In [1]:

```
import pandas as pd
import numpy as np
from matplotlib import pyplot as plt
import matplotlib.dates as mdates
import scipy as sp
import seaborn as sns
from scipy import signal
from statsmodels.tsa.stattools import adfuller
from IPython.display import Markdown as md
import copy
```

Fourier Histograms, Stationarity and Crosscorrelation

Individuals Who Drank More Than 4 Times

In [2]:

```
datafile = "/Users/djpassey/Data/Muri/SHINE_EMA_Round1_19May2020.csv"
ema = pd.read_csv(datafile, parse_dates=True)
# Convert notification time to a datetime object
ema['Notification.Time'] = pd.to_datetime(ema['Notification.Time'])
# 'Num_Alcohol is our new column containing the drinking data we want to measure
# we are interested in 'if' the individual drank or not so we simply set the col
# rather than summing up the number of drinks of each type the individual report
ema['Num_Alcohol'] = ema.HadAlcohol
```

In [3]:

```
# Constants for determining if a prompt occured in the morning or evening
MORNING = ['FirstMorning', 'Morning']
EVENING = ['Evening']
# p-value for this notebook
PVAL = 0.01
# Notebook color scheme
COLORS = ["salmon", "teal", "grey", "green"]

def drink_sessions(df, prompt=None):
    """ Function for removing data from prompts where drinking was not assessed

        Parameters
        ----------
        df (pandas Dataframe): ema data
        prompt (string): one of `["morning", "evening", None]`. Specifies if the
        function should return only data from morning or evening prompts. Defaul
        to None and therefore returns data from both morning and evening prompts

        Returns
        -------
        ds (pandas Dataframe): data frame containing only prompts where drinking
        assessed. If `prompt` was not none, the data only contains information f
        either morning or evening prompts. The dataframe is also sorted by notif
    """
    if prompt is None:
        ds = df[df["Session.Name"].isin(MORNING+EVENING)]
    if prompt is "morning":
        ds = df[df["Session.Name"].isin(MORNING)]
```

```
    if prompt is "evening":
        ds = df[df["Session.Name"].isin(EVENING)]
    ds.fillna({"Num_Alcohol":0, "HadAlcohol":0})
    ds.sort_values("Notification.Time", inplace=True)
    return ds

def fourier_transform(t, y):
    """ Take the fourier transform of a signal, rescale and provide a frequency
        array for easy plotting

        Parameters
        ----------
        t (array): Evenly spaced time values
        y (array): Time series, `y[i]` corresponds to the value of the
        time series at time `t[i]`
    """
    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 hist_templ(
    *data,
    xlab="Value",
    ylab="Frequency",
    title="Histogram",
    label=["Morning Prompt", "Evening Prompt"],
    bins=20,
    alpha=0.6
):
    """Histogram template function"""
    for i, x in enumerate(data):
        plt.hist(x, bins=bins, color=COLORS[i], alpha=0.6, label=label[i])
    plt.legend()
    plt.ylabel(ylab)
    plt.xlabel(xlab)
    p = plt.title(title)
    return p
```

Extract Mood and Drinking Time Series

We separate by morning and evening prompt so that there are 24 hours between each datapoint. The dictionary `processed_data` contains all of the processed data that we study in this notebook. Here is a summary of the entries in the `processed_data` dictionary. (Some of these entries are added later

1. `processesed_data["id"]` is a 1D array of id numbers. All of the following arrays are kept in order corresponding to id number.

2. `processesed_data["drink.morning"]` is a 2D array where the `i` th row is a drinking time series corresponding to the individual with id number equal to

`processesed_data["id"][i]`. Each drinking time series here has 28 entries corresponding to the 28 *morning* prompts.

3. `processesed_data["drink.evening"]` is a 2D array where the `i` th row is a drinking time series corresponding to the individual with id number equal to `processesed_data["id"][i]`. Each drinking time series here has 28 entries corresponding to the 28 *evening* prompts.

4. `processesed_data["mood.morning"]` is a 2D array where the `i` th row is a positive mood time series corresponding to the individual with id number equal to `processesed_data["id"][i]`. Each mood time series here has 28 entries corresponding to the 28 *morning* prompts.

5. `processesed_data["mood.evening"]` is a 2D array where the `i` th row is a positive mood time series corresponding to the individual with id number equal to `processesed_data["id"][i]`. Each mood time series here has 28 entries corresponding to the 28 *morning* prompts.

6. `processed_data["{mood or drink}.{morning or evening}.ft"]` For entries 2-5 above, appending `".ft"` onto the end of the key (e.g. `"mood.evening" -> "mood.evening.ft")` produces a 2D array where each row is the fourier transform of the corresponding row in the original time series array. (e.g. `processesed_data["mood.evening.ft"][2, :]` contains the fourier transform of `processesed_data["mood.evening"][2, :]`)

7. `processed_data["{mood or drink}.{morning or evening}.adfuller"]` For entries 2-5 above, appending `".adfuller"` onto the end of the key (e.g. `"mood.evening" -> "mood.evening.adfuller")` produces a 1D array where the `i` th entry is a p-value corresponding to an Augmented Dickey-Fuller unit root test (a statistical test for stationarity) applied to the `i` th row of the corresponding time series array. (e.g. `processesed_data["mood.evening.ft"][2]` contains the p-value corresponding to a Augmented Dickey-Fuller test run on `processesed_data["mood.evening"][2, :]`)

In [4]:

```
processed_data = {
    "id" : [],
    "drink.morning" : [],
    "drink.evening" : [],
    "mood.morning" : [],
    "mood.evening" : []
}

time_series_keys = ["drink.morning", "drink.evening", "mood.morning", "mood.even

# Separate morning and evening prompts
morn = drink_sessions(ema, prompt="morning")
eve = drink_sessions(ema, prompt="evening")
```

```
/usr/local/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:32: Setti
```

```
ngWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stab
le/user_guide/indexing.html#returning-a-view-versus-a-copy
```

In [10]:

```python
# Participants to exclude
EXCLUDE_ID = [52927]

# Minimum number of times an individual must drink
DRINK_MIN = 4

# Drinking and Mood data tuples
drinkmorn = tuple()
drinkeve = tuple()
moodmorn = tuple()
moodeve = tuple()

for idnum in ema.ID.unique():
    if idnum not in EXCLUDE_ID:
        # Look at subset of data corresponding to the current ID
        morn_id = morn[morn.ID == idnum]
        eve_id = eve[eve.ID == idnum]
        morning_drink = morn_id["Num_Alcohol"].fillna(0).values
        if sum(morning_drink) > DRINK_MIN:
            # add ID numbers
            processed_data["id"].append(idnum)
            # Extract morning and evening drinks time series and append it to tu
            drinkmorn += (morn_id["Num_Alcohol"].fillna(0).values,)
            drinkeve += (eve_id["Num_Alcohol"].fillna(0).values,)
            # Extract morning and eveing positive mood time series
            morn_m = morn_id.PositiveMood
            eve_m = eve_id.PositiveMood
            # Fill nans with the mean and append to tuple
            moodmorn += (morn_m.fillna(np.mean(morn_m)).values,)
            moodeve += (eve_m.fillna(np.mean(eve_m)).values,)

# Turn tuple of timeseries into arrays
processed_data["drink.morning"] = np.vstack(drinkmorn)
processed_data["drink.evening"] = np.vstack(drinkeve)
processed_data["mood.morning"] = np.vstack(moodmorn)
processed_data["mood.evening"] = np.vstack(moodeve)
```

In [11]:

```python
n = processed_data["drink.morning"].shape[0]
print(f"{n} Individuals drank more than {DRINK_MIN} times during the study")
```

```
53 Individuals drank more than 4 times during the study
```

In [12]:

```python
# Take fourier transform of each time series type
for key in time_series_keys:
    Yf = tuple()
    for ts in processed_data[key]:
        x = np.arange(28)
        xf, yf = fourier_transform(x, ts)
        Yf += (yf,)
    processed_data[key + ".ft"] = np.vstack(Yf)
```

Distribution at Each Frequency

Fourier transform analysis of each drinking time series in the population. Frequency information is extracted from individual drinking time series and gives information about the relative importance of different oscillatory periods in the individual's time series. For example, we hypothesize that a seven day cycle should be an important component of a drinking time series, given the prevalence of drinking each weekend. Each plot shows the distribution of the importance of the specified frequency across the population. For example, the upper left plot shows the distribution of the importance of a 28 day cycle across the population and the lower right plot shows the distribution of a 2.2 day cycle across the population. Shorter cycles are plotted in lighter colors.

Permutation testing of drinking frequency distributions

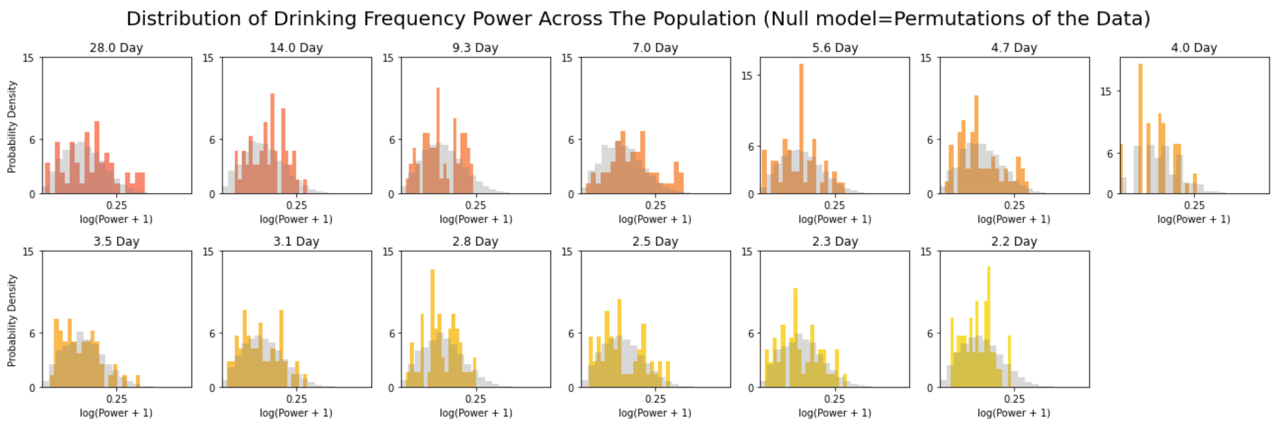
In [20]:

```
# This code takes several hour to run. It is commented out so it isn't run on ac

# Number of times to permute the entire dataset
N = 10000
# Make a copy of the morning drinking time series
D = copy.deepcopy(processed_data['drink.morning'])
permYf = tuple()
for k in range(N):
    # For each individual
    for ts in D:
        x = np.arange(28)
        # Permute their drinkine time series randomly
        perm = np.random.permutation(ts)
        # Take the transform
        xf, yf = fourier_transform(x, perm)
        # Save for later
        permYf += (yf,)
permYf = np.vstack(permYf)
np.savez("/Users/djpassey/Data/Muri/permuted_data_null_gtr4.npz", permYf)
```

In [168…

```
plt.rcParams["figure.figsize"] = [18, 6]

# Load saved Null
permYf = np.load("/Users/djpassey/Data/Muri/permuted_data_null_gtr4.npz")["arr_0

# Frequency axis (For fourier transform)
total_time = 28.0
N = 28
xf = np.arange(N)/ (total_time)
xf = xf[:N//2]

salmon = np.array([250,131,117]) / 256
# Lets do a gradient
color_grad_step = np.array([0, 7, -5]) / 256
drinker_idx = np.where(np.mean(processed_data["drink.morning"], axis=1) != 0)[0]
drinkers = processed_data["drink.morning.ft"][drinker_idx, :]
cols = drinkers.shape[1]

for j in range(1, cols):
    plt.subplot(2,7,j)
```

```
    freq_dist = np.log(drinkers[:, j] + 1)
    null_dist = np.log(permYf[:, j] + 1)
    plt.hist(freq_dist, color=salmon + j*color_grad_step, bins=20, density=True)
    plt.hist(null_dist, bins=20, color="grey", alpha=.3, density=True)

    plt.xlim(0,.5)
    #plt.ylim(0, 1)
    plt.xticks([0.25])
    plt.yticks([0, 6, 15])
    plt.title(f"{round(1/xf[j],1)} Day")
    if j % 7 == 1:
        plt.ylabel("Probability Density")
    plt.xlabel("log(Power + 1)")

plt.suptitle("Distribution of Drinking Frequency Power Across The Population (Nu
plt.tight_layout()
plt.show()
```



Is there a problem with the bin widths? Permutation test on an individual's data. What is the probability that the individual was drawn from noise v.s. has a oscillatory component in their drinking time series Are the same people appearing in the 28 day, 14 day, 7 day peaks (harmonics)

Histogram of Mood Fourier Transform

Permutation Testing of Mood Fourier Transform

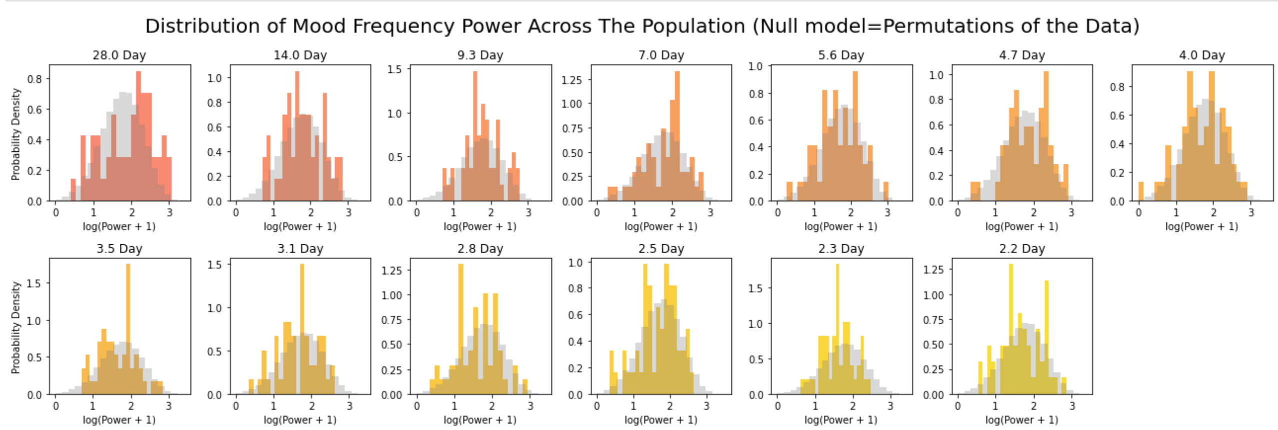
In [25]:

```
# # This code takes several hour to run. It is commented out so it isn't run on

# # Number of times to permute the entire dataset
# N = 10000
# # Make a copy of the morning mood time series
# M = copy.deepcopy(processed_data['mood.morning'])
# permMf = tuple()
# for k in range(N):
#     # For each individual
#     for ts in M:
#         x = np.arange(28)
#         # Permute their drinkine time series randomly
#         perm = np.random.permutation(ts)
#         # Take the transform
#         xf, mf = fourier_transform(x, perm)
#         # Save for later
```

```
#          permMf += (mf,)
# permMf = np.vstack(permMf)
# np.savez("/Users/djpassey/Data/Muri/permuted_data_null_gtr4_mood.npz", permMf)
```

In [41]:

```
plt.rcParams["figure.figsize"] = [18, 6]

# Load saved Null
permMf = np.load("/Users/djpassey/Data/Muri/permuted_data_null_gtr4_mood.npz")["

# Frequency axis (For fourier transform)
total_time = 28.0
N = 28
xf = np.arange(N)/ (total_time)
xf = xf[:N//2]

salmon = np.array([250,131,117]) / 256
# Lets do a color gradient
color_grad_step = np.array([0, 7, -5]) / 256
cols = processed_data["mood.morning.ft"].shape[1]

for j in range(1, cols):
    plt.subplot(2,7,j)
    freq_dist = np.log(processed_data["mood.morning.ft"][:, j] + 1)
    null_dist = np.log(permMf[:, j]+ 1)
    plt.hist(freq_dist, color=salmon + j*color_grad_step, bins=20, density=True)
    plt.hist(null_dist, bins=20, color="grey", alpha=.3, density=True)

    #plt.xlim(0,.5)
    #plt.ylim(0, 1)
    #plt.xticks([0.25])
    #plt.yticks([0, .5])
    plt.title(f"{round(1/xf[j],1)} Day")
    if j % 7 == 1:
        plt.ylabel("Probability Density")
    plt.xlabel("log(Power + 1)")

plt.suptitle("Distribution of Mood Frequency Power Across The Population (Null m
plt.tight_layout()
plt.show()
```



In [43]:

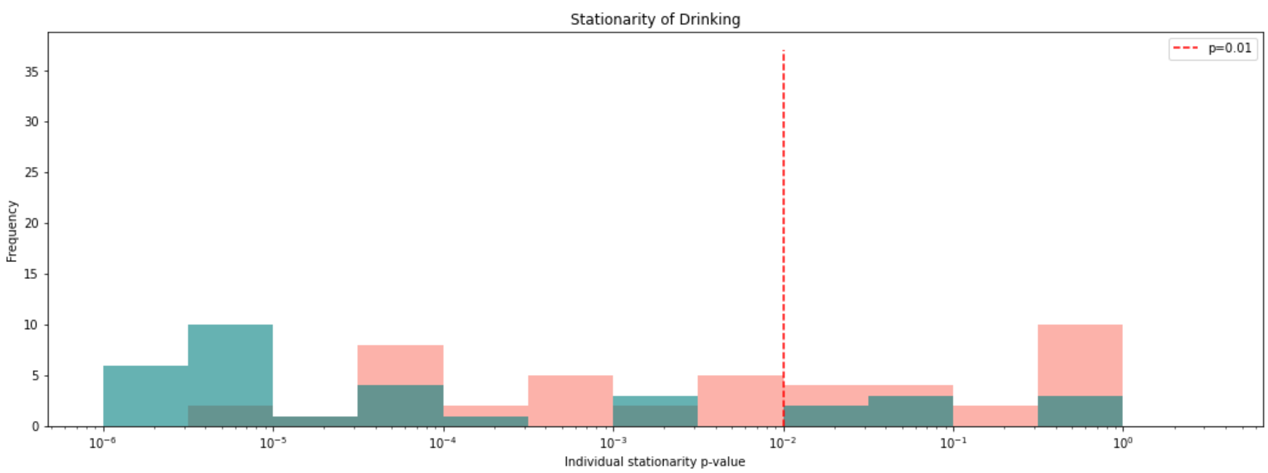
```
with np.errstate(divide='ignore'):
    for key in time_series_keys:
        ts = processed_data[key]
```

```
        pvals = [adfuller(x)[1] for x in ts]
        processed_data[key + ".adfuller"] = np.array(pvals)
```

Stationarity of Drinking

In [45]:

```
bins = 10**(np.arange(-6.0, 1, 0.5))
dmp = processed_data["drink.morning.adfuller"]
dep = processed_data["drink.evening.adfuller"]
plt.xscale('log')
plt.hist(dmp, bins=bins, color=COLORS[0], alpha=0.6)
plt.hist(dep, bins=bins, color=COLORS[1], alpha=0.6)
plt.plot(np.ones(38)*PVAL, np.arange(0,38), "--", c="r", label=f"p={PVAL}")
plt.xlabel("Individual stationarity p-value")
plt.ylabel("Frequency")
plt.title("Stationarity of Drinking")
plt.legend()
plt.show()

adf_sig = lambda x: np.sum(x < PVAL)
print(f"{adf_sig(dmp)} / {n} Participants show stationarity in drinking (Morning
print(f"{adf_sig(dep)} / {n} Participants show stationarity in drinking (Evening
```



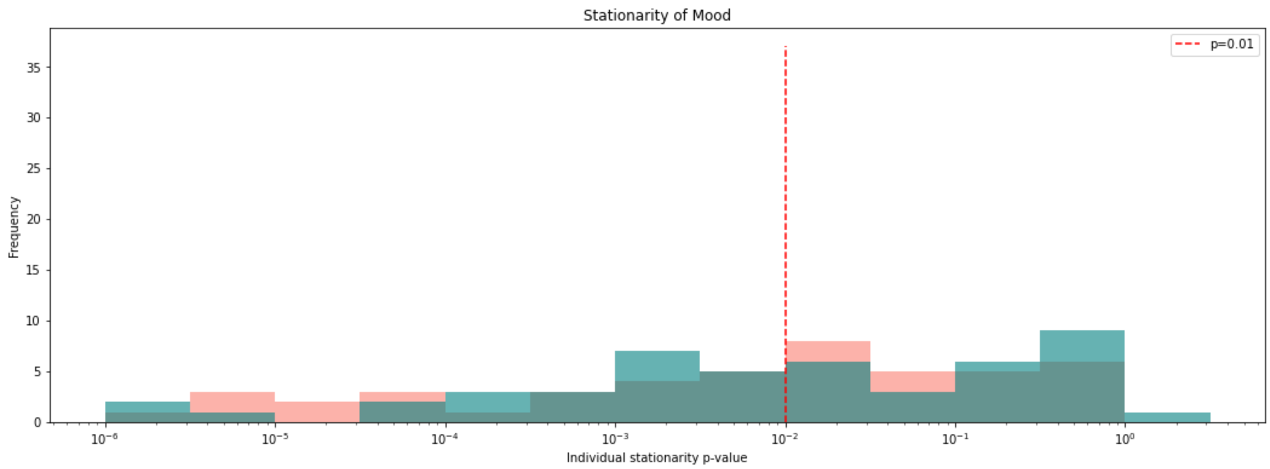

```
33 / 53 Participants show stationarity in drinking (Morning)
35 / 53 Participants show stationarity in drinking (Evening)
```

Stationarity of Mood

In [46]:

```
bins = 10**(np.arange(-6.0, 1, 0.5))
mmp = processed_data["mood.morning.adfuller"]
mep = processed_data["mood.evening.adfuller"]

plt.xscale('log')
plt.hist(mmp, bins=bins, color=COLORS[0], alpha=0.6)
plt.hist(mep, bins=bins, color=COLORS[1], alpha=0.6)
plt.title("Stationarity of Mood")
plt.xlabel("Individual stationarity p-value")
plt.ylabel("Frequency")
plt.plot(np.ones(38)*PVAL, np.arange(0,38), "--", c="r", label=f"p={PVAL}")
plt.legend()
plt.show()
```

```
print(f"{adf_sig(mmp)} / {n} Participants show stationarity in mood (Morning)")
print(f"{adf_sig(mep)} / {n} Participants show stationarity in mood (Evening)")
```




```
29 / 53 Participants show stationarity in mood (Morning)
28 / 53 Participants show stationarity in mood (Evening)
```

How many were stationary in mood, drinking, both, just one or the other? (In a table)

In [48]:

```
pval = 0.01
# Remove non drinkers
drink_station = processed_data["drink.morning.adfuller"][drinker_idx]
mood_station = processed_data["mood.morning.adfuller"][drinker_idx]

sta_mood_sta_drink = sum((drink_station < pval) * (mood_station < pval) )
sta_mood_not_drink = sum((drink_station > pval) * (mood_station < pval) )
not_mood_sta_drink = sum((drink_station < pval) * (mood_station > pval) )
not_mood_not_drink = sum((drink_station > pval) * (mood_station > pval) )

stationarity_table = f"""#### Morning Mood and Drinking Stationarity

|  | Stationary Drinking | Non-Stationary Drinking | Totals |
| --- | --- | --- | --- |
| **Stationary Mood**|{sta_mood_sta_drink} |{sta_mood_not_drink} | {sta_mood_sta
| **Non Stationary Mood**| {not_mood_sta_drink}| {not_mood_not_drink}| {not_mood
| **Totals**| {sta_mood_sta_drink + not_mood_sta_drink}| {sta_mood_not_drink + n

"""
md(stationarity_table)
```

Out[48]:

Morning Mood and Drinking Stationarity

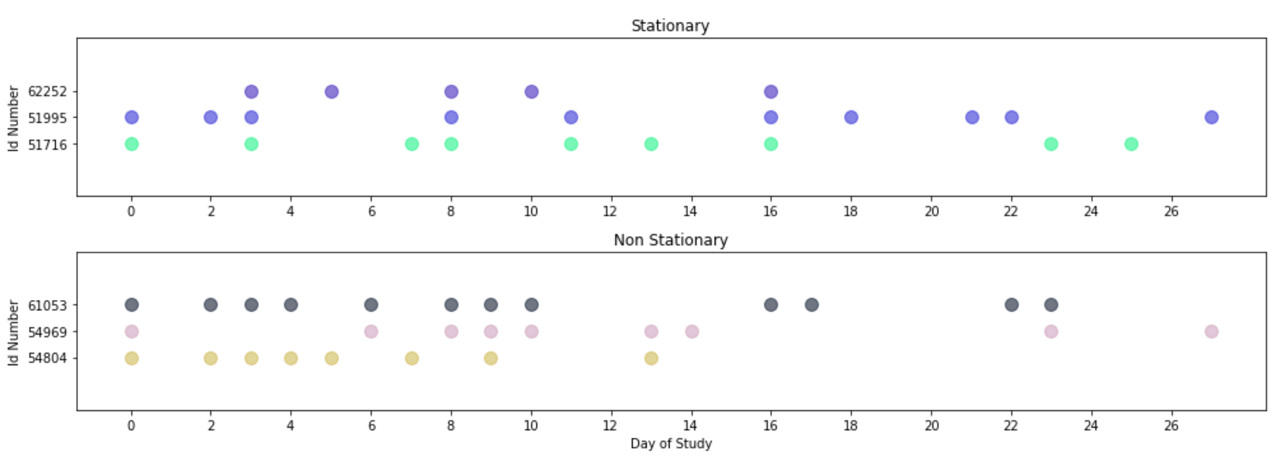
	Stationary Drinking	Non-Stationary Drinking	Totals
Stationary Mood	18	11	29
Non Stationary Mood	15	9	24
Totals	33	20	53

This table displays a grouping of individuals by mood and drinking stationarity. Stationarity is a property of a time series indicating if the series is flat, i.e. does not contain increasing or decreasing trends. For this dataset, we apply a statistical test to determine if an individuals drinking or mood time series are flat over the course of the study.

We group the 53 participants who drank more than four times into four groups in the table above, indicating the number of individuals with each combination of stationarity and non-stationarity in mood and drinking. We use a p-value of 0.01 as our cutoff. An additional table below shows the same result for a p-value of 0.1.

In [49]:

```
plt.rcParams["figure.figsize"] = [14, 5]

plt.subplot(2,1,1)
station = np.where(processed_data["drink.morning.adfuller"] < 1e-6)[0][:3]
idnum = 0
for i in station:
    drinks = processed_data["drink.morning"][i, :]
    times = np.where(drinks == 1)[0]
    plt.scatter(times, idnum*np.ones(len(times)), s=100, alpha=0.6, c=np.random.
    idnum += 1

plt.ylim(-2,4)
plt.yticks([0, 1, 2], [processed_data["id"][int(idx)] for idx in station])
plt.ylabel("Id Number")
plt.title("Stationary")
plt.xticks(np.arange(0,28,2))

plt.subplot(2,1,2)
non_station = np.where(processed_data["drink.morning.adfuller"] > .4)[0][:3]
idnum = 0
for i in non_station:
    drinks = processed_data["drink.morning"][i, :]
    times = np.where(drinks == 1)[0]
    plt.scatter(times, idnum*np.ones(len(times)), s=100, alpha=0.6, c=np.random.
    idnum += 1

plt.ylim(-2,4)
plt.yticks([0, 1, 2], [processed_data["id"][int(idx)] for idx in non_station])
plt.ylabel("Id Number")
plt.title("Non Stationary")
plt.xticks(np.arange(0,28,2))
plt.xlabel("Day of Study")

plt.tight_layout()
plt.show()
```



In [50]:

```
pval = 0.1
# Remove non drinkers
```

```
drink_station = processed_data["drink.morning.adfuller"][drinker_idx]
mood_station = processed_data["mood.morning.adfuller"][drinker_idx]

sta_mood_sta_drink = sum((drink_station < pval) * (mood_station < pval) )
sta_mood_not_drink = sum((drink_station > pval) * (mood_station < pval) )
not_mood_sta_drink = sum((drink_station < pval) * (mood_station > pval) )
not_mood_not_drink = sum((drink_station > pval) * (mood_station > pval) )

stationarity_table = f"""#### Morning Mood and Drinking Stationarity

|  | Stationary Drinking | Non-Stationary Drinking | Totals |
| --- | --- | --- | --- |
| **Stationary Mood**|{sta_mood_sta_drink} |{sta_mood_not_drink} | {sta_mood_sta
| **Non Stationary Mood**| {not_mood_sta_drink}| {not_mood_not_drink}| {not_mood
| **Totals**| {sta_mood_sta_drink + not_mood_sta_drink}| {sta_mood_not_drink + n

"""
md(stationarity_table)
```

Out[50]:

Morning Mood and Drinking Stationarity

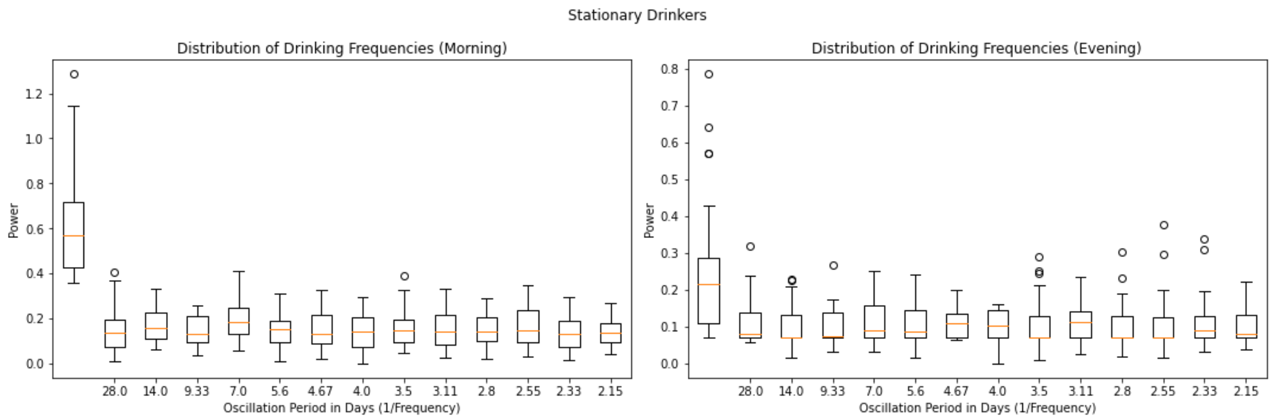
	Stationary Drinking	Non-Stationary Drinking	Totals
Stationary Mood	33	9	42
Non Stationary Mood	8	3	11
Totals	41	12	53

Fourier Transform of Stationary Drinkers

In [53]:

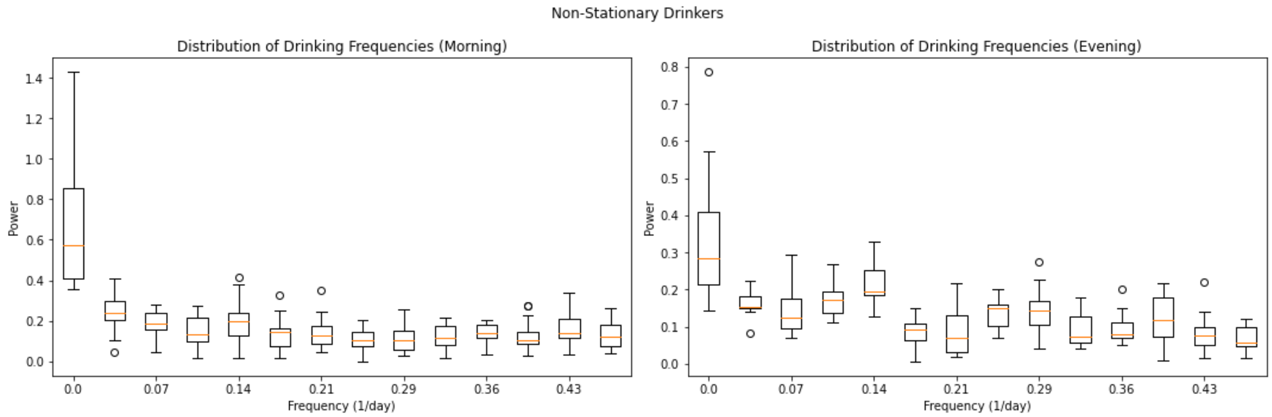
```
plt.rcParams["figure.figsize"] = [15, 5]

# Frequency axis (For fourier transform)
total_time = 28.0
N = 28
xf = np.arange(N)/ (total_time)
xf = xf[:N//2]
# Exlude non drinkers and nonstationary drinkers
station_morning = (processed_data["drink.morning.adfuller"] < 0.01) * (np.mean(p
station_evening = (processed_data["drink.evening.adfuller"] < 0.01) * (np.mean(p

plt.subplot(1, 2, 1) # Fourier transform morning
plt.boxplot(processed_data["drink.morning.ft"][station_morning, :])
plt.xticks(np.arange(2,15), np.round(1/xf[1:],2))
plt.xlabel("Oscillation Period in Days (1/Frequency)")
plt.title("Distribution of Drinking Frequencies (Morning)")
plt.ylabel("Power")
#plt.ylim(-.1, 2.50)

plt.subplot(1, 2, 2) # Fourier transform evening
plt.boxplot(processed_data["drink.evening.ft"][station_evening, :])
plt.xticks(np.arange(2,15), np.round(1/xf[1:],2))
plt.title("Distribution of Drinking Frequencies (Evening)")
plt.ylabel("Power")
#plt.ylim(-.1, 2.50)
plt.xlabel("Oscillation Period in Days (1/Frequency)")
```

```
plt.suptitle("Stationary Drinkers")
plt.tight_layout()
plt.show()
```



In [54]:

```
plt.rcParams["figure.figsize"] = [15, 5]

# Frequency axis (For fourier transform)
total_time = 28.0
N = 28
xf = np.arange(N)/ (total_time)
xf = xf[:N//2]
# Exlude non drinkers and nonstationary drinkers
station_morning = (processed_data["drink.morning.adfuller"] > 0.01) * (np.mean(p
station_evening = (processed_data["drink.evening.adfuller"] > 0.01) * (np.mean(p

plt.subplot(1, 2, 1) # Fourier transform morning
plt.boxplot(processed_data["drink.morning.ft"][station_morning, :])
plt.xticks(np.arange(1,15,2), np.round(xf[::2],2))
plt.title("Distribution of Drinking Frequencies (Morning)")
plt.ylabel("Power")
#plt.ylim(-.1, 2.50)
plt.xlabel("Frequency (1/day)")

plt.subplot(1, 2, 2) # Fourier transform evening
plt.boxplot(processed_data["drink.evening.ft"][station_evening, :])
plt.xticks(np.arange(1,15,2), np.round(xf[::2],2))
plt.title("Distribution of Drinking Frequencies (Evening)")
plt.ylabel("Power")
#plt.ylim(-.1, 2.50)
plt.xlabel("Frequency (1/day)")

plt.suptitle("Non-Stationary Drinkers")

plt.tight_layout()
plt.show()
```



Are there enough to draw conclusions? ($n = 20$)

Autocorrelation of Drinking

In [153…

```
def ccf(x, y, lag_max = 100, return_lags=False):
    """ Python version of R ccf function """

    result = signal.correlate(y - np.mean(y), x - np.mean(x), method='direct') /
    length = (len(result) - 1) // 2
    lo = length - lag_max
    hi = length + (lag_max + 1)
    if return_lags:
        return np.arange(lo, hi), result[lo:hi]
    return result[lo:hi]

def ccf_lags(x, y, ccf_output):
    """ Lags corresponding to output of ccf """



def autocorr(x):
    return ccf(x, x)
```

In [ ]:

In [133…

```
2/(53 - 7)**.5
```

Out[133…

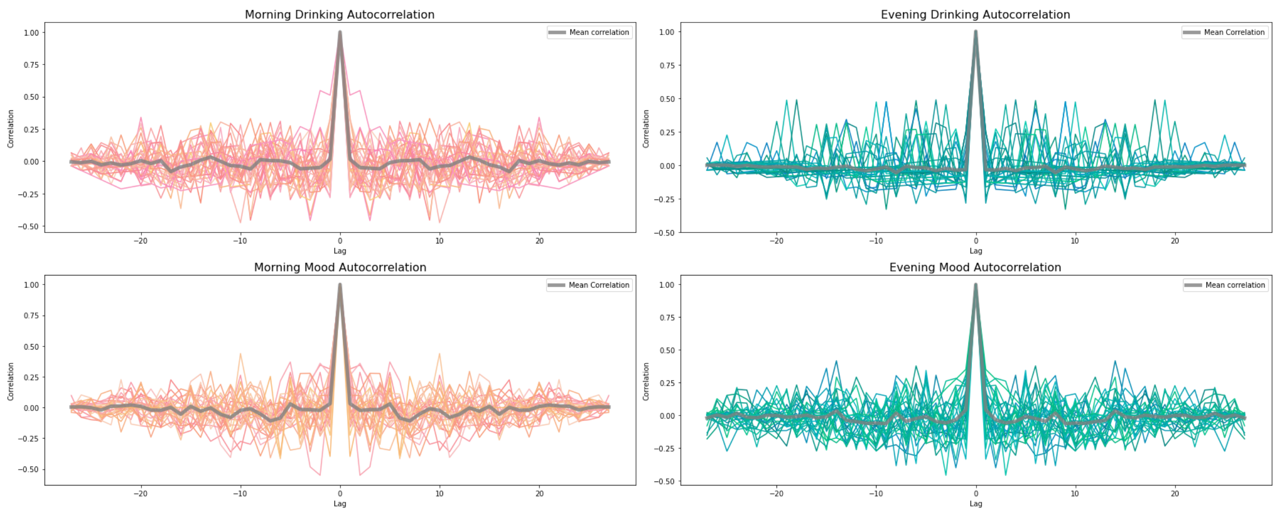
```
0.29488391230979427
```

In [134…

```
plt.rcParams["figure.figsize"] = [25, 10]
lags = np.arange(-27, 28)

plt.subplot(2,2,1)
mu_mm_ac = np.zeros(55)
n = 0
salmon = np.array([250,131,117]) / 256
for x, p in zip(processed_data["drink.morning"], processed_data["drink.morning.a

    if p < 0.01:
        ac = autocorr(x)
```

```
        mu_mm_ac += ac
        n +=1
        jitter = np.random.rand(3) * 0.3
        jitter[0] = 0
        plt.plot(lags, ac, c=salmon + jitter)

plt.plot(lags, mu_mm_ac/n, lw=5, alpha=0.8, c="gray", label="Mean correlation")
plt.title("Morning Drinking Autocorrelation", fontsize=16)
plt.xlabel("Lag")
plt.yticks([-.5, -.25, 0., .25, .5, .75, 1])
plt.ylabel("Correlation")
plt.legend()

plt.subplot(2,2,2)
mu_em_ac = np.zeros(55)
n = 0
teal = np.array([4,128,128]) / 256
for x, p in zip(processed_data["drink.evening"], processed_data["drink.evening.a

    if p < 0.01:
        ac = autocorr(x)
        mu_em_ac += ac
        n +=1
        jitter = np.random.rand(3) * 0.3
        jitter[0] = 0
        plt.plot(lags, ac, c=teal + jitter)
plt.plot(lags, mu_em_ac/n, lw=5, alpha=0.8, c="gray", label="Mean Correlation")
plt.title("Evening Drinking Autocorrelation", fontsize=16)
plt.xlabel("Lag")
plt.yticks([-.5, -.25, 0., .25, .5, .75, 1])
plt.ylabel("Correlation")
plt.legend()

plt.subplot(2,2,3)
mu_mm_ac = np.zeros(55)
n = 0
salmon = np.array([250,131,117]) / 256
for x, p in zip(processed_data["mood.morning"], processed_data["mood.morning.adf

    if p < 0.01:
        ac = autocorr(x)
        mu_mm_ac += ac
        n +=1
        jitter = np.random.rand(3) * 0.3
        jitter[0] = 0
        plt.plot(lags, ac, c=salmon + jitter)
plt.plot(lags, mu_mm_ac/n, lw=5, alpha=0.8, c="gray", label="Mean Correlation")
plt.title("Morning Mood Autocorrelation", fontsize=16)
plt.xlabel("Lag")
plt.yticks([-.5, -.25, 0., .25, .5, .75, 1])
plt.ylabel("Correlation")
plt.legend()

plt.subplot(2,2,4)
mu_em_ac = np.zeros(55)
n = 0
teal = np.array([4,128,128]) / 256
for x, p in zip(processed_data["mood.evening"], processed_data["mood.evening.adf

    if p < 0.01:
        ac = autocorr(x)
```

```
        mu_em_ac += ac
        n +=1
        jitter = np.random.rand(3) * 0.3
        jitter[0] = 0
        plt.plot(lags, ac, c=teal + jitter)
plt.plot(lags, mu_em_ac/n, lw=5, alpha=0.8, c="gray", label="Mean correlation")
plt.title("Evening Mood Autocorrelation", fontsize=16)
plt.xlabel("Lag")
plt.yticks([-.5, -.25, 0., .25, .5, .75, 1])
plt.ylabel("Correlation")
plt.legend()

plt.tight_layout()
plt.show()
```

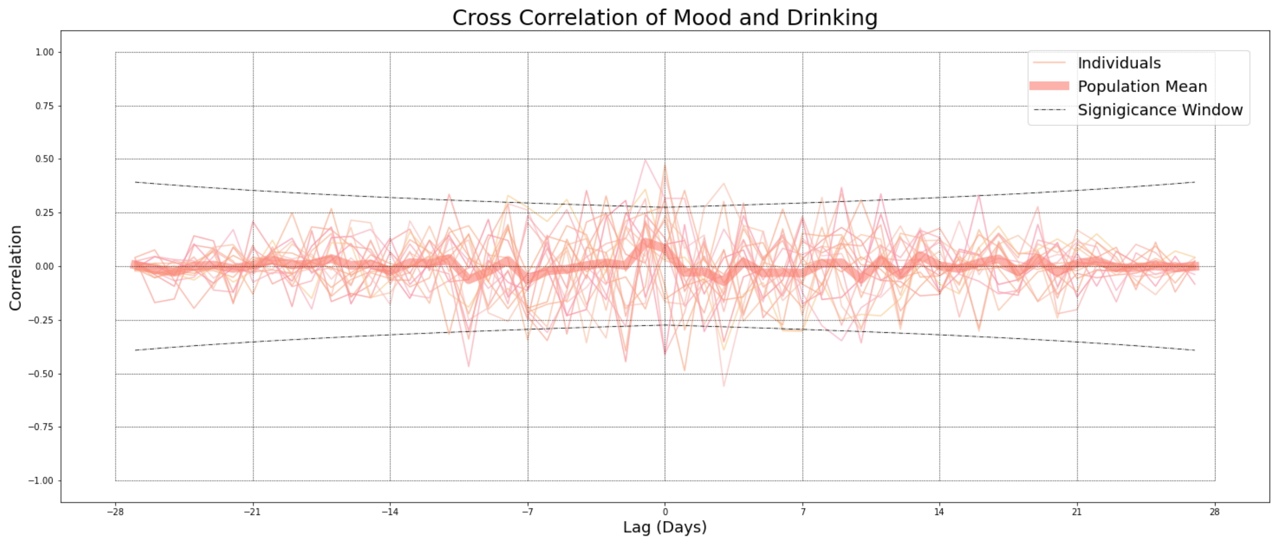


Cross Correlation of Mood and Drinking

In [162…

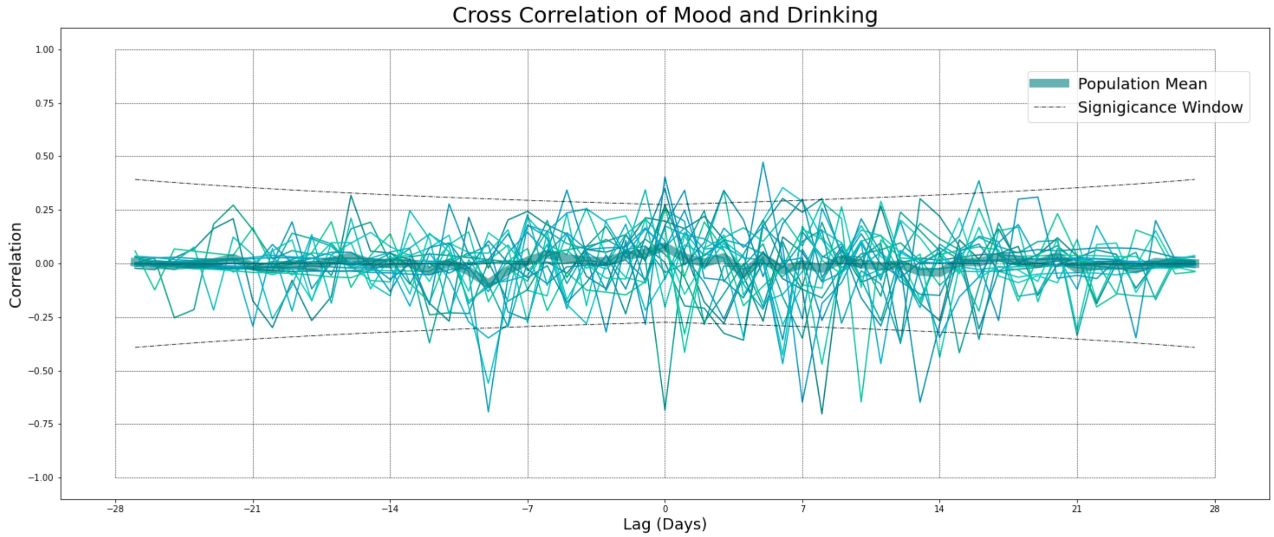
```
mu_cc = np.zeros(55)
n = 0

for m, mp, d, dp in zip(processed_data["mood.morning"], processed_data["mood.mor
    if (mp < 0.01) and (dp < 0.01):
        cc = ccf(d, m)
        mu_cc += cc
        n +=1
        jitter = np.random.rand(3) * 0.3
        jitter[0] = 0
        plt.plot(lags, cc, c=salmon + jitter, alpha=0.7)
# Extra point to add a label to the legend
plt.plot(lags[0], cc[0], c=salmon + jitter, alpha=0.7, label="Individuals")
# Population mean
plt.plot(lags, mu_cc/n, lw=10, alpha=0.6, c="salmon", label="Population Mean")
# Significance curve
plt.plot(lags , 2/(53 - np.abs(lags))**.5, "-.", c="k", lw=0.8, label="Signigica
plt.plot(lags , -2/(53 - np.abs(lags))**.5, "-.", c="k", lw=0.8)


xtick_locs = np.arange(-28, 29, 7)
# Grid lines
for y in np.arange(-1, 1.25, 0.25):
    plt.plot(xtick_locs, y*np.ones_like(xtick_locs), "--", c="k", lw=0.5)
for x in xtick_locs:
```

```
    plt.plot(x*np.ones_like(lags), np.linspace(-1, 1, len(lags)), "--", c="k", l

plt.title("Cross Correlation of Mood and Drinking", fontsize=25)
plt.xlabel("Lag (Days)", fontsize=18)
plt.ylabel("Correlation", fontsize=18)
plt.xticks(xtick_locs)
plt.legend(loc=(0.8, 0.8), fontsize=18)
plt.show()
```



In [167…

```
mu_cc = np.zeros(55)
n = 0

for m, mp, d, dp in zip(processed_data["mood.evening"], processed_data["mood.eve

    if (mp < 0.01) and (dp < 0.01):
        cc = ccf(m, d)
        mu_cc += cc
        n +=1
        jitter = np.random.rand(3) * 0.3
        jitter[0] = 0
        plt.plot(lags, cc, c=teal + jitter)
plt.plot(lags, mu_cc/n, lw=10, alpha=0.6, c="teal", label="Population Mean")

# Significance curve
plt.plot(lags , 2/(53 - np.abs(lags))**.5, "-.", c="k", lw=0.8, label="Signigica
plt.plot(lags , -2/(53 - np.abs(lags))**.5, "-.", c="k", lw=0.8)


xtick_locs = np.arange(-28, 29, 7)
# Grid lines
for y in np.arange(-1, 1.25, 0.25):
    plt.plot(xtick_locs, y*np.ones_like(xtick_locs), "--", c="k", lw=0.5)
for x in xtick_locs:
    plt.plot(x*np.ones_like(lags), np.linspace(-1, 1, len(lags)), "--", c="k", l

plt.title("Cross Correlation of Mood and Drinking", fontsize=25)
plt.xlabel("Lag (Days)", fontsize=18)
plt.ylabel("Correlation", fontsize=18)
plt.xticks(xtick_locs)
plt.legend(loc=(0.8, 0.8), fontsize=18)
plt.show()
```


Cross Correlation of Mood and Drinking
Population Mean
Signigicance Window
Correlation
Lag (Days)
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
−28
−21
−14
−7
0
7
14
21
28

In [ ]: