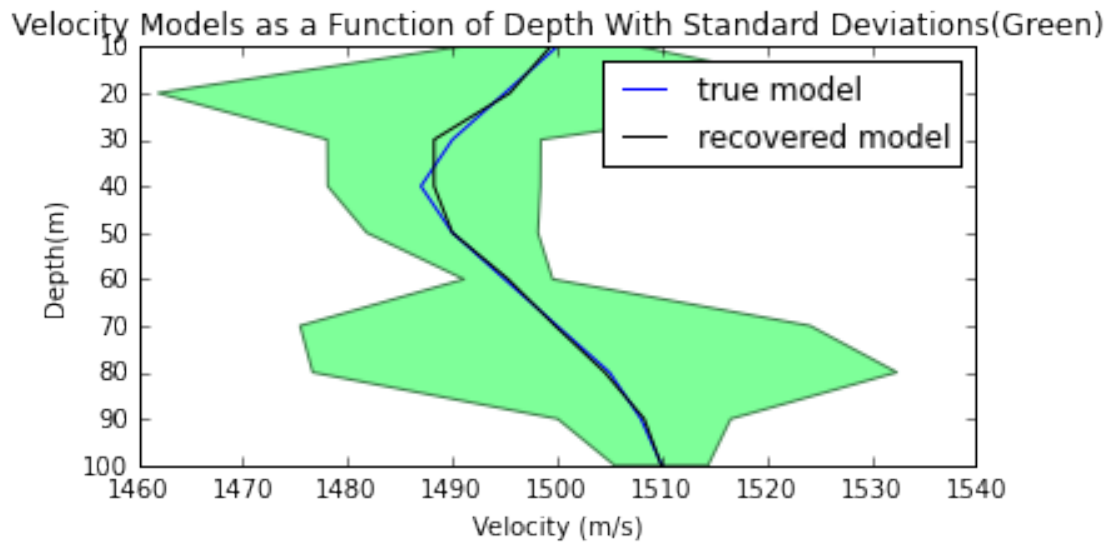
```

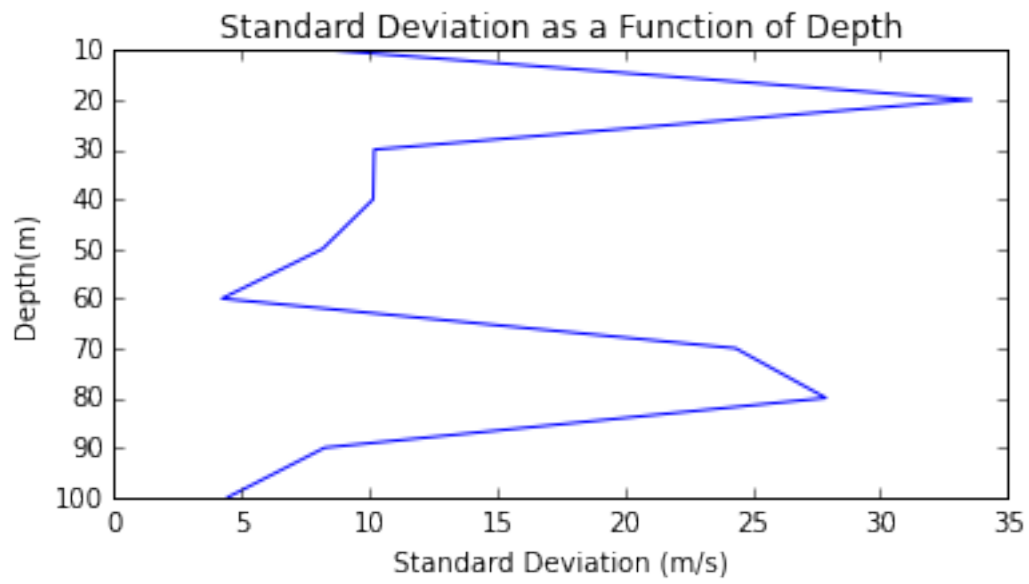

Rows 1-27 of sensitivity matrix normalized by max



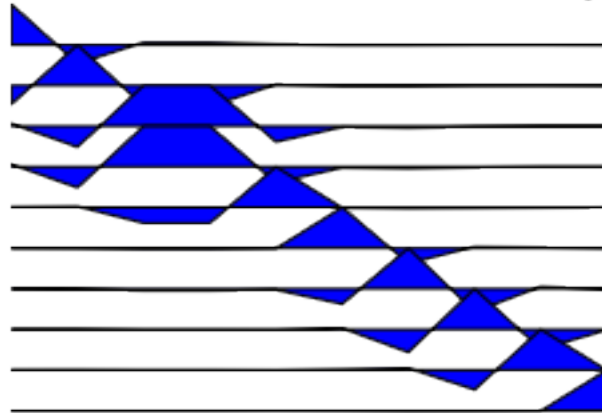


[8.47764225 33.56998242 10.19009931 10.14910666 8.16627981
 4.22770806 24.33654021 27.87467854 8.25470384 4.45561484]

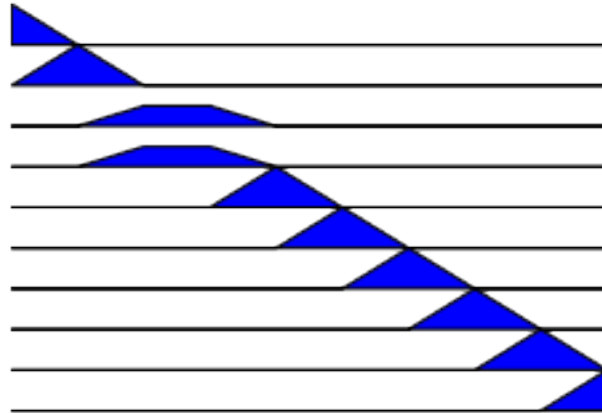




Rows of Correlation matrix normalized by max



Rows of Model Resolution matrix normalized by max



the SVD pseudo inverse did a good job of reconstructing the true model. There was 9 singular values for the model correlation and resolution matrices resembled those in part c). The standard deviation varied distance from the source, at 0m,50m,90m the deviation was smallest.

In []: