

# hw7

March 13, 2023

## 0.1 A.)

Estimate the attenuation for waves of 30 s period (0.033 Hz) for PcP ray paths at vertical incidence. Consider only the intrinsic attenuation along the ray paths; do not include the reflection coefficient at the core–mantle boundary or geometrical spreading. Be sure to count both the surface-to- CMB and CMB-to-surface legs. You can get the PREM P velocities from Figure 1.1 (Copied below) or the values tabulated in Appendix A. You may estimate the travel times through the different Q layers in PREM by assuming a fixed velocity within each layer (e.g., use the average velocity between 3 and 80 km, the average between 80 and 220 km, etc.). Note that in this case, the “surface” is assumed to be the bottom of the ocean at 3 km depth. Compute  $t_{\text{star}}$  for PcP. Finally, give the attenuated amplitude of the PcP ray, assuming the ray had an initial amplitude of one.

```
[1]: # PcP = Surface through mantle, off core, to surface
```

```
# calculate attenuation using eq. 6.86
#  $A(w) = A_0(w) * \exp((-w*t_{\text{star}}) / 2)$ 
#  $t_{\text{star}} = \int (dt / Q(r)) = 1/Q(r) * \int_{\text{path}}(dt)$ 
```

```
[2]: import numpy as np
```

```
# depth of different Q layers
```

```
depth = np.array([
    (80-3),
    (220-80),
    (670-220),
    (2891-670),
    (2891-670),
    (670-220),
    (220-80),
    (80-3),
])
```

```
# calculate mean alpha for each velocity change in Q layer
```

```
alpha = np.array([
    np.mean((5.8, 6.8, 8.11, 8.08)),
    np.mean((8.08, 8.02, 7.99)),
    np.mean((8.56, 8.66, 8.85, 8.91, 9.13, 9.5, 10.01, 10.16, 1.16, 10.27)),
    np.mean(
```

```

        (10.75, 11.07, 11.24, 11.42, 11.58, 11.73, 11.88, 12.02, 12.1, 12.29, 12.
↪42,
        12.54, 12.67, 12.78, 12.9, 13.02, 13.13, 13.25, 13.36, 13.48, 13.60, 13.
↪68,
        13.69, 13.71, 13.72)
    ),
    np.mean(
        (10.75, 11.07, 11.24, 11.42, 11.58, 11.73, 11.88, 12.02, 12.1, 12.29, 12.
↪42,
        12.54, 12.67, 12.78, 12.9, 13.02, 13.13, 13.25, 13.36, 13.48, 13.60, 13.
↪68,
        13.69, 13.71, 13.72)
    ),
    np.mean((8.56, 8.66, 8.85, 8.91, 9.13, 9.5, 10.01, 10.16, 1.16, 10.27)),
    np.mean((8.08, 8.02, 7.99)),
    np.mean((5.8, 6.8, 8.11, 8.08)),
])

# Q values to outer core from PREM
Q = np.array([600, 80,143, 312, 312, 143, 80, 600])

```

```

[3]: #  $v = d / t \rightarrow t = d / v$ 
dt = depth / alpha
tstar = dt / Q

```

```

[4]: w = 2 * np.pi * 0.033
A_0 = 1
A = []
for i in range(0,8,1):
    A_0 = A_0 * np.exp(-w * tstar[i] / 2)
    A.append(A_0)
att_amp = A[-1]
print(f'The final attenuated amplitud for the PcP wave is: {att_amp}')

```

The final attenuated amplitud for the PcP wave is: 0.784300449848276

## 0.2 B.)

Using the approximation  $t=4t$ , compute the attenuated amplitude of ScS at 30 s period.

```

[5]: tstar_b = 4 * tstar

```

```

[6]: w = (2 * np.pi) / 30
A_0 = 1
A = []

```

```

for i in range(0,8,1):
    A_0 = A_0 * np.exp(-w * tstar_b[i] / 2)
    A.append(A_0)
att_amp = A[-1]
print(f'The final attenuated amplitud for the ScS wave is: {att_amp}')

```

The final attenuated amplitud for the ScS wave is: 0.37468518513264615

### 0.3 C.)

Repeat (a) and (b) for 1 s period (1 Hz) PcP and ScS waves.

```

[7]: w = 2 * np.pi

A_0 = 1
A = []
for i in range(0,8,1):
    A_0 = A_0 * np.exp(-w * tstar[i] / 2)
    A.append(A_0)
att_amp = A[-1]
print(f'The final attenuated amplitud for the PcP wave is: {att_amp}')

A_0 = 1
A = []
for i in range(0,8,1):
    A_0 = A_0 * np.exp(-w * tstar_b[i] / 2)
    A.append(A_0)
att_amp = A[-1]
print(f'The final attenuated amplitud for the ScS wave is: {att_amp}')

```

The final attenuated amplitud for the PcP wave is: 0.0006345983116549022

The final attenuated amplitud for the ScS wave is: 1.6217938504235532e-13

### 0.4 D.)

Repeat your calculations for the PcP and ScS attenuated amplitudes at 1 Hz, but this time, use the Warren and Shearer (2000)  $Q_\alpha$  values from the figure below (Figure 6.17). How do the predicted amplitudes compare to the PREM model predictions? What do these results predict for the observability of teleseismic S arrivals at 1 Hz?

```

[8]: w = 2 * np.pi

Q = [1/0.0043,1/0.0007,1/0.0007,1/0.0007,1/0.0007,1/0.0007,1/0.0007,1/0.0043]
tstar = dt / Q
tstar_b = 4 * tstar

A_0 = 1
A = []

```

```

for i in range(0,8,1):
    A_0 = A_0 * np.exp(-w * tstar[i] / 2)
    A.append(A_0)
att_amp = A[-1]
print(f'The final attenuated amplitud for the PcP is: {att_amp}')

A_0 = 1
A = []
for i in range(0,8,1):
    A_0 = A_0 * np.exp(-w * tstar_b[i] / 2)
    A.append(A_0)
att_amp = A[-1]
print(f'The final attenuated amplitud for the ScS wave is: {att_amp}')

```

The final attenuated amplitud for the PcP is: 0.25267159680837875

The final attenuated amplitud for the ScS wave is: 0.004075920455865417

The values from Warren and Shearer are much higher, and will drastically increase the observability of teleseismic S arrivals at 1 Hz

## 1 2.

This question relates to chapter 12.2 in noise seismology. It is modified from question 2 of chapter 12. Simulate the summations of cross-correlation functions from uniformly distributed noise sources

### 1.1 A.)

Produce your own version of the 2D example of Figure 12.3c by summing contributions from cross-correlations of a uniform azimuthal distribution of plane-wave sources. You should assume the cross-correlation functions are simple spike functions, as in Figure 12.3b. You will need to choose  $d\theta$  small enough that you get a smooth  $v(t)$  function, given your chosen sample rate for  $v(t)$ .

```

[9]: from scipy import signal
import matplotlib.pyplot as plt

```

```

[10]: # Sample rate
fs = 10

# window length
twin = 5

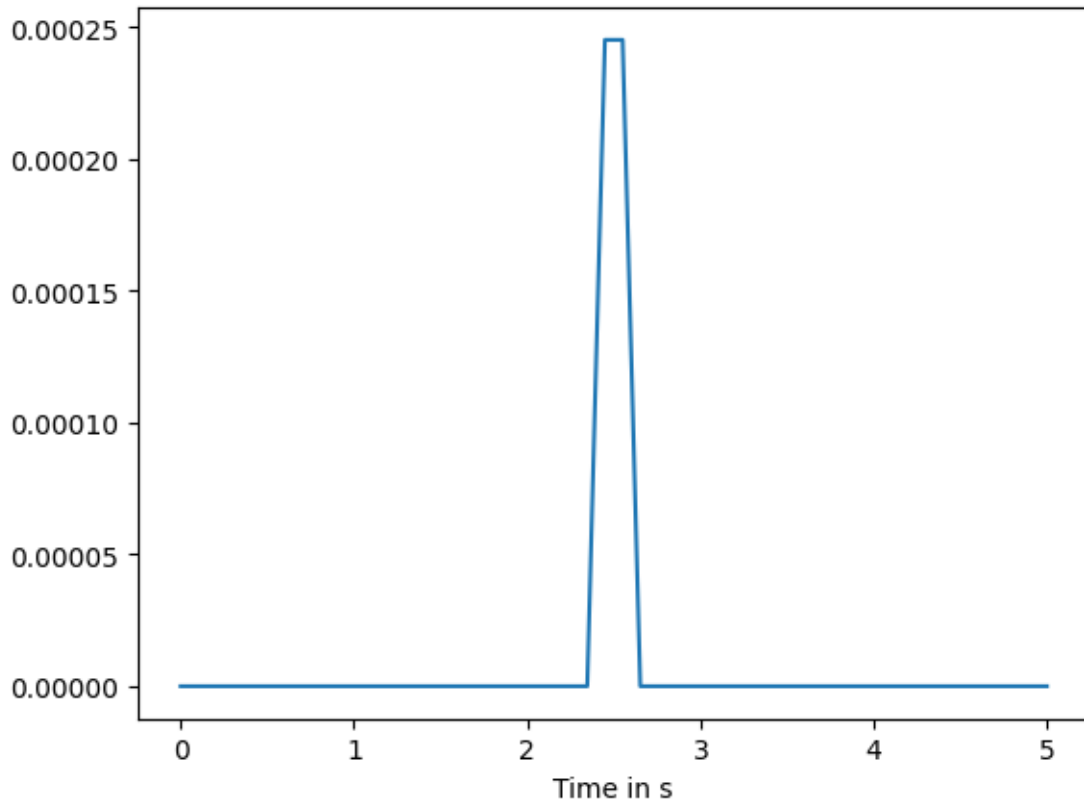
# points
t = np.linspace(0, twin, int(twin*fs))

# a single Ricker wavelet
a = 0.1 # width of the Ricker wavelet in s
ta = np.linspace(0, a, int(a*fs))

```

```
s = signal.ricker(len(t), a)
plt.plot(t,-s)
plt.xlabel('Time in s')
```

[10]: Text(0.5, 0, 'Time in s')



```
[11]: # initialize the seismograms with zeros
n_1_x = np.zeros(len(t))
n_1_y = np.zeros(len(t))

# seismic wavespeed
c = 3

# station location
x = [-5.,0.]
y = [5.,0]
r = 10. # radius of the circle that has the noise sources

# assume a theta (in radian)
theta_1 = np.pi/3
```

```
[12]: # calculate the distance and travel times
dt_1_x = np.sqrt(
    (r*np.cos(theta_1) - x[0])**2 + (r*np.sin(theta_1) - x[1])**2
)/c

dt_1_y = np.sqrt(
    (r*np.cos(theta_1) - y[0])**2 + (r*np.sin(theta_1) - y[1])**2
)/c

print("travel time between sources and receivers ",dt_1_x," s",dt_1_y," s")
# indexes where the arrival time will be centered
# shift also with the ricker wavelet width to avoid acausal signals
# (ricker wavelet is centered at a)
i_1_x = int(dt_1_x*fs)
i_1_y = int(dt_1_y*fs)
print(i_1_x,i_1_y)
```

```
travel time between sources and receivers  4.409585518440984  s
2.8867513459481287  s
44 28
```

```
[13]: tcorr = np.linspace(-twin,twin,int(2*len(t)-1))
```

```
[14]: N = 1000 # we will create N noise sources
# initialize the cross correlations
Corr = np.zeros(shape=(N,len(tcorr)))
for i in range(N):
    theta = 2*np.pi/N*i
    # calculate the distance between each noise source and the receivers
    dt_x = np.sqrt(
        (r*np.cos(theta) - x[0])**2 + (r*np.sin(theta) - x[1])**2
    )/c

    dt_y = np.sqrt(
        (r*np.cos(theta) - y[0])**2 + (r*np.sin(theta) - y[1])**2
    )/c

    i_x = int(dt_x*fs)
    i_y = int(dt_y*fs)

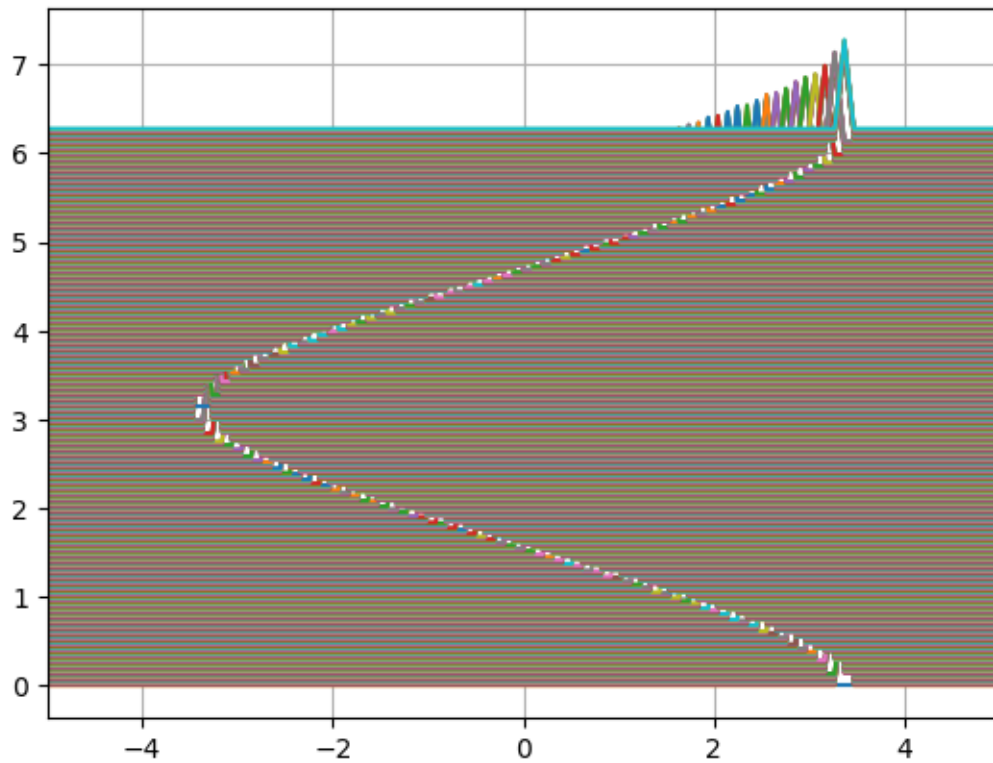
    n_x= np.zeros(len(t))
    n_x[ i_x:i_x+1]=1

    n_y= np.zeros(len(t))
    n_y[ i_y:i_y+1]=1
    Corr[i,:] = np.correlate(n_x,n_y,'full')
    plt.plot(
```

```

        tcorr,
        Corr[i,:]+theta
    )
    plt.xlim([-5,5])
plt.grid()

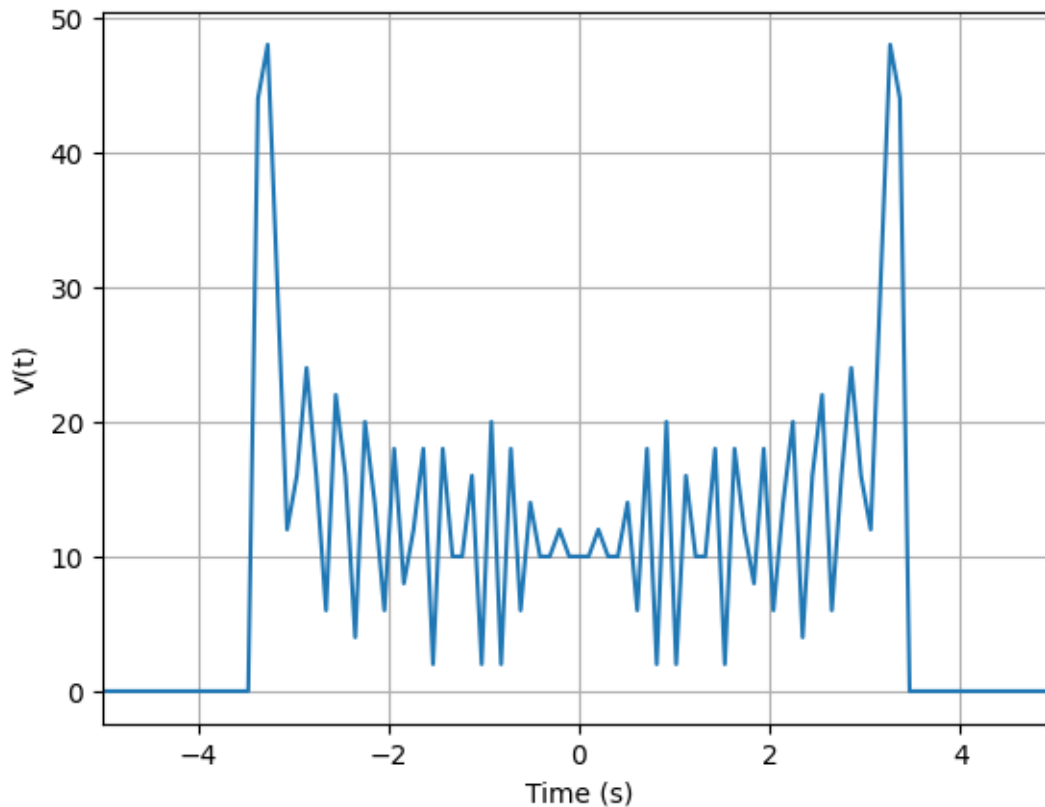
```



```

[15]: plt.plot(tcorr,np.sum(Corr,axis=0))
plt.xlim(-5,5)
plt.xlabel('Time (s)')
plt.ylabel('V(t)')
plt.grid()

```



## 1.2 B.)

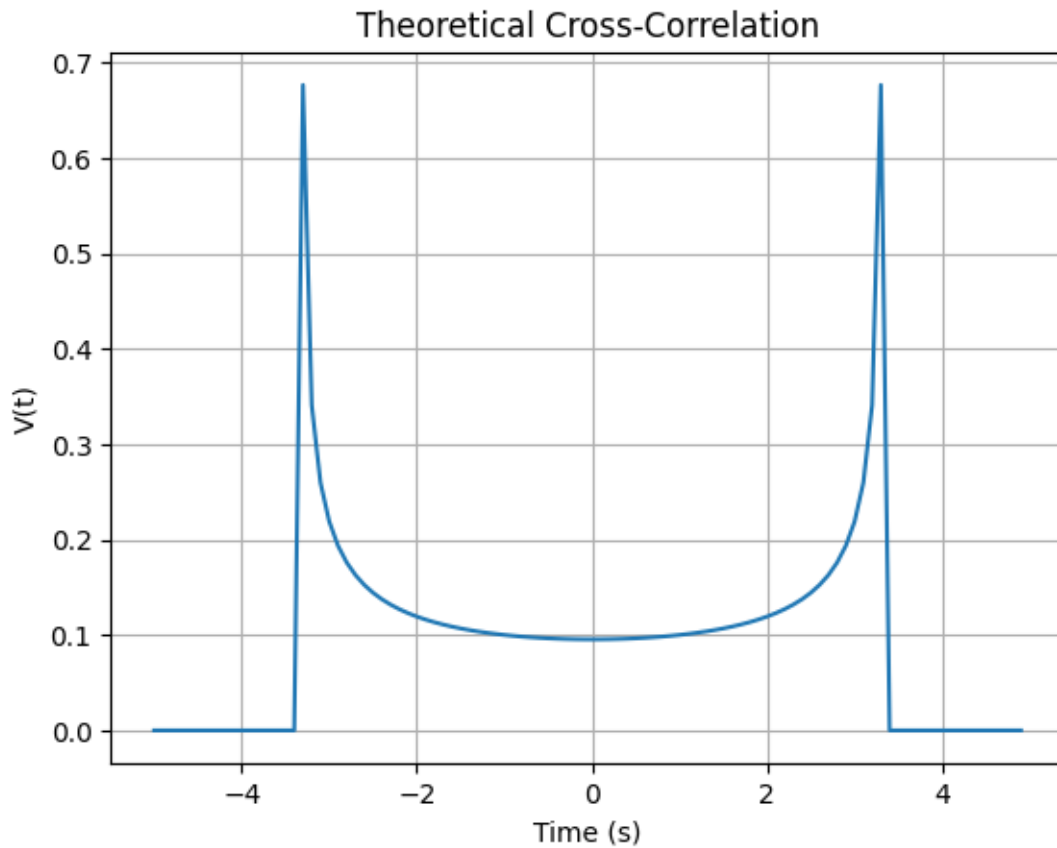
Show that your numerical integration results are consistent with equation 12.13 by plotting these analytical functions on the same plots. The equations in the books are:

```
[16]: v_t = []
for t in np.arange(-5, 5, 0.1):
    if abs(t) >= r/c:
        v = 0
    else:
        v = 1 / (np.pi * np.sqrt((r**2 / c**2) - t**2))
    v_t.append(v)
    # break
```

```
[17]: plt.plot(
    np.arange(-5,5,0.1),
    v_t
)
plt.title('Theoretical Cross-Correlation')
plt.xlabel('Time (s)')
plt.ylabel('V(t)')
```



```
plt.grid()
```



### 1.3 C.)

Perform partial integrations to look at the effects of imperfect noise source distributions. Only integrate from  $-\pi/4$  to  $\pi/4$ . This assumes that the sources are only from one side of the station axis. Can you comment on the cross-correlation, and discuss the possible issues that will arise in practical examples? Try with angles from  $\pi/4$  to  $3\pi/2$ , what do you notice?

```
[18]: N = 1000 # we will create N noise sources
      # initialize the cross correlations
      t = np.linspace(0,twin,int(twin*fs))

      Corr = np.zeros(shape=(N,len(tcorr)))
      for i in range(N):
          theta = -np.pi/(4)+i*1*np.pi/(2*N)
          # calculate the distance between each noise source and the receivers
          dt_x = np.sqrt(
              (r*np.cos(theta) - x[0])**2 + (r*np.sin(theta) - x[1])**2
          )/c
```

```

dt_y = np.sqrt(
    (r*np.cos(theta) - y[0])**2 + (r*np.sin(theta) - y[1])**2
)/c

i_x = int(dt_x*fs)
i_y = int(dt_y*fs)

n_x = np.zeros(len(t))
n_x[ i_x:i_x+1]=1

n_y= np.zeros(len(t))
n_y[ i_y:i_y+1]=1
Corr[i,:] = np.correlate(n_x,n_y,'full')
plt.plot(
    tcorr,
    np.sum(Corr,axis=0),
    'r-',
    label='-pi/4 to pi/4')

N = 1000
for i in range(N):
    theta = +0.25*np.pi+i*3*np.pi/(2*N)
    # calculate the distance between each noise source and the receivers
    dt_x = np.sqrt(
        (r*np.cos(theta) - x[0])**2 + (r*np.sin(theta) - x[1])**2
    )/c

    dt_y = np.sqrt(
        (r*np.cos(theta) - y[0])**2 + (r*np.sin(theta) - y[1])**2
    )/c

    i_x = int(dt_x*fs)
    i_y = int(dt_y*fs)

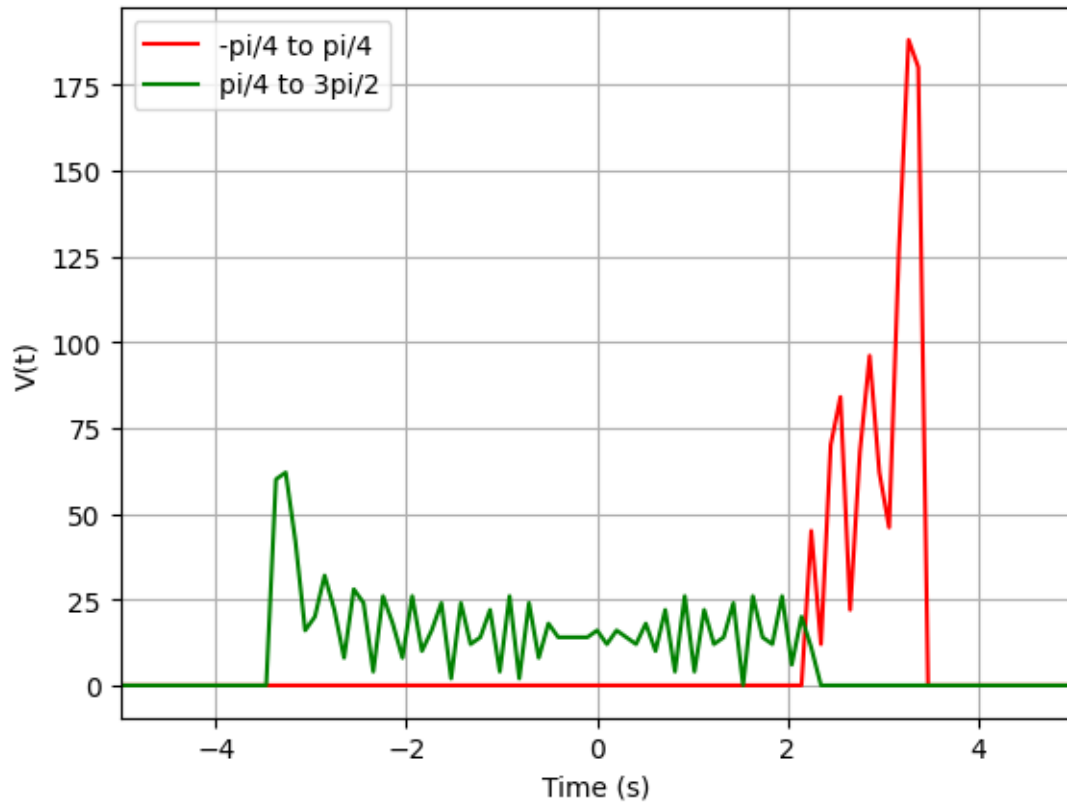
    n_x = np.zeros(len(t))
    n_x[ i_x:i_x+1]=1

    n_y= np.zeros(len(t))
    n_y[ i_y:i_y+1]=1
    Corr[i,:] = np.correlate(n_x,n_y,'full')
plt.plot(
    tcorr,
    np.sum(Corr,axis=0),
    'g-',
    label='pi/4 to 3pi/2'
)

```

```
plt.xlim([-5,5])
plt.xlabel('Time (s)')
plt.ylabel('V(t)')
plt.grid()
plt.legend()
```

[18]: <matplotlib.legend.Legend at 0x7f971758c340>



The correlations seem to be strongly dependant on location relative to source.

[ ]: