In [1]:

```
import pandas as pd
import numpy as np
from matplotlib import pyplot as plt
import scipy as sp
```

Signal Analysis of Day to Day Mood

Functions

In [2]:

```
def fourier_transform(t, y):
    """ Take the fourier transform of a signal, rescale and provide a frequency
        for easy plotting
    """
    total_time = float(t[-1] - t[0])
    N = len(y)
    xf = np.arange(N)/ (total_time)
    yf = sp.fft.fft(y) / N
    # Take half of the dfft and multiply by 2 because it is a mirror image
    yf = 2*np.abs(yf[:N//2])
    xf = xf[:N//2]
    return xf, yf

def nans_to_lines(y):
    """ This function fills in nans in time series data by find valid points
    that bookend a given series of nans, then replacing the nans with a line bet
    It also trims leading/trailing nans.
    """
    m = len(y)
    clean_y = np.zeros(m)
    i = 0
    nani = 0
    a = 0
    b = 0
    found_nan = False
    # Count initial nans
    initnan = 0
    if np.isnan(y[0]):
        while np.isnan(y[initnan]):
            initnan += 1
    i = initnan
    for i in range(m):
        if np.isnan(y[i]) and not found_nan:
            a = y[i-1]
            nani = i
            found_nan = True
        if ~np.isnan(y[i]) and found_nan:
            b = y[i]
            clean_y[i] = b
            clean_y[nani:i] = np.linspace(a, b, i - nani + 2)[1:-1]
            found_nan = False
        else:
            clean_y[i] = y[i]
    return clean_y[initnan:nani] # Remove training nans

def autocorr(y):
```

```
    """ Autocorrelation of a signal. Algorithm taken from:
        https://www.itl.nist.gov/div898/handbook/eda/section3/eda331.htm
    """
    mu = np.mean(y)
    N = len(y)
    auto = np.zeros(N)
    for h in range(N):
        auto[h] = np.sum((y[:N - h] - mu) * (y[h:] - mu)) / N
    var = np.sum((y - mu)**2)/N
    return auto/var

def randblue():
    return [.2*np.random.rand(), np.random.rand(), 0.18 * np.random.rand() + .8]

def randgreen():
    return [.5*np.random.rand(), .2*np.random.rand() + 0.8, 0.5 * np.random.rand
```

In [3]:

```
EMA = pd.read_csv("/Users/djpassey/Data/Muri/SHINE_EMA_Round1_19May2020.csv")
moods = []
for pid in pd.unique(EMA.ID):
    m = EMA.PositiveMood[EMA.ID == pid]
    mood_points = list(m[0::2])
    moods.append(mood_points)
M = np.array(moods)

neg_moods = []
for pid in pd.unique(EMA.ID):
    m = EMA.NegativeMood[EMA.ID == pid]
    mood_points = list(m[0::2])
    neg_moods.append(mood_points)
nM = np.array(neg_moods)
```

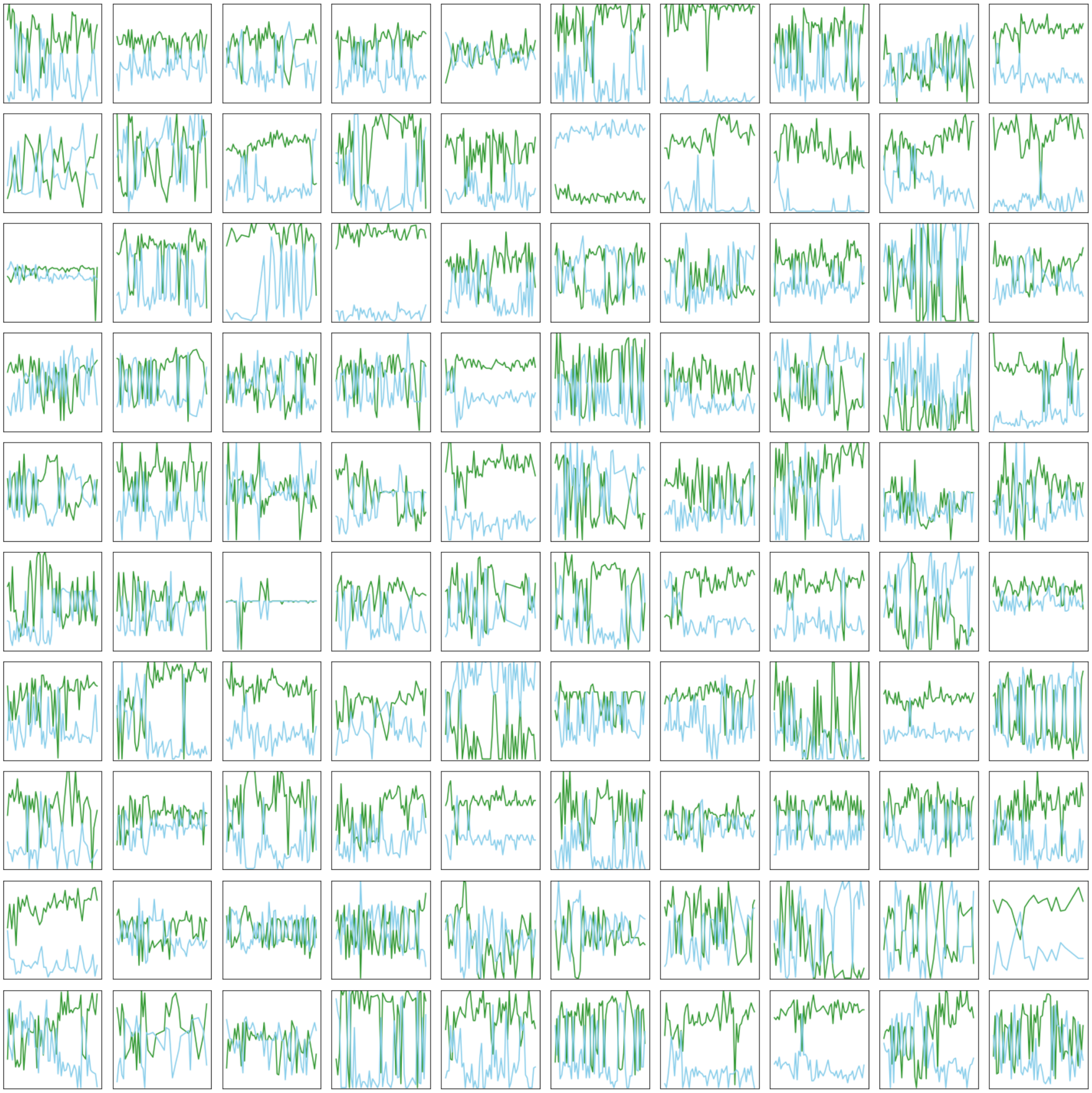
100 Mood Curves from the EMA Data

Posive mood in green, negative mood in blue

In [4]:

```
plt.rcParams["figure.figsize"] = [20, 20]

skip = [3]
offset = 0
for i in range(100 + len(skip)):
    if i + offset in skip:
        offset += 1
    else:
        plt.subplot(10,10,i + 1 - offset)
        plt.plot(nans_to_lines(M[i + offset]), c="green", alpha=0.8)
        plt.plot(nans_to_lines(nM[i + offset]), c="skyblue")
        #plt.ylabel("Positive Mood Effect")
        #plt.xlabel("Day")
        plt.ylim(0, 100)
        plt.xticks([],[])
        plt.yticks([], [])
        #plt.title("Positive mood by day")
plt.tight_layout()
```

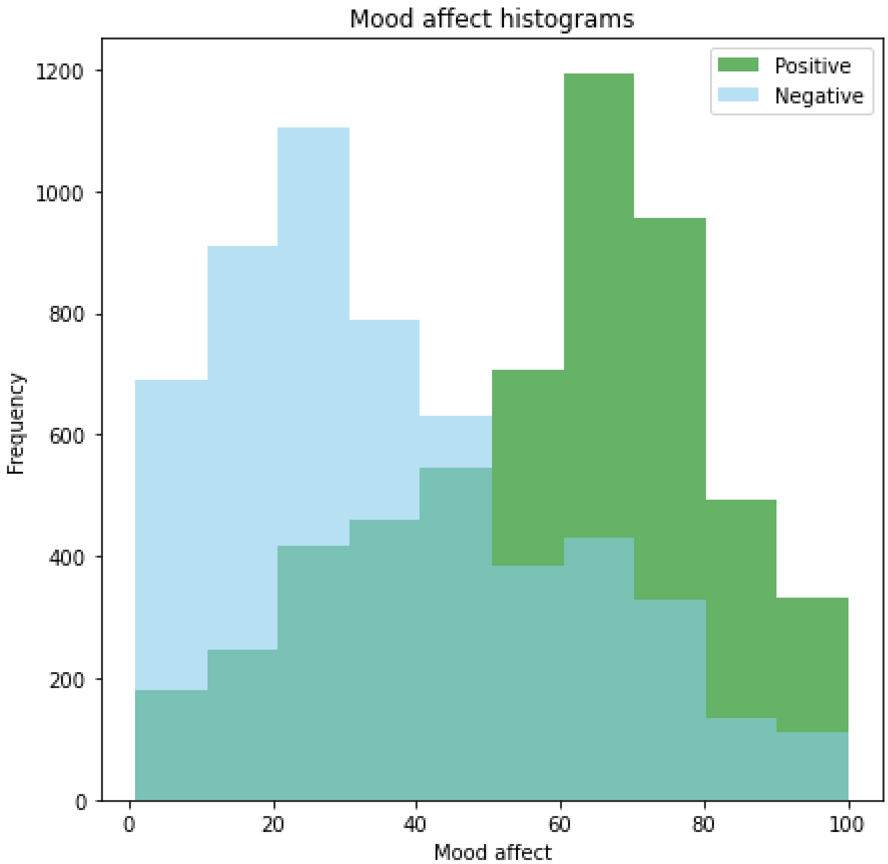


Histogram of Mood Affect

The most frequent ranges of the two moods were near 75 for positive and near 25 for negative,

In [5]:

```
plt.rcParams["figure.figsize"] = [7,7]
plt.hist(np.ravel(M), bins=10, color="green", alpha=0.6, label="Positive")
plt.hist(np.ravel(nM), bins=10, color="skyblue", alpha=.6, label="Negative")
plt.legend()
plt.ylabel("Frequency")
plt.xlabel("Mood affect")
plt.title("Mood affect histograms")
plt.show()
```



Fourier Transform

Take the fourier transform of each mood, then average

In [6]:

```
Xf = []
Yf = []
for i in range(M.shape[0]):
    yc = nans_to_lines(M[i])
    t = np.arange(0, len(yc))
    xf, yf = fourier_transform(t, yc)
    Xf.append(xf)
    Yf.append(yf)

siglen = np.array([l for l in map(len, Xf)])
inds = np.where(siglen == 28)[0]
muf = np.zeros(28)
k = len(inds)
for i in inds:
    muf += Yf[i]
muf /= k

nXf = []
nYf = []
for i in range(nM.shape[0]):
    yc = nans_to_lines(nM[i])
    t = np.arange(0, len(yc))
    xf, yf = fourier_transform(t, yc)
    nXf.append(xf)
    nYf.append(yf)
```

```
siglen = np.array([l for l in map(len, nXf)])
inds = np.where(siglen == 28)[0]
neg_muf = np.zeros(28)
k = len(inds)
for i in inds:
    neg_muf += nYf[i]
neg_muf /= k
print(k)

plt.rcParams["figure.figsize"] = [7, 7]
# 1/f scale
plt.plot(Xf[i][1:], muf[1:], c="green", lw=3, label="Positive Mood FT")
plt.plot(nXf[i][1:], neg_muf[1:], c="skyblue", lw=3, label="Negative Mood FT")
plt.plot(Xf[i][1:], 1/(6*Xf[i][1:]) + 2.7, c="gray", label="1/Period")

plt.legend(fontsize=12)
plt.title("Mean Fourier Transform of Day to Day Mood", fontsize=16)
plt.ylabel("Amplitude")
plt.xlabel("Oscillation Period", fontsize=12)
plt.xticks([1/10, 1/7, 1/4.5, 1/3.25, 1/2], ["10d", "7d", "4.5d", "3.25d", "2d"
plt.show()

## Log log plot
plt.loglog(Xf[i][1:], muf[1:], c="green", lw=3, label="Positive Mood FT")
plt.loglog(nXf[i][1:], neg_muf[1:], c="skyblue", lw=3, label="Negative Mood FT")

# Underlying distribution
plt.loglog(Xf[i][1:], 1/(6*Xf[i][1:]) + 2.7, c="gray", label="1/Period")

plt.legend(fontsize=12)
plt.title("Mean Fourier Transform of Day to Day Mood (Log-log)", fontsize=16)
plt.ylabel("Amplitude")
plt.xlabel("Oscillation Period", fontsize=12)
plt.xticks([1/10, 1/7, 1/4.5, 1/3.25, 1/2], ["10d", "7d", "4.5d", "3.25d", "2d"
plt.show()
```

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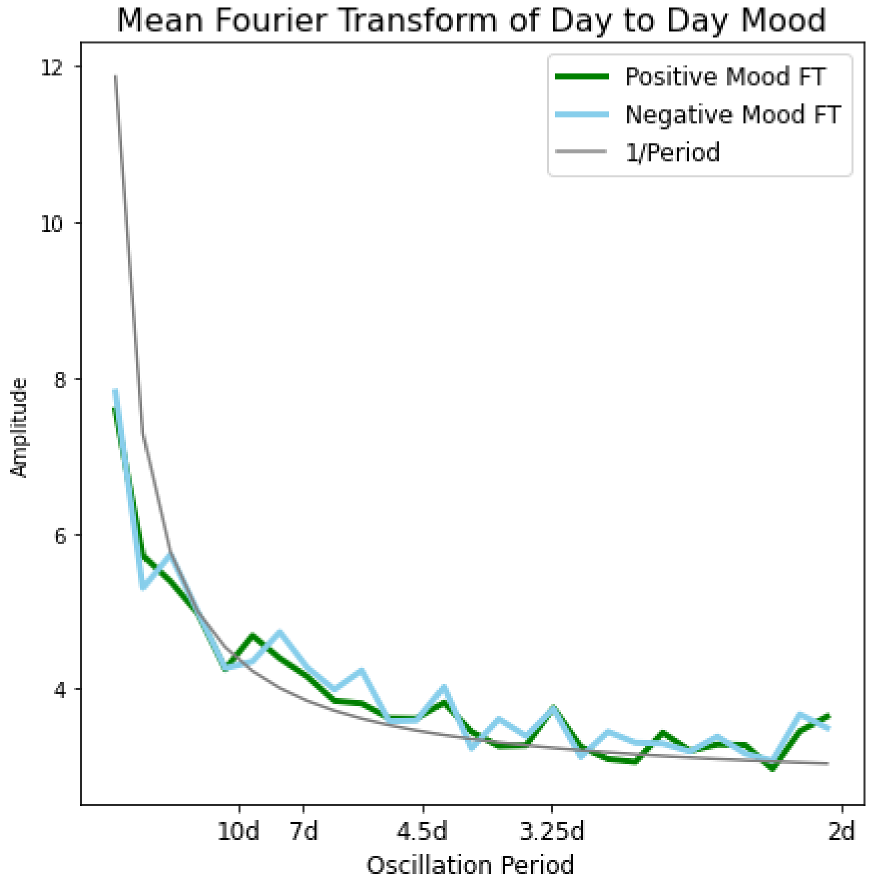
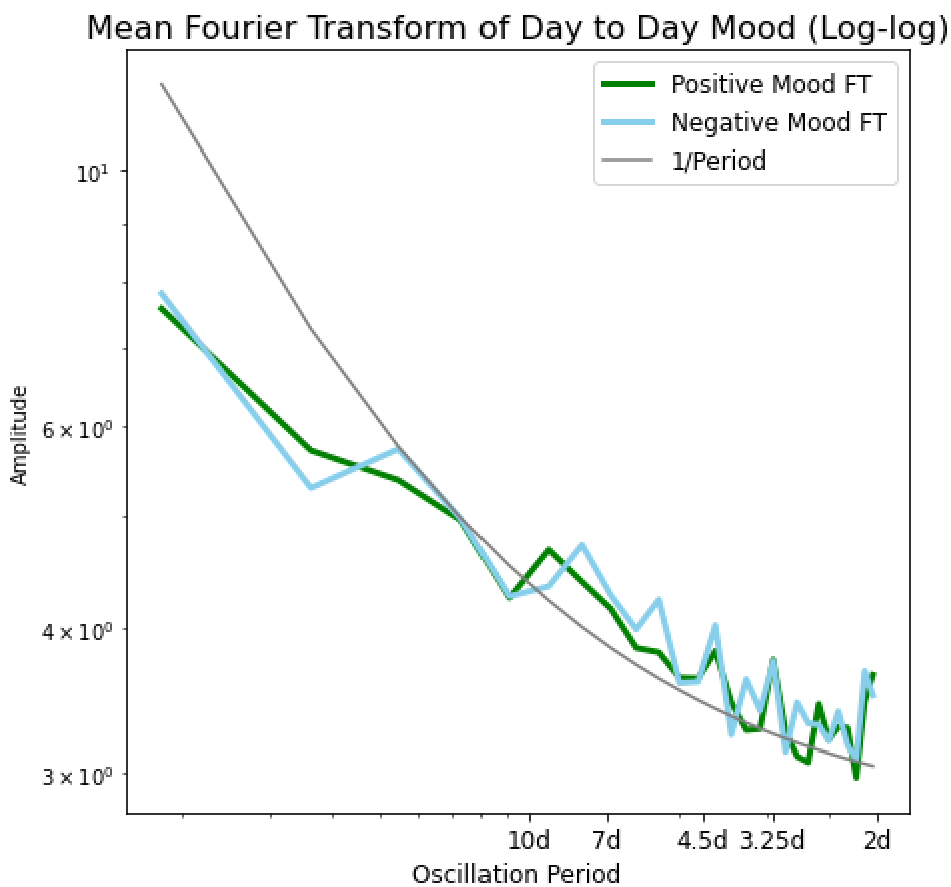
```





In neuronal networks, there is an assumed underlying 1/f distribution of frequencies. Places where the spectrum departs from this underlying distribution are highlighted as "peaks" and appear or disapear based on activity. Interestingly, there appears to be an underlying 1/f distribution in mood spectrum. There also appear to be standard frequency peaks that appear in both positive and negative mood.

Autocorrelation

Take the autocorrelation of each mood, then average over all data points

In [7]:

```
# Compute autocorrelation of each mood signal
Ac = []
negAc = []
for mi, nmi in zip(M, nM):
    Ac.append(autocorr(nans_to_lines(mi)))
    negAc.append(autocorr(nans_to_lines(nmi)))

# Mean positive mood autocorrelation
siglen = np.array([l for l in map(len, Ac)])
inds = np.where(siglen == 56)[0]
mu_ac = np.zeros(56)
k = len(inds)
for i in inds:
    mu_ac += Ac[i]
mu_ac /= k
print(k)

# Mean positive mood autocorrelation
siglen = np.array([l for l in map(len, negAc)])
inds = np.where(siglen == 56)[0]
neg_mu_ac = np.zeros(56)
k = len(inds)
for i in inds:
    neg_mu_ac += negAc[i]
neg_mu_ac /= k
print(k)

lag = np.arange(1, 56)

white_mean_ac = np.mean([autocorr(np.random.rand(56)) for i in range(50)], axis=


plt.rcParams["figure.figsize"] = [7, 7]
plt.plot(lag, mu_ac[1:], c="green", label="Positive Mood", lw=3)
plt.plot(lag, neg_mu_ac[1:], c="skyblue", label="Negative Mood", lw=3)
plt.plot(lag, white_mean_ac[1:], c="gray", label="White Noise", lw=3)
plt.plot(lag, np.zeros_like(lag), "--", c="k", lw=0.7)
plt.legend(fontsize=12)
plt.title("Mean Autocorrelation of Day to Day Mood", fontsize=16)
plt.xlabel("Lag")
plt.ylabel("Autocorrelation")
plt.show()
```

```
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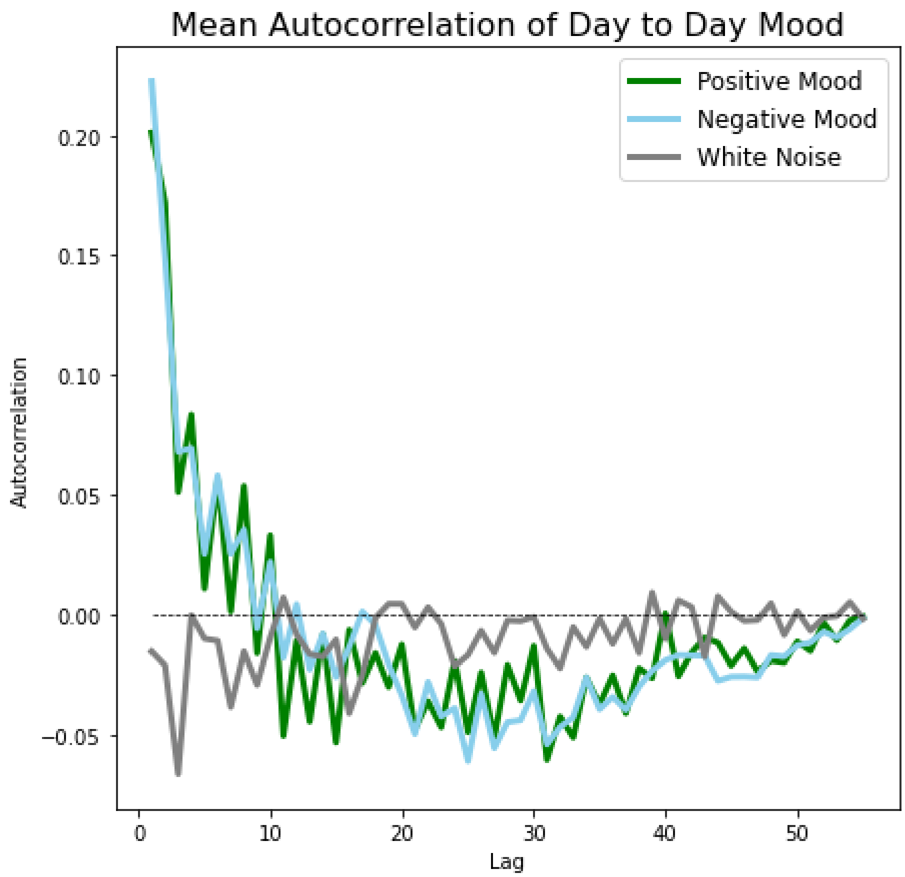
74
```



This looks similar to local field potential in the brain, see here. Open question: What does the 1/f fourier curve look like in the time domain.