```
In [1]: import numpy as np
        from matplotlib import pyplot as plt
        import scipy as scipy
        from tqdm import tqdm
        from scipy.signal import find_peaks
```

Structure of notebook

Question 1

Question 2

Question 3

```
(this is just code plus some comments on the code)

** Initial parameters/ Data process
-------------------------
** Functions
-------------------------
** Code execution/ loops
-------------------------
```

Question 4

```
** Results/Comments
-------------------------
```

1. Question: Gaussian Case

The Gaussian model is given by: $d_i = \sum_{j=1}^{q} \frac{A_j}{\sqrt{2\pi} c_j} \exp\left[-\frac{(z_i - f_j)^2}{2c_j^2}\right]$

1. Partial derivative with respect to (A_p):

$$\frac{\partial g_i}{\partial A_p} = \frac{1}{\sqrt{2\pi} c_p} \exp\left[-\frac{(z_i - f_p)^2}{2c_p^2}\right]$$

2. Partial derivative with respect to (f_p):

$$\frac{\partial g_i}{\partial f_p} = \frac{A_p (z_i - f_p)}{\sqrt{2\pi} c_p^3} \exp\left[-\frac{(z_i - f_p)^2}{2c_p^2}\right]$$

3. Partial derivative with respect to (c_p):

$$\frac{\partial g_i}{\partial c_p} = \frac{A_p (z_i - f_p)^2}{\sqrt{2\pi} c_p^4} \exp\left[-\frac{(z_i - f_p)^2}{2c_p^2}\right]$$

2. Question: Lorentzian Case

The Lorentzian model is given by:

$$d_i = \sum_{j=1}^{q} \frac{A_j c_j^2}{(z_i - f_j)^2 + c_j^2}$$

1. Partial derivative with respect to (A_p):

$$\frac{\partial g_i}{\partial A_p} = \frac{c_p^2}{(z_i - f_p)^2 + c_p^2}$$

2. Partial derivative with respect to (f_p):

$$\frac{\partial g_i}{\partial f_p} = -\frac{2A_p(z_i - f_p)}{(z_i - f_p)^2 + c_p^2}$$

3. Partial derivative with respect to (c_p):

$$\frac{\partial g_i}{\partial c_p} = \frac{2A_p c_p (z_i - f_p)^2}{((z_i - f_p)^2 + c_p^2)^2}$$

3. Question

In [2]:
```
path = 'mars_soil.txt'
data = np.loadtxt(path)
np.shape(data)
```

Out[2]:
```
(512, 2)
```

The data are not so easy to work on the way they are, so I will flip them upside down and bring the "base" to zero

In [3]:
```
# offset
offset = data[0,1]              # add offset, so it's easier to fit later
print('offset:', offset)

# data
z = data[:,0]                        # Velocity, mm/s
ydata = -1*(data[:,1] - offset)      # Observed Data [counts]: add offset and flip
sigma_d = 0.03 * 10**4              # Uncertainty, observed data
```

```
offset: 12623.0
```

Functions

In [4]:
```
def gaussian(z, A, f, c):
    '''
    This function adds up the peaks that are considered to be Gaussian
    '''

    pi = np.pi
    gauss = np.zeros(len(z))
    for i in range(len(A)):
        gauss += (A[i]/(np.sqrt(2*pi)*c[i])) * np.exp(-(z-f[i])**2 / (2*c[i]**2))
    return gauss

def lorentzian(z, A, f, c):
    '''
    This function adds up the peaks that are considered to be lorentzian
    '''
    lorentz = np.zeros(len(z))

    for i in range(len(A)):
        lorentz += A[i]*c[i]**2/((z-f[i])**2 + c[i]**2)

    return lorentz
```

In [5]:
```python
def calc_g(M_, z_, gauss=True):
    '''
    Here we evaluate g_k(m_k) by looping over the number of peaks

    returns a 1 x 512 array
    '''
    z, M = z_.copy(), M_.copy()
    l = int(len(M)/3)
    A, f, c = unpack(M)

    pi = np.pi
    g = np.zeros(len(z))

    for i in range(l):
        if gauss:
            g += (A[i]/(np.sqrt(2*pi)*c[i])) * np.exp(-(z-f[i])**2 / (2*c[i]**2))
        else:
            g += A[i]*c[i]**2/((z-f[i])**2 + c[i]**2)

    return g
```

In [6]:
```python
def calc_Cd(data_, s_d):
    '''
    Correlation of data
    returns  a 512 x 512 array
    '''
    l = len(data_)
    cov_d = np.eye(l) * s_d
    return cov_d
```

In order to test how much we are fitting on the data we have we re going ot use χ^2

In [7]:
```python
def chi_square(data, comp_data, s_d):
    chi_square = np.sum( (data - comp_data)/s_d)**2
    return chi_square
```

In [8]:
```python
def prior(A, f, c):
    '''
    In this function I take all the parameters and combine into the prior parameters.
    '''
    M_prior = []
    for i in range(len(A)):
        M_prior.append(A[i])
        M_prior.append(f[i])
        M_prior.append(c[i])

    return np.array(M_prior)

def unpack(M):
    '''
    In this function I just unpack the prior into the parameters
    '''
    return M[0::3], M[1::3], M[2::3]
```

In [9]:
```
ef gaussian_derivatives(M, q, z):
    '''
    This function calculates the derivatives for the Gaussian function
    '''
    if q>19:    # in case
        print('Warning, q exceeds number of parameters in M')

    pi = np.pi
    A = M[q*3]
    f = M[1+q*3]
    c = M[2+q*3]

    diff_A = (1/(np.sqrt(2*pi)*c)) * np.exp(- (z-f)**2 / (2*c**2))
    diff_f = (A/(np.sqrt(2*pi)*c)) * ((z-f)/(c**2)) * np.exp(-(z-f)**2 / (2*c**2))
    diff_c = -(A/(np.sqrt(2*pi)*c**2)) * np.exp(-(z-f)**2 /(2*c**2))  +  (A/(np.sqrt(2*pi)*c

    return diff_A, diff_f, diff_c

ef lorentzian_derivatives(M, q, z):
    '''
    This function calculates the derivatives for the Lorentzian function
    '''
    A = M[0+q*3]
    f = M[1+q*3]
    c = M[2+q*3]

    diff_A = c**2/((z-f)**2 + c**2)
    diff_f = A*c**2/((z-f)**2 + c**2)**2 * 2 * (z-f)
    diff_c = 2*A*c/((z-f)**2 + c**2) - 2*A*c**3/(((z-f)**2 + c**2)**2)

    return diff_A, diff_f, diff_c
```

In [10]:
```
def calc_G(M, z, gauss=True):

    l = len(M)                  # 60

    if gauss:
        for i in range(int (l/3) ):
            diff = np.array(gaussian_derivatives(M, i, z))
            if i == 0:
                G = diff
            else:
                G = np.vstack((G, diff))

    else:
        for i in range(int (l/3) ):
            diff = np.array(lorentzian_derivatives(M, i, z))

            if i == 0:
               G = diff
            else:
               G = np.vstack((G, diff))

    G = G.T
    return G
```

In [11]:
```
def calc_Cm(M_, gauss_, s_Ag, s_fg, s_cg, s_Al, s_fl, s_cl):
    '''
    Evaluate model Covariance Matrix, C_m
    '''
    M = M_.copy()
    descr = unpack(M)
    A, f, c = descr[0], descr[1], descr[2]

    if gauss_:
        sA = s_Ag*A
        sf = np.abs(s_fg*f)
        sc = s_cg*c
    else:           # Lorentzian
        sA = s_Al*A
        sf = np.abs(s_fl*f)
        sc = s_cl*c

    C_m = np.zeros((60,60))
    diag = []

    for i in range(len(A)):
        diag.append(sA[i]**2)
        diag.append(sf[i]**2)
        diag.append(sc[i]**2)

    np.fill_diagonal(C_m, diag)
    return C_m
```

In [12]:
```
def calc_eps(C_m, G, C_d, g_m, d_obs, M_, M_prior_):
    '''
    Evaluate epsilon at each step
    '''
    M, M_prior = M_.copy(), M_prior_.copy()

    gamma = C_m @ G.T @ np.linalg.inv(C_d) @ (g_m - d_obs) + M - M_prior

    eps = (gamma.T @ np.linalg.inv(C_m) @ gamma) / (gamma.T @ (G.T @ np.linalg.inv(C_d) @ (
    return eps
```

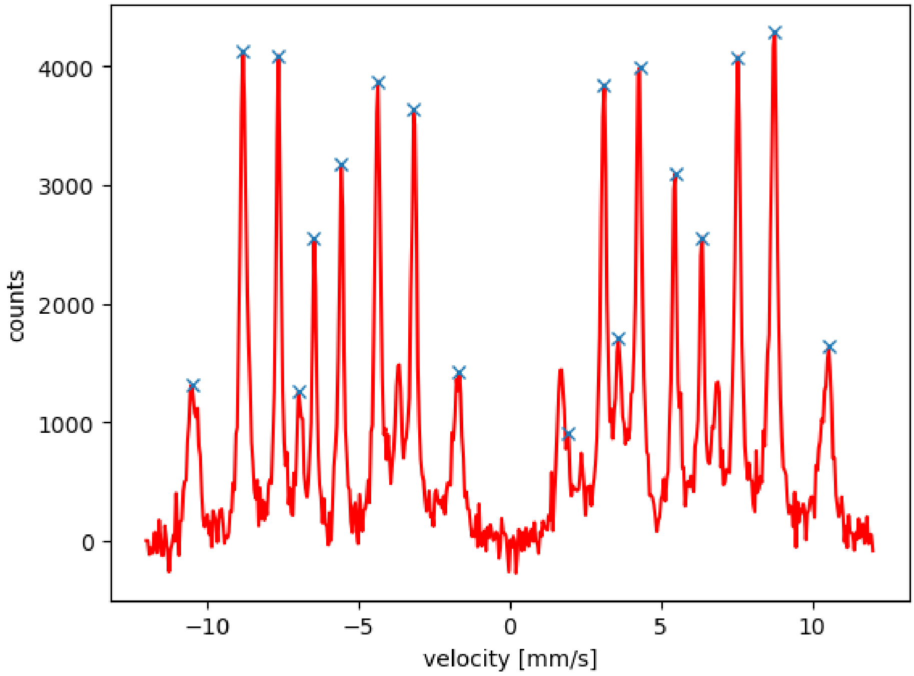
In [13]:
```
def update_m(M_, M_prior_, z, d_obs_, C_d, gauss_):
    M, M_prior, d_obs = M_.copy(), M_prior_.copy(), d_obs_.copy()

    G = calc_G(M, z, gauss=gauss_)
    g = calc_g(M, z, gauss=gauss_)
    C_m = calc_Cm(M, gauss_,s_Ag, s_fg, s_cg, s_Al, s_fl, s_cl)
    eps = calc_eps(C_m, G, C_d, g, d_obs, M, M_prior)

    M_new = M - eps*(C_m @ G.T @ np.linalg.inv(C_d) @ (g - d_obs) + (M - M_prior))
    return M_new, eps, M_new - M
```

Code execution

finding the peaks

I will use the "find_peaks" function to estimate the height of the gaussians

In [14]:
```
peaks, _ = find_peaks(ydata, height=900,threshold=30, distance=10)
y_peaks =  z[peaks]
x_peaks = peaks

## Plot data
plt.plot(z, ydata, 'r', label='data')   # plot of data
# amplitude plot: Ampl.

plt.plot(z[peaks], ydata[peaks], "x")

plt.xlabel('velocity [mm/s]')
plt.ylabel('counts')
plt.show()
```



In [15]:
```
ydata[peaks]
```

Out[15]:
```
array([1315., 4127., 4093., 1255., 2548., 3174., 3875., 3639., 1420.,
        908., 3846., 1705., 3988., 3098., 2557., 4081., 4293., 1635.])
```

The result of the function find_peaks is not that bad, it will be used for getting the heights of a good amount of the peaks. I added 100 as the peaks don't start at the absolute 0. The ones that are not detected by the code will be eyballed

Starting with the Gaussian Prior

I start by guestimating the parameters for the gaussian model.

In [16]:
```
# Heights for each gaussian peak:
heights = [1415, 4227, 4193, 1355, 2648, 3274, 3975,  1520,3739, 1520, 1150, 3946, 1805, 4
# Mean estimates, for peaks
fs = [-10.50, -8.8, -7.65, -7.0, -6.5, -5.65, -4.4, -3.7, -3.2, -1.75, 1.65, 3.05, 3.6, 4.
# Widths: c
cs = np.array([0.85, 0.6, 0.5, 0.2, 0.3, 0.7, 0.6, 0.2, 0.6, 0.7, 0.6, 0.5, 0.4, 0.6, 0.6,
```

Next, I evaluate the initial values and the uncertainties that will be used for the parameterrs. They are of course 100% eyballed apart from the heights as I explained before

In [17]:
```
s_f0 = 0.25
cs[np.argwhere(cs<0.1)] = 0.1
s_c0 = 0.1
s_c = cs * s_c0
```

In [18]:
```
As = heights * cs * (np.sqrt(2*np.pi))
s_amp = 50/heights[0]
print('s_amp:', s_amp)

# uncertainty on area:
k = 0
s_A = np.sqrt((heights[k]*(1/np.sqrt(2*np.pi)))**2 * s_c**2 +  (cs[k]*(1/np.sqrt(2*np.pi))
s_A0 = 6*s_A / As[0]
```

```
s_amp: 0.0353356890459364
```

In [19]:
```
A = 1.5*As
# A = 1.8*A_
c = 1.5*cs # x1.5
f = fs

# for plot later
gauss_ = gaussian(z, A, f, c)
```

The prior i wouldn't say that is that bad and the uncertainty seems to contain the data so I believe it is more than enough to start applying the ypdate function.

Now for the Lorentzian Prior

as before I will guestimate the parameters

In [20]:
```
# Area
A_lor = (A.copy())
# A_lor = 1.2* (A.copy())
A_lor[0] = 1200
A_lor[1] = 3900
A_lor[2] = 4000
A_lor[3] = 1000
A_lor[4] = 2500
A_lor[5] = 3000
A_lor[6] = 3800
A_lor[7] = 1200
A_lor[8] = 3800
A_lor[9] = 1500
A_lor[-1] = 1700
A_lor[-2] = 4100
A_lor[-3] = 3800
A_lor[-4] = 1000
A_lor[-5] = 2400
A_lor[-6] = 3000
A_lor[-7] = 3800
A_lor[-8] = 1200
A_lor[-9] = 4000
A_lor[-10] = 1200
s_A1 = 2*200 / A_lor[1]

f_lor = f.copy()
s_f1 = s_f0

# widths
c_lor = 0.6*c
c_lor[0] = 0.17
s_c1 = 0.04/c_lor[0]
# for plot later
lor0 = lorentzian(z, A_lor, f_lor, c_lor)
```

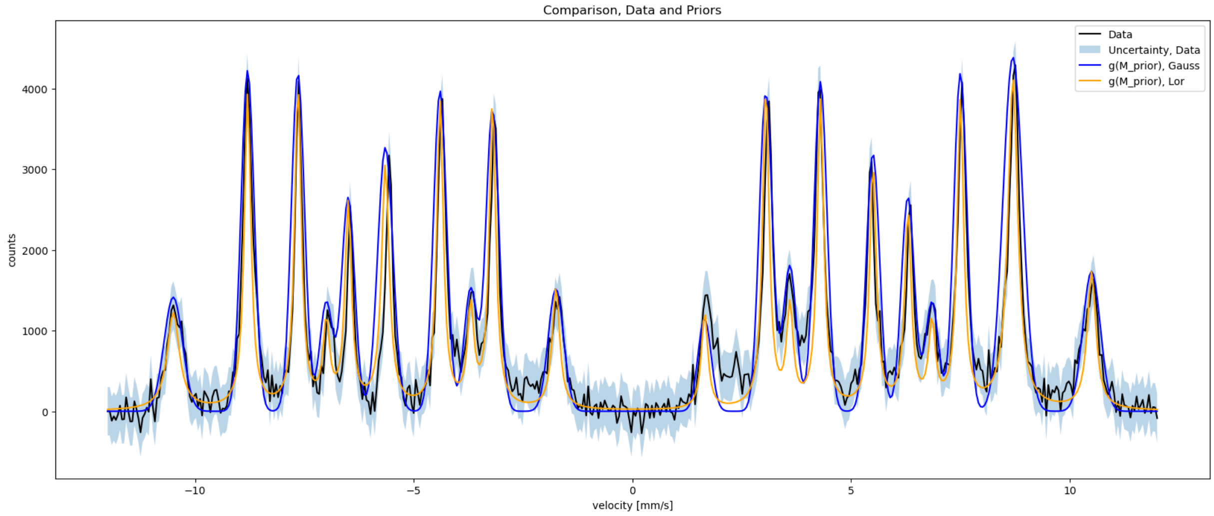
In [21]:
```
# Chi Square, Priors
chi_pr1 = chi_square(ydata, gauss_, sigma_d)
chi_pr2 = chi_square(ydata, lor0, sigma_d)
print('Prior, gauss:', chi_pr1, ', Lorentzian:', chi_pr2)
print('Chi2 / DOF, gauss:', chi_pr1 / 452, ', Lorentzian:', chi_pr2 / 452)
```

```
Prior, gauss: 69697.79963828469 , Lorentzian: 52052.93218164368
Chi2 / DOF, gauss: 154.19867176611658 , Lorentzian: 115.16135438416742
```

It seems by calculating χ^2 that the lorentzian prior is slightly better then the gaussian, but of course this changes according to the estimations that I make.

In [22]:
```
# Plot Both Priors below

plt.figure(figsize = (20,8))
plt.plot(z, ydata, 'k-', label='Data')  # plot data
plt.fill_between(z, ydata - sigma_d, ydata + sigma_d, alpha=0.3, label='Uncertainty, Data'
plt.plot(z, gauss_, 'b-', markersize='5', label='g(M_prior), Gauss')
plt.plot(z, lor0, 'orange', linestyle='-', label='g(M_prior), Lor')
plt.title('Comparison, Data and Priors')
plt.xlabel('velocity [mm/s]')
plt.ylabel('counts')
plt.legend()
```

Out[22]: <matplotlib.legend.Legend at 0x12f396a70>



Starting with loop

In [23]:
```
G = calc_G(prior(A_lor, f_lor, c_lor), z, False)
test_Cd = calc_Cd(ydata, sigma_d)
C_d = calc_Cd(ydata, sigma_d)

s_Ag=s_A0
s_fg=s_f0
s_cg=s_c0
s_Al=s_A1
s_fl=s_f1
s_cl=s_c1

C_m = calc_Cm(prior(A, f, c), True,s_Ag, s_fg, s_cg, s_Al, s_fl, s_cl)
```

In [24]:
```
# test run
M_prior = prior(As,fs,cs)
eps = calc_eps(C_m, G, C_d, gauss_, ydata, M_prior, M_prior)
print('initial value epsilon:', '\n', eps)
```

```
initial value epsilon:
 4.9924901628402934e-08
```

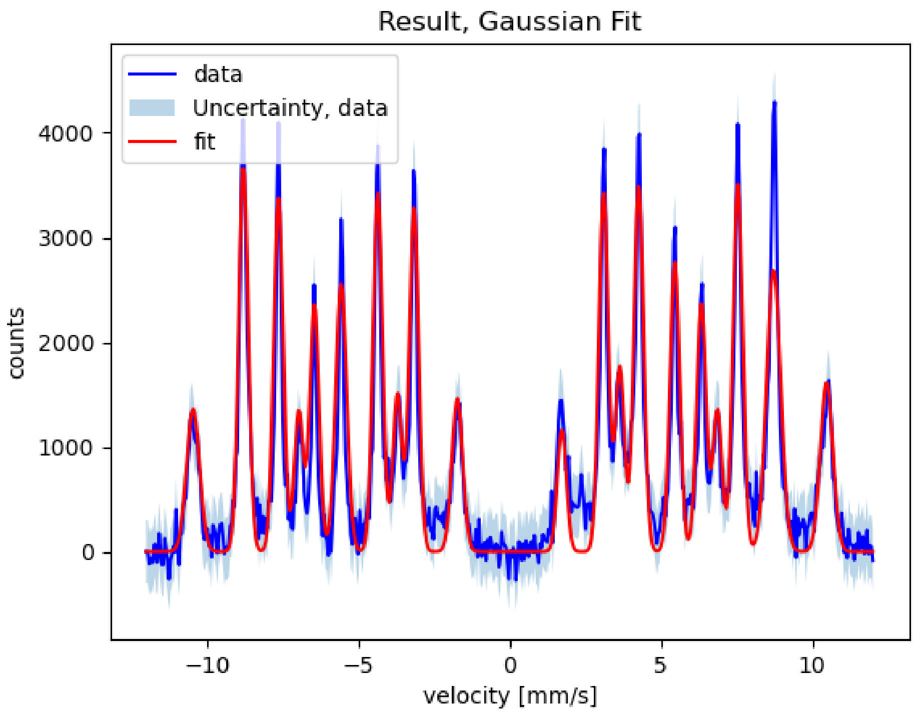
In [25]:
```python
def run_M(M_init, M_prior_, z_, d_obs_, C_d, gauss, max_N=1000, converge=1e-08):
    M_prior, z, d_obs = M_prior_.copy(), z_.copy(), d_obs_.copy()

    M_new = M_init.copy()
    eps_list = []
    k = 0

    total_iterations = max_N
    progress_bar = tqdm(total=total_iterations, desc="Processing")

    # Run
    while k < max_N:
        upd = update_m(M_new, M_prior, z, d_obs, C_d, gauss)
        M_new = upd[0]
        eps_list.append(upd[1])

        k += 1
        progress_bar.update(1)

    return M_new, upd[1], upd[2], k, eps_list
```

In [26]:
```python
test_run = run_M(prior(A, f, c), prior(A, f, c), z, ydata, C_d, True)
```

```
Processing: 100%|██████████| 1000/1000 [00:29<00:00, 34.37it/s]
```

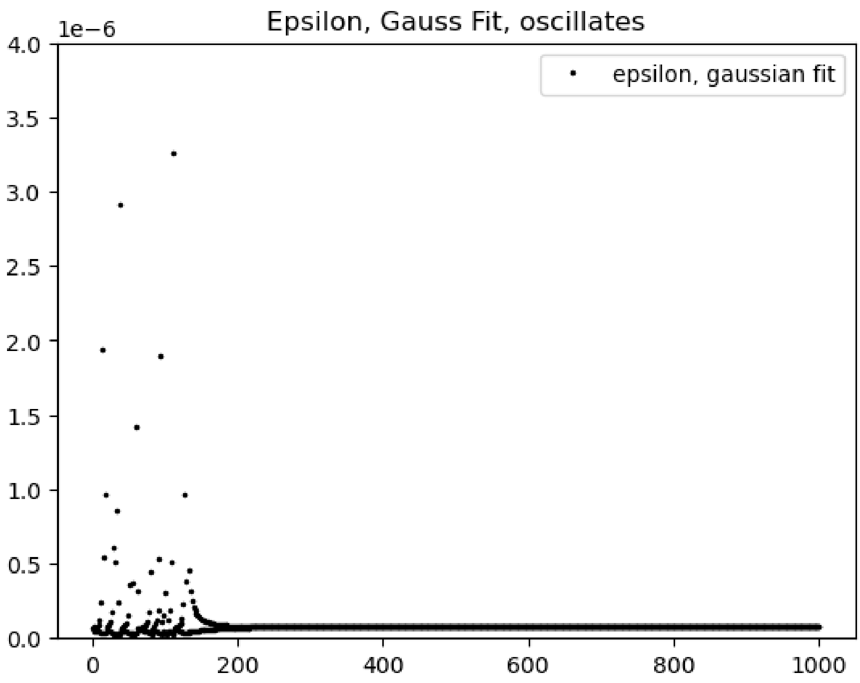
Plot Gaussian Fit

In [27]:
```python
M = test_run[0]

descr1 = unpack(M)
A1, f1, c1 = descr1[0], descr1[1], descr1[2]

fit_gauss = calc_g(M, z, gauss=True)

# plot
plt.figure()
plt.plot(z, ydata, 'b', label='data')       # Data
plt.fill_between(z, ydata - sigma_d, ydata + sigma_d, alpha=0.3, label='Uncertainty, data'
plt.plot(z, fit_gauss, 'r', label='fit')
plt.title('Result, Gaussian Fit')
plt.legend()
plt.xlabel('velocity [mm/s]')
plt.ylabel('counts')
plt.show()
```



In [28]:
```python
# Check epsilon
np.shape(test_run[-1])

eps1 = test_run[-1]
plt.figure()
plt.plot(np.linspace(1, len(eps1), len(eps1)), eps1, 'k.', markersize=3, label='epsilon, ga
plt.title('Epsilon, Gauss Fit, oscillates')
plt.ylim(0, 4e-06)
plt.legend()
```

Out[28]:
```
<matplotlib.legend.Legend at 0x12f4a15a0>
```



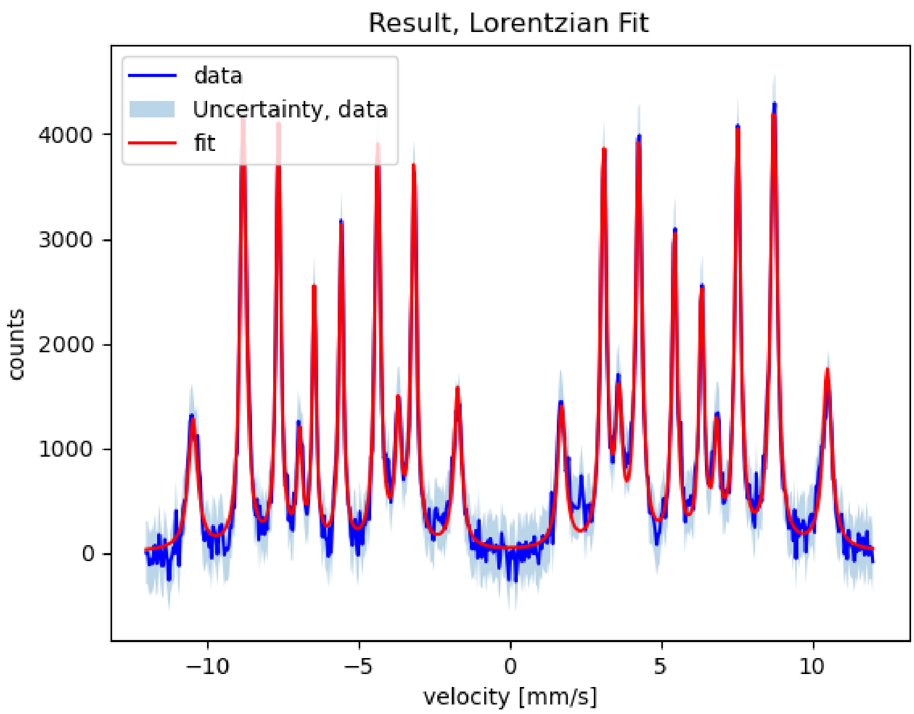
Lorentzian Fit

In [29]:
```python
result_lor =  run_M(prior(A_lor, f_lor, c_lor), prior(A_lor, f_lor, c_lor), z, ydata, C_d,

print('epsilon:', result_lor[1])            # last epsilon
print('norm, result - data:', np.linalg.norm(calc_g(result_lor[0], z, gauss=False) - ydata
np.linalg.norm(result_lor[-2])            # norm  of residual m_k+1 - m_k, is < +1e-07...
```

```
Processing: 100%|██████████████████████████| 1000/1000 [00:31<00:00, 31.52it/s]

epsilon: 3.4586444647130987e-07
norm, result - data: 3021.56266034863
```

Out[29]:
```
1000.0
```

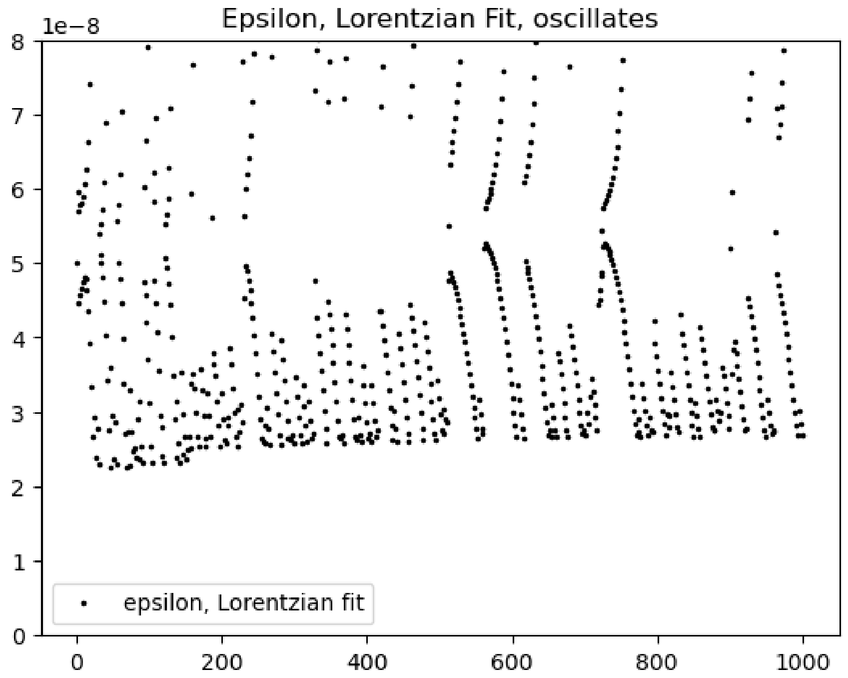
In [30]:
```python
# Plot Results
M_l = result_lor[0]

descr2 = unpack(M_l)
A2, f2, c2 = descr2[0], descr2[1], descr2[2]
f2[5] = f1[5]
M_l = prior(A2, f2, c2)
# print('f1:', f1)
# print('f2:', f2)

    # Plot Result

fit_lor = calc_g(M_l, z, gauss=False)

# plot
plt.figure()
plt.plot(z, ydata, 'b', label='data')       # Data
plt.fill_between(z, ydata - sigma_d, ydata + sigma_d, alpha=0.3, label='Uncertainty, data'
plt.plot(z, fit_lor, 'r', linestyle='-', label='fit')

plt.title('Result, Lorentzian Fit')
plt.legend()
plt.xlabel('velocity [mm/s]')
plt.ylabel('counts')
plt.show()

# Lorentzian Chi square
chi_sq_lor_ = chi_square(ydata, fit_lor, sigma_d)
print('chi sq, Lor:', chi_sq_lor_)
```




```
chi sq, Lor: 3.9241587295253355
```

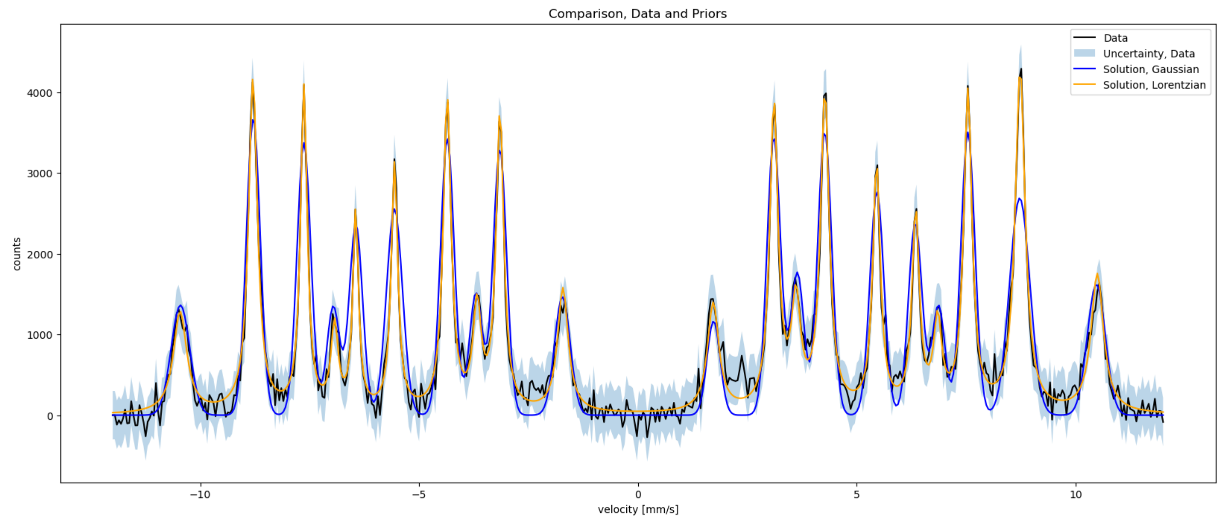
In [31]:
```
eps2 = result_lor[-1]
np.shape(eps2)

plt.figure()
plt.plot(np.linspace(1, len(eps2), len(eps2)), eps2, 'k.', markersize=3, label='epsilon, Lo
plt.title('Epsilon, Lorentzian Fit, oscillates')
plt.ylim(0, 8e-8)
plt.legend()
```

Out[31]: <matplotlib.legend.Legend at 0x12f5ff430>



In [32]:
```
# Final Result

# Plot Fits below
plt.figure(figsize = (20,8))
plt.plot(z, ydata, 'k-', label='Data')  # plot data
plt.fill_between(z, ydata - sigma_d, ydata + sigma_d, alpha=0.3, label='Uncertainty, Data'
plt.plot(z, fit_gauss, 'b-', markersize='5', label='Solution, Gaussian')    # Fit, Gaussiai
plt.plot(z, fit_lor, 'orange', linestyle='-', label='Solution, Lorentzian')      # Fit, Lo
plt.title('Comparison, Data and Priors')
plt.xlabel('velocity [mm/s]')
plt.ylabel('counts')
plt.legend()
```

Out[32]: <matplotlib.legend.Legend at 0x12f705ab0>



4. Question. Results

Tryibng to somewhat judge quantitatively I tried to use the χ^2 values

In [33]:
```
print("           x^2 values")
print("     ------Posteriori-------")
# gaussian Chi square
chi_sq_gauss = chi_square(ydata, fit_gauss, sigma_d)

# Lorentzian Chi square
chi_sq_lor = chi_square(ydata, fit_lor, sigma_d)
print('Gauss:,', chi_sq_gauss, ', Lorentzian:', chi_sq_lor)

print("     ------Prior-------")

# Chi Square, Priors
chi_pr1 = chi_square(ydata, gauss_, sigma_d)
chi_pr2 = chi_square(ydata, lor0, sigma_d)
print('Gauss:,', chi_pr1, ', Lorentzian:', chi_pr2)
```

```
           x^2 values
     ------Posteriori-------
Gauss:, 6899.217847566544 , Lorentzian: 3.9241587295253355
     ------Prior-------
Gauss:, 69697.79963828469 , Lorentzian: 52052.93218164368
```

In [34]:
```
# p-test
# scipy.stats.chi2.sf(chi2 value, NDOF)
ndof = 452
p1 = scipy.stats.chi2.sf(chi_sq_gauss, ndof)           # estimate p-values
p2 = scipy.stats.chi2.sf(chi_sq_lor, ndof)

print('p1:', p1)
print('p2:', p2)
```

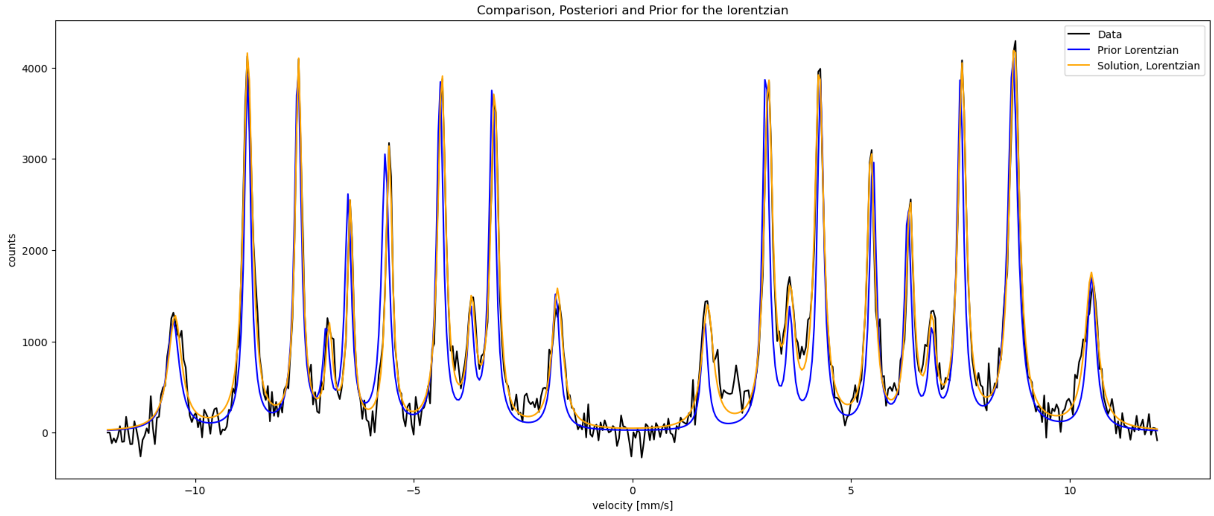
```
p1: 0.0
p2: 1.0
```

the p-values can't be trusted as I would prefer avalue in between 0 and 1 and not 0 or 1. Eitherway, it seems that the Gaussian is far from reality and the lorentzia is too good to be true.

Lorentzian: Initial and result

In [35]:
```
# Lorentzian Fits below
plt.figure(figsize = (20,8))
plt.plot(z, ydata, 'k-', label='Data')  # plot data
plt.plot(z, lor0, 'b-', markersize='5', label='Prior Lorentzian')
plt.plot(z, fit_lor, 'orange', linestyle='-', label='Solution, Lorentzian')
plt.title('Comparison, Posteriori and Prior for the lorentzian')
plt.xlabel('velocity [mm/s]')
plt.ylabel('counts')
plt.legend()
```

Out[35]: <matplotlib.legend.Legend at 0x12f7b1720>

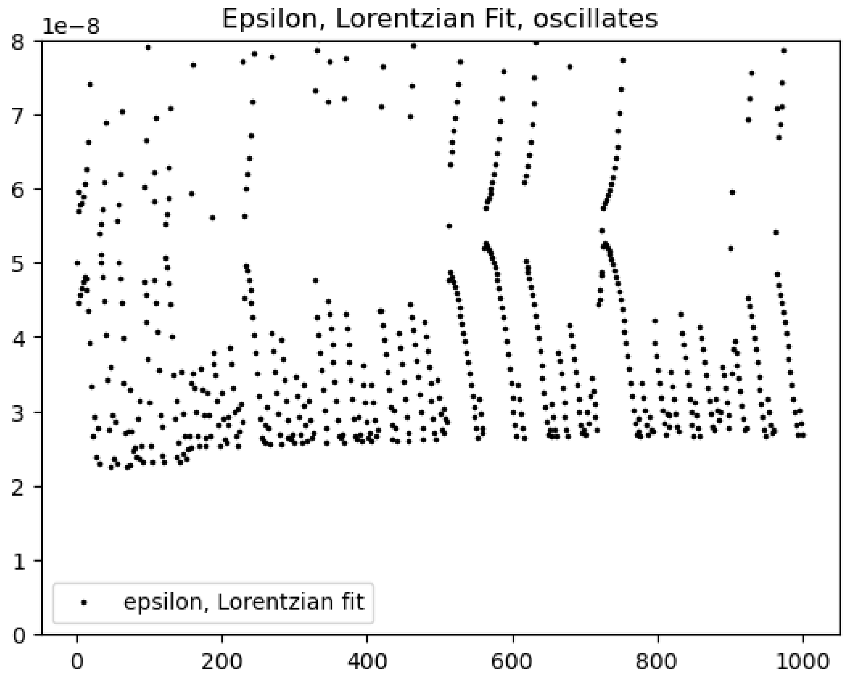


The plot above shows the lorentzian fit before and after the process. It is quite clear that the fitting is much better than the initial one as the top of the points are where the should be and also the valeys seem to be better

In [36]:

```
eps2 = result_lor[-1]       # 302 iterations
np.shape(eps2)

plt.figure()
plt.plot(np.linspace(1, len(eps2), len(eps2)), eps2, 'k.', markersize=3, label='epsilon, Lo
plt.title('Epsilon, Lorentzian Fit, oscillates')
plt.ylim(0, 8e-8)
plt.legend()
```

Out[36]: <matplotlib.legend.Legend at 0x12f6724a0>

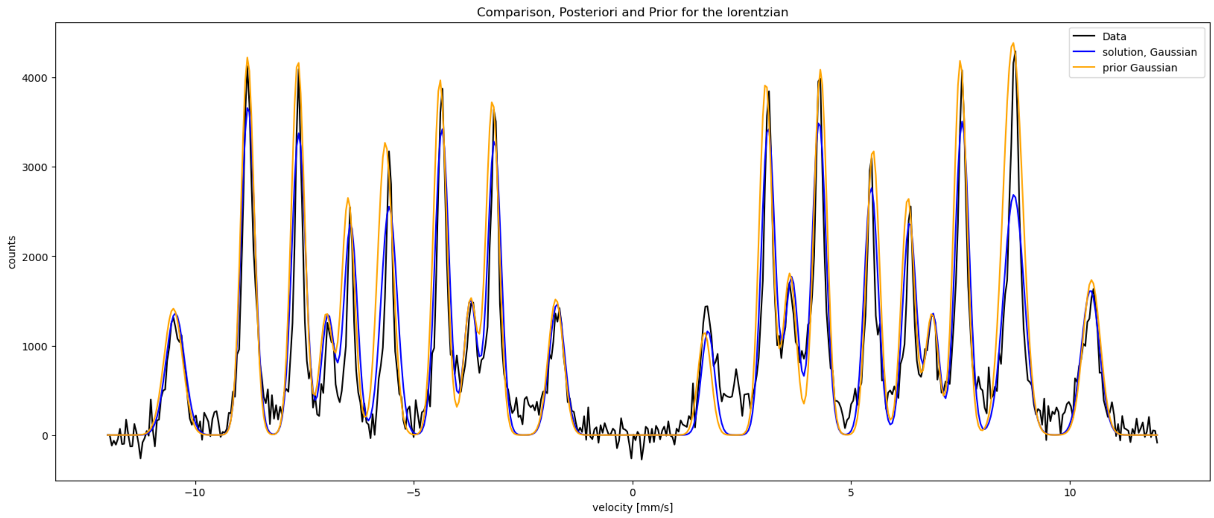


also, judging from the epsilon it seems that is resonating over a quite small value which seems some kind of conversion. From the other side i would expect in the first steps to have a higher value and as my initial fit was not as good as the solution

Gaussian: Initial and result

In [37]:
```
# Lorentzian Fits below
plt.figure(figsize = (20,8))
plt.plot(z, ydata, 'k-', label='Data')  # plot data
plt.plot(z, fit_gauss, 'b-', markersize='5', label='solution, Gaussian ')
plt.plot(z, gauss_, 'orange', linestyle='-', label='prior Gaussian')
plt.title('Comparison, Posteriori and Prior for the lorentzian')
plt.xlabel('velocity [mm/s]')
plt.ylabel('counts')
plt.legend()
```

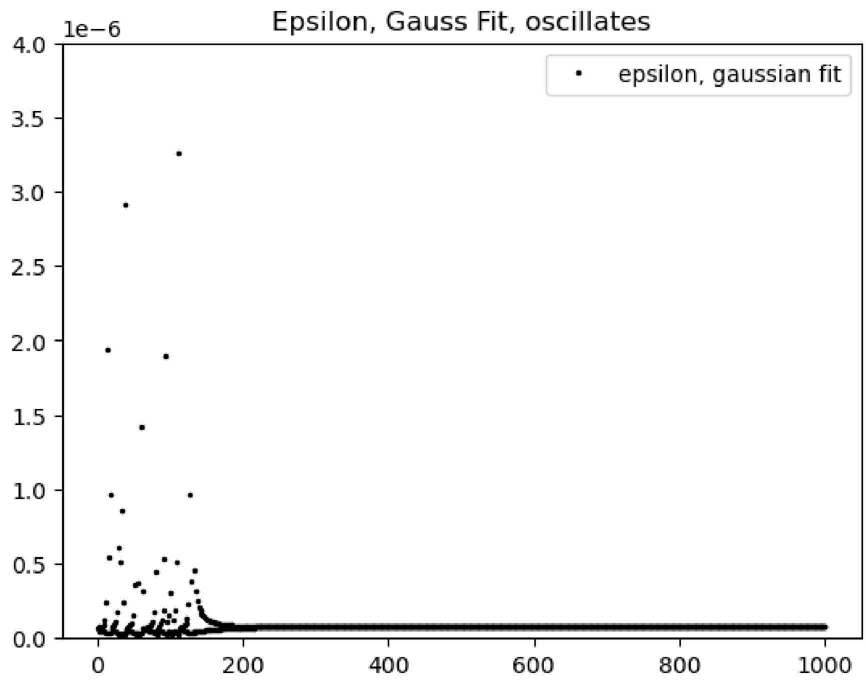
Out[37]:
```
<matplotlib.legend.Legend at 0x12f4a18d0>
```



In that case it seems that the gaussian turns to be get worse and worse even though i tried more than 10000 iterations

In [38]:
```python
# Check epsilon
np.shape(test_run[-1])

eps1 = test_run[-1]
plt.figure()
plt.plot(np.linspace(1, len(eps1), len(eps1)), eps1, 'k.', markersize=3, label='epsilon, ga
plt.title('Epsilon, Gauss Fit, oscillates')
plt.ylim(0, 4e-06)
plt.legend()
```

Out[38]: <matplotlib.legend.Legend at 0x12f51d630>

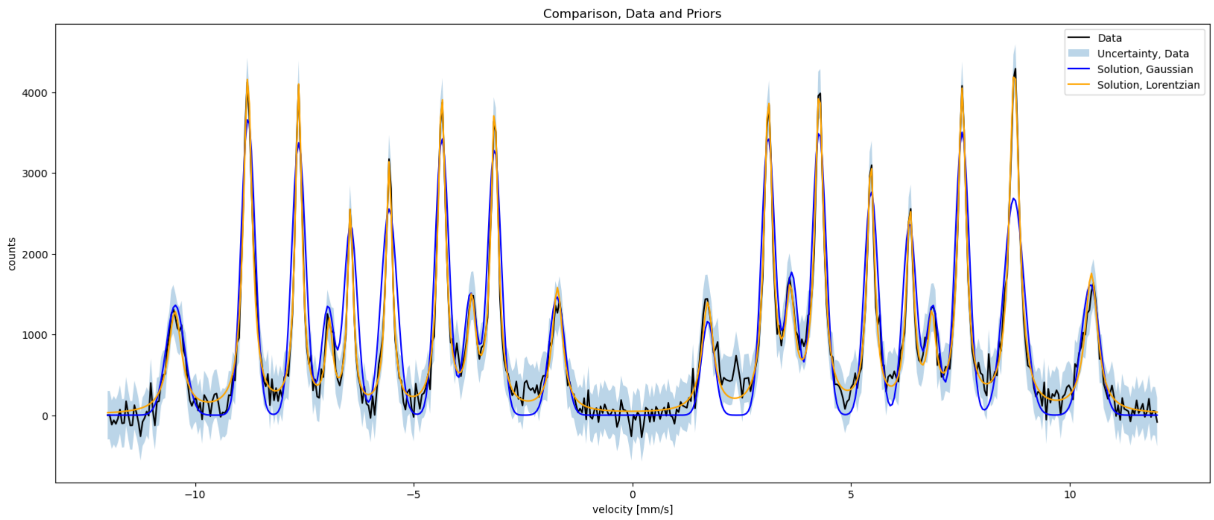


This epsilon looks more to something that I would predict, a value converging towards a value starting from high. As I mentioned earlier the gaussian initial fit was abit worse than the gaussians so this could explain the high values of epsilon at the first steps

Combined results

In [39]:
```
# Final Result

# Plot Fits below
plt.figure(figsize = (20,8))
plt.plot(z, ydata, 'k-', label='Data')  # plot data
plt.fill_between(z, ydata - sigma_d, ydata + sigma_d, alpha=0.3, label='Uncertainty, Data'
plt.plot(z, fit_gauss, 'b-', markersize='5', label='Solution, Gaussian')
plt.plot(z, fit_lor, 'orange', linestyle='-', label='Solution, Lorentzian')
plt.title('Comparison, Data and Priors')
plt.xlabel('velocity [mm/s]')
plt.ylabel('counts')
plt.legend()
```

Out[39]: <matplotlib.legend.Legend at 0x12f51d270>



To conclude, judging from the plot above which includes the results for the lorentzian and the Gaussian model, it seems that the lorentzian fits our data much better even though the initial fit seemed to beet for the gaussian.