AS1

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1 Assignment 1

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```
In [1]: from netCDF4 import Dataset, num2date
        import numpy as np
        import matplotlib.pyplot as plt
        import matplotlib.dates as mdates
        import pandas as pd

        from netCDF4 import Dataset,num2date
        from datetime import datetime
        from dateutil.rrule import rrule, MONTHLY
        from scipy import stats
        from mpl_toolkits.basemap import Basemap,maskoceans,interp,shiftgrid
        import scipy
        from scipy.integrate import quad
        import sys
        sys.path.append('/Users/allen/Documents/Python/PlotGallary')

        from matplotlibconfig import basic

        #configure plot
        basic()
```

```
In [102]: # some utility functions

          def visualize(lon, lat, data, stipple=None, **figkwargs):
              """
              Args:
              ---------------
              :figkwargs - dict; {
                                    'ylabel': '',
                                    'cmap': 'seismic',
                                    'cRange': (-1,1),
                                    'title': '',
                                    'extent': tuple; (llclon, llclat, urclon, urclat)
```

```
                        'projection': str; default 'npstere'
                        }
    """

    ylabel= figkwargs.get('ylabel', '')
    cmapName= figkwargs.get('cmap', 'seismic')
    cRange= figkwargs.get('cRange', (-1,1))
    title= figkwargs.get('title', '')
    lllon, lllat, urlon, urlat= figkwargs.get('extent', (-180, -90, 180, 90))
    proj= figkwargs.get('projection', 'npstere')

    if proj!='npstere':
        rnd= False
    else: rnd=True


    cmin = cRange[0]; cmax = cRange[1];
    cint = 0.2; clevs = np.round(np.arange(cmin,cmax,cint),1)
    nlevs = len(clevs)-1

    plt.gca()
    cmap = plt.get_cmap(name= cmapName,lut=nlevs)
    m = Basemap(llcrnrlon=lllon, llcrnrlat=lllat, urcrnrlon=urlon, urcrnrlat=urlat,
                projection=proj, lon_0=-100, boundinglat=20, round=rnd)

    x,y = m(lon,lat)
    m.drawcoastlines(linewidth=3)
    m.drawmapboundary(linewidth=2)
#     m.drawmeridians(range(-90, 90, 10))
#     m.drawparallels(range(-180, 180, 20))
    if stipple is not None:
        m.plot(x[stipple][::3],y[stipple][::3],'o',color='Gold',markersize=1.5) #
    cs = m.contourf(x, y, data)
    cbar = m.colorbar(cs)
    cbar.ax.set_ylabel(ylabel)
    plt.title(title,name='Arial',weight='bold',size=20)

    return m
```

1.1 Question 1

This problem examines the statistical relationship between 500 hPa heights and the El Niño-Southern Oscillation (ENSO) during boreal winter (December, January and February). For this question, you will use two files: (1) ENSO.txt, which contains monthly-mean standardized values of an index measuring ENSO strength and (2) Z500.nc, which contains gridded monthly-mean 500 hPa geopotenal heights globally from 1950 - 2019. The steps for the analysis and final product will be as follows:

```
In [113]: # read in geopotential heights data
          with Dataset('GPH500.nc', 'r') as nc:
              lonHeights= np.array(nc.variables['lon'][:])
              latHeights= np.array(nc.variables['lat'][:])
              time= nc.variables['time'][:]
              timeUnits= nc.variables['time'].units
              heightDate= num2date(time, timeUnits, calendar='standard')
              heightMonth= np.array([date.month for date in heightDate])
              heightYear= np.array([date.year for date in heightDate])
              heights= np.array(nc.variables['hgt'][:])
```

```
In [114]: heights[heights<0]= np.nan
```

```
In [115]: # read in ENSO data
          ENSOfile= np.loadtxt('ENSO.txt', skiprows=2)
          ENSOyear= ENSOfile[:,0]
          ENSOmonth= ENSOfile[:,1]
          ENSO= ENSOfile[:,2]
```

1. Calculate 500 hPa height anomalies, use the 1981 – 2010 base period as your climatology / mean.

✓ X need to do this by month! (see Class Example)

```
In [116]: # select monthly height from 1981 to 2010
          indices= np.where((heightYear>=1981) & (heightYear<=2010))
          # compute the climatology and corresponding date
          anoHeights= heights - np.nanmean(heights[indices], axis=0)
```

2. Calculate the Dec - Feb mean 500 hPa geopotential height anomaly field and ENSO index from each complete winter season in the dataset

need to average DJF.

```
In [117]: # subselect DJF anomalies and corresponding date
          anoIndex= np.where((ENSOmonth==12) | (ENSOmonth==1) | (ENSOmonth==2))
          anoHeights= anoHeights[anoIndex]
          ENSO= ENSO[anoIndex]
```

✓ the index is already standardized, so you could just use ±1

```
In [118]: posENSO= ENSO[ENSO>= np.std(ENSO)]
          negENSO= ENSO[ENSO<= -np.std(ENSO)]

          posIndex= np.where(ENSO>= np.std(ENSO))
          negIndex= np.where(ENSO<= -np.std(ENSO))
```

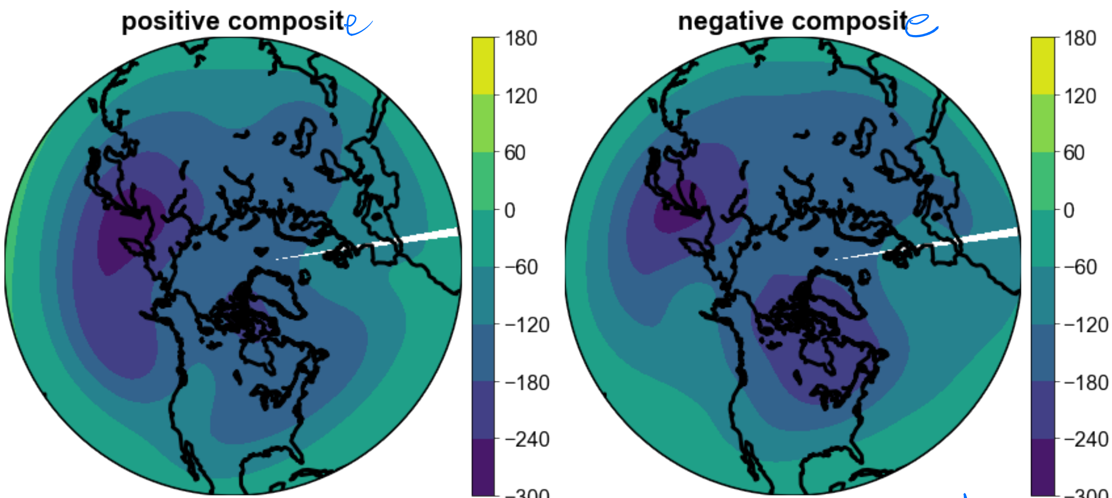
3. Generate composite DJF-mean 500 hPa height anomaly plots for times when ENSO index exceeds 1σ and exceeds -1σ. Use shaded contours for plotting.

```
In [119]: posComp= anoHeights[posIndex]
          negComp= anoHeights[negIndex]
```

```
In [120]: posCompMean= np.array(posComp).mean(axis=0)
          negCompMean= np.array(negComp).mean(axis=0)
```

```
In [121]: lons, lats= np.meshgrid(lonHeights, latHeights)
```

```
In [122]: fig= plt.figure(figsize=(12,8))
          ax1= fig.add_subplot(121)
          map= visualize(lons, lats, posCompMean, title='positive composit')
          ax2= fig.add_subplot(122)
          map= visualize(lons, lats, negCompMean,  title='negative composit')
```



units?

figure caption?

this doesn't look right → should be ⊕ heights across N Pacific

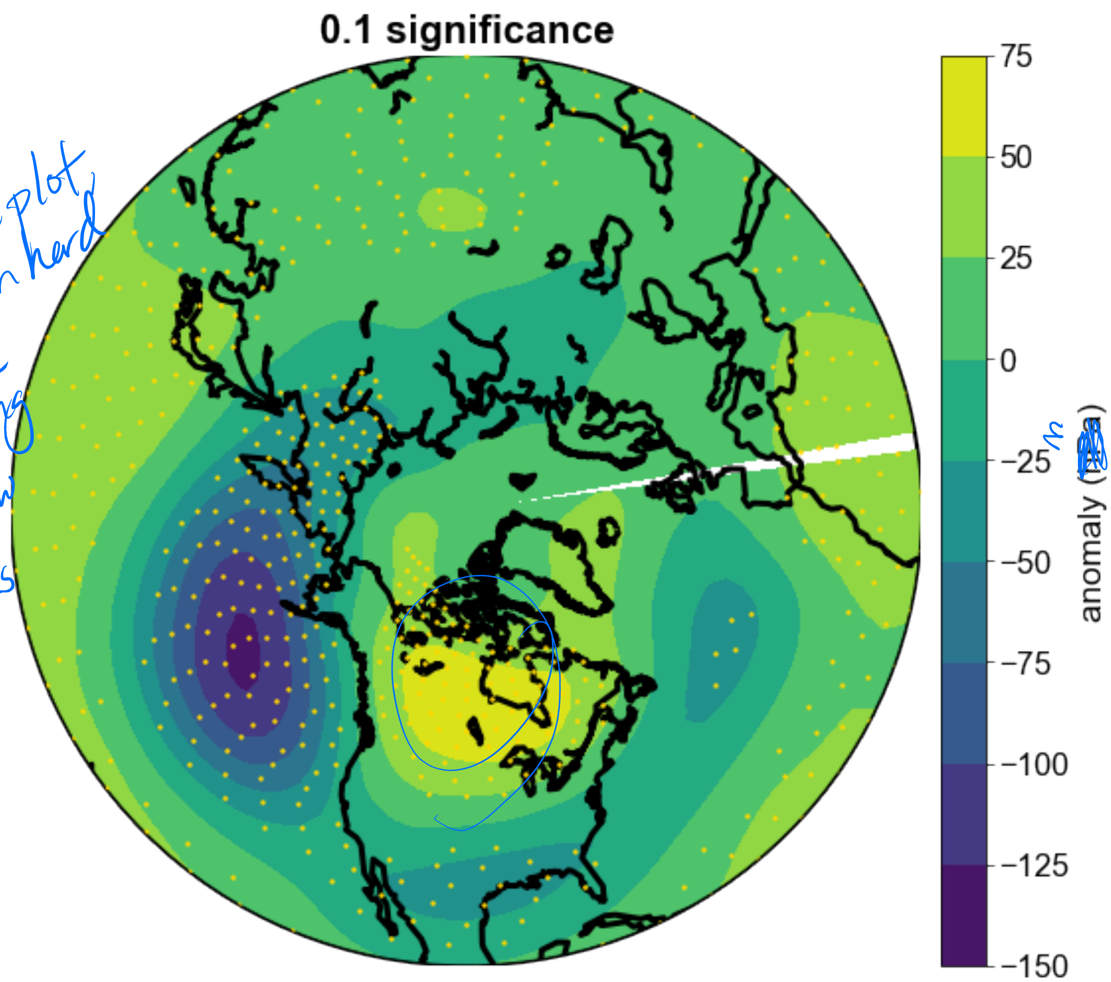
4. Compute the composite difference. Identify regions where the composite difference is significant at the p<0.1 level using either a t-test or a Monte Carlo test. Consider each event as a degree of freedom for the calculation. Outline or stipple these significant regions on the composite difference plot

```
In [123]: compDiff= posCompMean- negCompMean
```

```
In [124]: # t-statistics evaluation


          n1 = len(posENSO)
          n2 = len(negENSO)
          dof = n1+n2-2

          s1 = np.std(posComp, axis=0)
          s2 = np.std(negComp, axis=0)
          sigma = ((n1*s1**2+n2*s2**2)/(n1+n2-1))**.5

          tStatistic = compDiff/sigma/((1/n1+1/n2)**.5)

          pval = 2*stats.t.cdf(-abs(tStatistic),dof*np.ones(tStatistic.shape))
```

```
In [127]: alpha= 0.1
          stipple= pval<=alpha
```

```
fig= plt.figure(figsize=(8,8))
ax= fig.add_subplot(111)
map= visualize(lons, lats, compDiff, stipple, title='0.1 significance',
               ylabel='anomaly (hPa)')
```



Nice plot, though hard to see stippling in yellow regions

```
In [128]: #==========================================================================
          # Calculate significance using Monte Carlo testing. Do this on a per point basis.
          #==========================================================================
          # select monthly height from 1981 to 2010
          indices= np.where((heightYear>=1981) & (heightYear<=2010))

          ano= heights - np.nanmean(heights[indices], axis=0)

          ENSO= ENSOfile[:,2]
          posENSO= ENSO[ENSO>= np.std(ENSO)]
          negENSO= ENSO[ENSO<= -np.std(ENSO)]
```

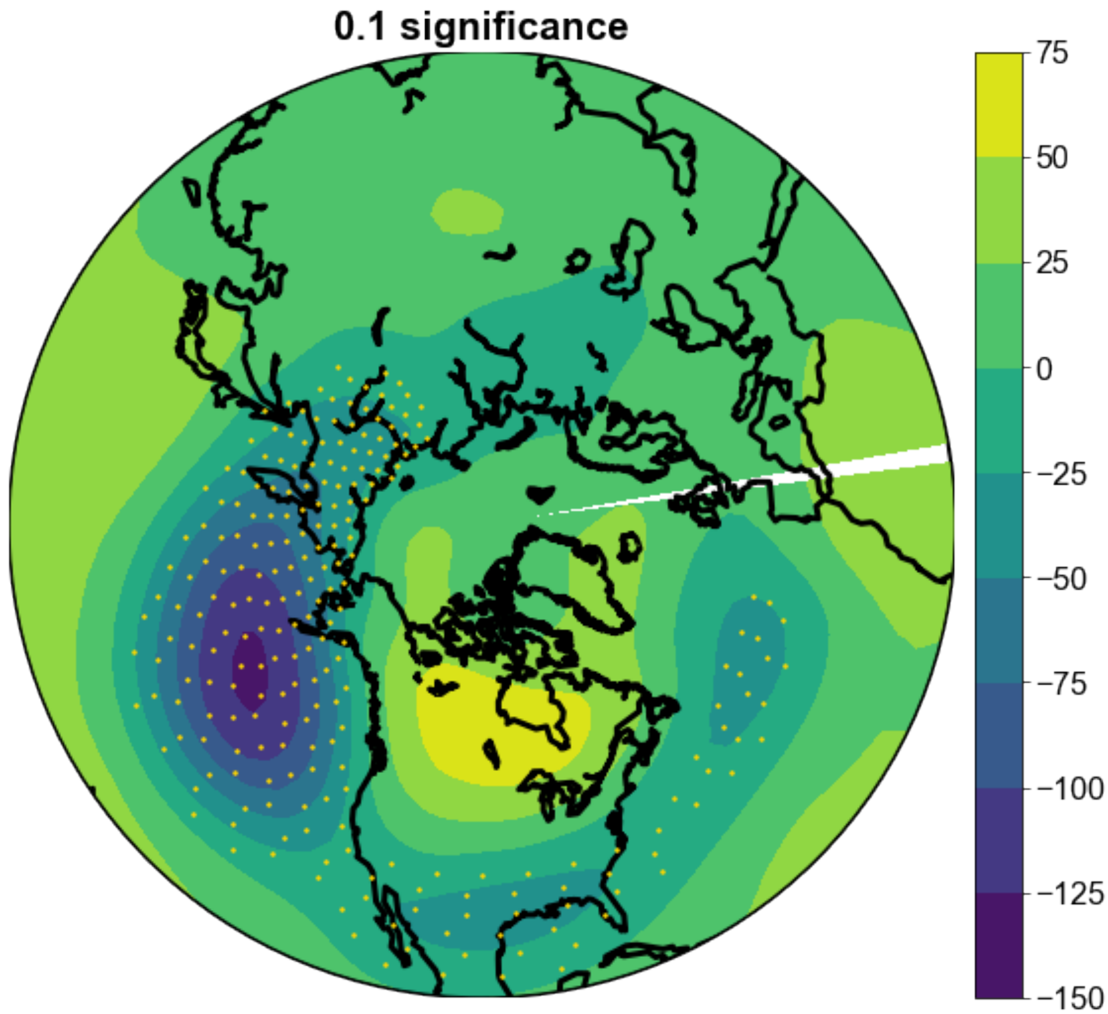
I need to randomly select from DJF-averaged array.

```
T,J,I = ano.shape
niter = 6000
djf = np.where( (ENSOmonth>=12) | (ENSOmonth<=2) )[0]
y = ano.reshape(T,J*I, order='F')
mcCompDiff = np.ones((niter,y.shape[-1]))*np.nan

for n in range(niter):
    c1 = np.random.choice(djf, len(posComp), replace=False)
    c2 = np.random.choice(djf, len(negComp), replace=False)
    mcPos = np.nanmean(y[c1,:],0)
    mcNeg = np.nanmean(y[c2,:],0)
    mcCompDiff[n,:] = mcPos-mcNeg

# Calculate the pvalue for each point
c12 = compDiff.reshape(J*I,order='F')
pval = np.array([stats.percentileofscore(mcCompDiff[:,i],c12[i])/100.
                 for i in range(c12.size)])
```

The Monte Carlo technique was performed overall correctly!

Good!

```
In [129]: alpha= 0.1
          stipple= pval<=alpha

          fig= plt.figure(figsize=(8,8))
          ax= fig.add_subplot(111)
          map= visualize(lons, lats, compDiff, stipple.reshape(lons.shape, order='F'),
                         title='0.1 significance')
```



5. Assemble the plots for presentation as a 3-panel plot, with the positive ENSO composite on top, the negative ENSO composite in the middle, and the composite difference on the bottom. Make the plot only for the Northern Hemisphere (i.e., 20-90 N).

```
In [134]: fig= plt.figure(figsize=(6,15))
          ax= fig.add_subplot(311)
          map= visualize(lons, lats, posCompMean, extent=(-180,20,180,90),
                         title='positive composite', ylabel='heights (500hPa)')
          ax= fig.add_subplot(312)
          map= visualize(lons, lats, negCompMean, extent=(-180,20,180,90),
                         title='negative composite', ylabel='heights (500hPa)')
          ax= fig.add_subplot(313)
          map= visualize(lons, lats, compDiff, extent=(-180,20,180,90),
                         title='composite difference', ylabel='heights (500hPa)')
          plt.tight_layout()
```

stippling?

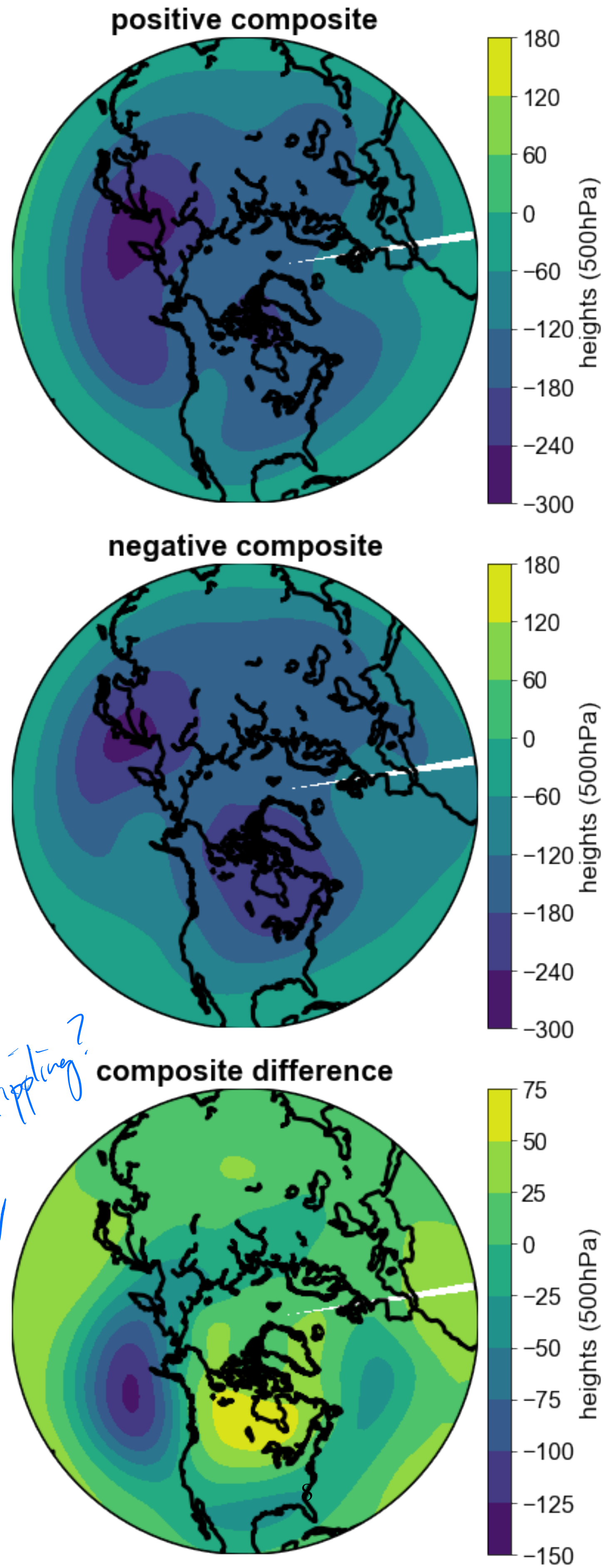


Figure caption?

Nice description of the composite difference

As from the significance test, both the t-test and Monte-Carlo test show that the differences of geopotential heights for positive ENSO and negative ENSO are significant in North Pacific Ocean, southern U.S., and part of North Atlantic Ocean. In these areas, the difference is significantly skewed towards negative, which indicates the negative ENSO indicator strongly affect this extratropical places, especially decreasing the 500 hPa geopotential height. As a consequence, this impact will change the global weather pattern (i.e., influence the precipitation distribution).

There are some differences between t-test and Monte-Carlo simulation as well. we can see the t-test result (stipples) cover more areas in the globe, suggesting the ENSO factors (positive and negative) have more places under significant differences.

↳ yes, but just a couple of missteps with the averaging

1.2 Question 2

```
In [231]: import pandas as pd
```

```
In [247]: precip= pd.read_csv('BostonMaxDailyPrecip.txt', sep='\t+', skiprows=2, header=None)
```

```
/usr/local/lib/python3.7/site-packages/ipykernel_launcher.py:1: ParserWarning: Falling back to
  """Entry point for launching an IPython kernel.
```

```
In [248]: precip.columns= ['precipInch', 'date', 'precipMM']
```

```
In [252]: precip.date= pd.to_datetime(precip.date)
```

1. Using the data provided, fit a Gumbel distribution to the Boston precipitation data in mm. Use the methods of moments to estimate the parameters for the distribution.

$$Gumbel = \frac{1}{\beta}exp(-exp(-\frac{x-\eta}{\beta}) - \frac{x-\eta}{\beta})$$

```
In [269]: def gumbel(x, eta, beta):
              pdf= 1/beta*np.exp(-np.exp(-(x-eta)/beta)-(x-eta)/beta)

              return pdf

          def est_beta(x):
              return np.std(x)*6**.5/np.pi

          def est_eta(x, beta):
              return x.mean()-0.5772*beta
```

```
In [270]: beta= est_beta(precip.precipMM)
          eta= est_eta(precip.precipMM, beta)
```

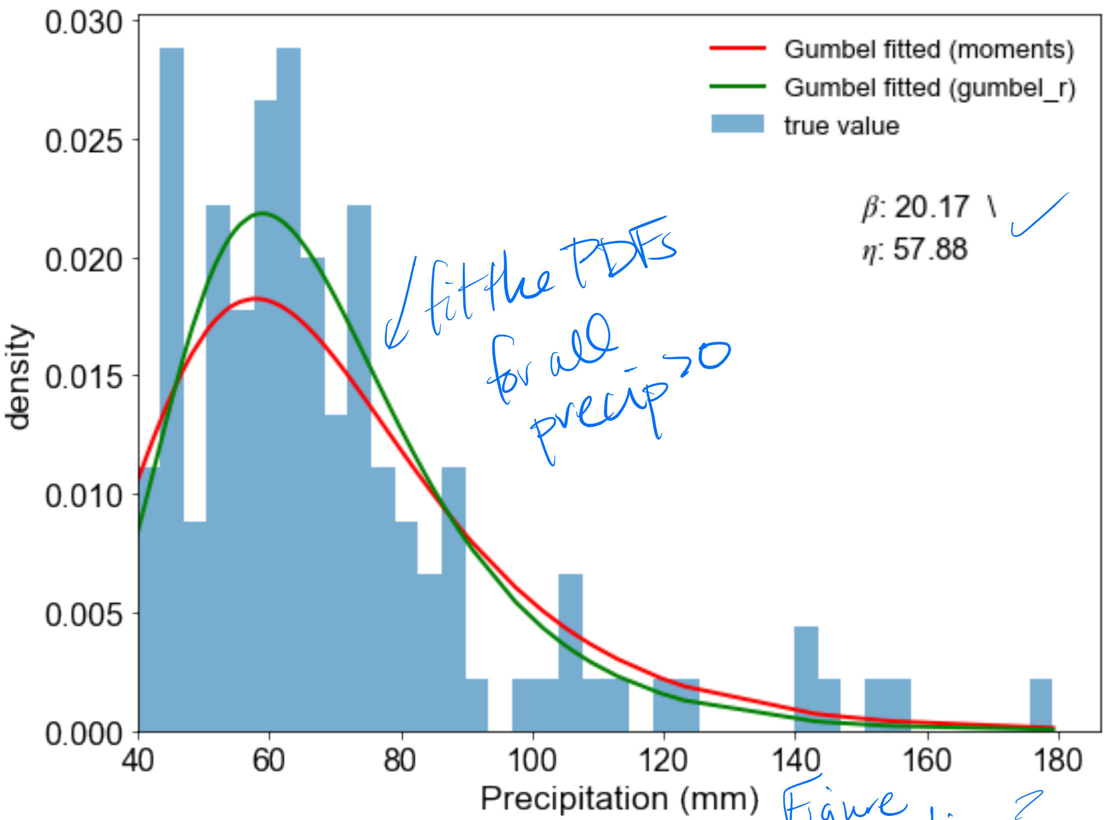
```
In [272]: print('estimated beta and eta are: %.2f, %.2f'%(beta, eta))
```

```
estimated beta and eta are: 20.17, 57.88
```

```
In [273]: gumbel_pdf= gumbel(precip.precipMM, eta, beta)
```

2. Make a plot with a histogram of the annual daily-maximum precipitation (in mm) and the fitted Gumbel distribution overlaid on the histogram. On your plot, indicate the values of β and η used for the fit.

```
In [425]: fig, ax= plt.subplots(1,1, figsize=(8,6))
          ax.hist(precip.precipMM, bins=40, density=True, label='true value', alpha=.6);
          ax.plot(sorted(precip.precipMM), gumbel_pdf[np.argsort(precip.precipMM)],
                  c='r', label='Gumbel fitted (moments)')
          ax.plot(sorted(precip.precipMM), gumbel_r.pdf(precip.precipMM,loc,scale)[np.argsort(p
                  color='g', label='Gumbel fitted (gumbel_r)')
          ax.set_xlim([40, None])
          ax.legend(frameon=False)
          ax.set_xlabel('Precipitation (mm)')
          ax.set_ylabel('density')
          ax.text(150,0.02, r'$\beta$: %.2f  \
          $\eta$: %.2f'%(beta, eta));
```



fit the PDFs for all precip > 0

Figure caption?

3. Using your fitted distribution, determine what the probability is that Boston will experience a year with a daily maximum precipitation amount (i) greater than 130 mm (about 5 in) and (ii) less than 50 mm (about 2 in).

$$P(x >= 130) = \int_{130}^{+\inf} pdf(x)dx$$

$$P(x <= 50) = \int_{0}^{50} pdf(x)dx$$

In [430]:
```
func= lambda x: gumbel(x, eta, beta)
prob, err= quad(func, 130, np.inf)
print('The probability exceeds 130 mm from Gumbel function is %.2f, with numerical er

prob, err= quad(func, 0, 50)
print('The probability blow 50 mm from Gumbel function is %.2f, with numerical error
```

```
The probability exceeds 130 mm from Gumbel function is 0.03, with numerical error of 1e-9
The probability blow 50 mm from Gumbel function is 0.23, with numerical error of 5e-9
```

In [431]:
```
# cross-check the answer with python inner module stats.gumbel_r

from scipy.stats import gumbel_r
loc, scale= gumbel_r.fit(precip.precipMM)
print(r'fitted beta: %.2f, eta: %.2f, the difference is (%.2f, %.2f) for (beta, eta)\
      relative error (%.2f%%, %.2f%%)'%(scale, loc, beta-scale, eta-loc, (beta-scale
```

```
fitted beta: 16.85, eta: 58.90, the difference is (3.32, -1.02) for (beta, eta)\
       relative error (16.48%, -1.76%)
```

I like that you checked the fit!

In [432]:
```
print('The true probability beyond 130 mm is %.2f, below 50 mm is %.2f'%(
    quad(lambda x: gumbel(x, loc, scale), 130, np.inf)[0], quad(lambda x: gumbel(x, l
```

```
The true probability beyond 130 mm is 0.01, below 50 mm is 0.18
```

4. Calculate the daily maximum precipitation amounts corresponding to a 1-in-50 year, 1-in-100 year, and 1-in-500 year event in Boston.

In [448]:
```
obj= lambda x: abs(quad(func, x, np.inf)[0]-0.02)
fifty= scipy.optimize.minimize(obj, 100, tol=1e-8).x
```

In [449]:
```
obj= lambda x: abs(quad(func, x, np.inf)[0]-0.01)
hundred= scipy.optimize.minimize(obj, 150, tol=1e-8).x
```

In [450]:
```
obj= lambda x: abs(quad(func, x, np.inf)[0]-0.002)
fivehundred= scipy.optimize.minimize(obj, 200, tol=1e-8).x
```

In [451]:
```
print('The daily maximum precipitation for 1-in-50 year, 1-in-100-year and 1-in-500 y
fifty, hundred, fivehundred))
```

I can't see the other values!

```
The daily maximum precipitation for 1-in-50 year, 1-in-100-year and 1-in-500 year are 136.60 mm
```

```
In [452]: print('The true daily maximum precipitation for 1-in-50 year, 1-in-100-year and 1-in-
          gumbel_r.ppf(1-0.02, loc, scale), gumbel_r.ppf(1-0.01, loc, scale), gumbel_r.ppf(1-0
```

```
The true daily maximum precipitation for 1-in-50 year, 1-in-100-year and 1-in-500 year are 124
```

1.3 Question 3

A popular topic in wintertime subseasonal and seasonal forecasting is using the state of the stratospheric polar vortex to make skillful predictions of tropospheric weather regimes. One mode of climate variability that forecasters seek to predict is the Northern Annular Mode (NAM) in both the stratosphere and the troposphere. For stratospheric levels, strongly positive (negative) values of the NAM index (e.g., NAM at 50 hPa; NAM50) typically mean that the stratospheric polar vortex is stronger (weaker) than normal i.e., climatological westerlies in the stratosphere are stronger (weaker) than average. In the troposphere, strongly positive (negative) values of the near-surface NAM index (e.g., NAM at 1000 hPa; NAM1000) indicate that the mean position of the polar jet stream is more poleward (equatorward) than normal, sugges ting warmer (colder) than normal temperatures across the Northern Hemisphere mid-latitudes. In this exercise, you will investigate how the probability density function (PDF) of NAM1000 may change given the background state of the stratospheric circulation.

```
In [473]: # read the data
          NAM1000= pd.read_csv('NAM1000.txt', skiprows=2, header=None, sep='\s+', names=['year
          NAM50= pd.read_csv('NAM50.txt', skiprows=2, header=None, sep='\s+', names=['year', 'n
```

1. Calculate the clamatological PDF of NAM_{1000} (i.e., all NDJFMA days). Then, on the same plot, overlay two other conditional PDFs:

   The PDF of NAM_{1000} for days when $NAM_{50} > +1\sigma$

   The PDF of NAM_{1000} for days when $NAM_{50} < -2\sigma$

```
In [503]: #composite
          ndjfma= np.where((NAM1000.month>=11) | (NAM1000.month<=4))[0]

          climNAM1000= NAM1000.iloc[ndjfma, :]
          climNAM50= NAM50.iloc[ndjfma, :]

          posInds= np.where((climNAM50.iloc[:,-1]> np.std(climNAM50.iloc[:,-1])))[0]
          negInds= np.where((climNAM50.iloc[:,-1]< -2* np.std(climNAM50.iloc[:,-1])))[0]

          posClimNAM1000= climNAM1000.iloc[posInds, -1]
          negClimNAM1000= climNAM1000.iloc[negInds, -1]

          #make plot
          fig, ax= plt.subplots(1,1, figsize=(12,6))
          climNAM1000.iloc[:,-1].plot.hist(alpha=.6, bins=50, density=True,label='PDF of NAM10
```

```
posClimNAM1000.plot.hist(alpha=.6, bins=50, density=True,label='PDF of NAM1000 condit
negClimNAM1000.plot.hist(alpha=.6,bins=50, density=True,label='PDF of NAM1000 condit
ax.legend()
ax.set_xlabel('NAM1000');
```

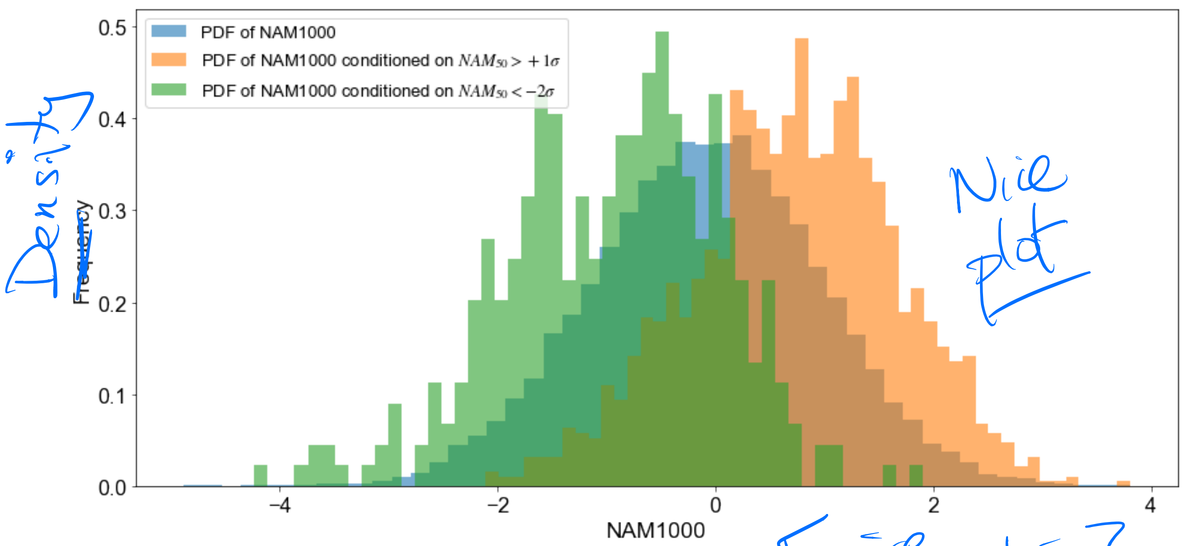


Figure caption?

By firstly looking at the distribution for three data, they behave more or less like normal. Thus, we decided to fit into a t-distribution. Then the next thing we need to do is to calibrate those parameters.

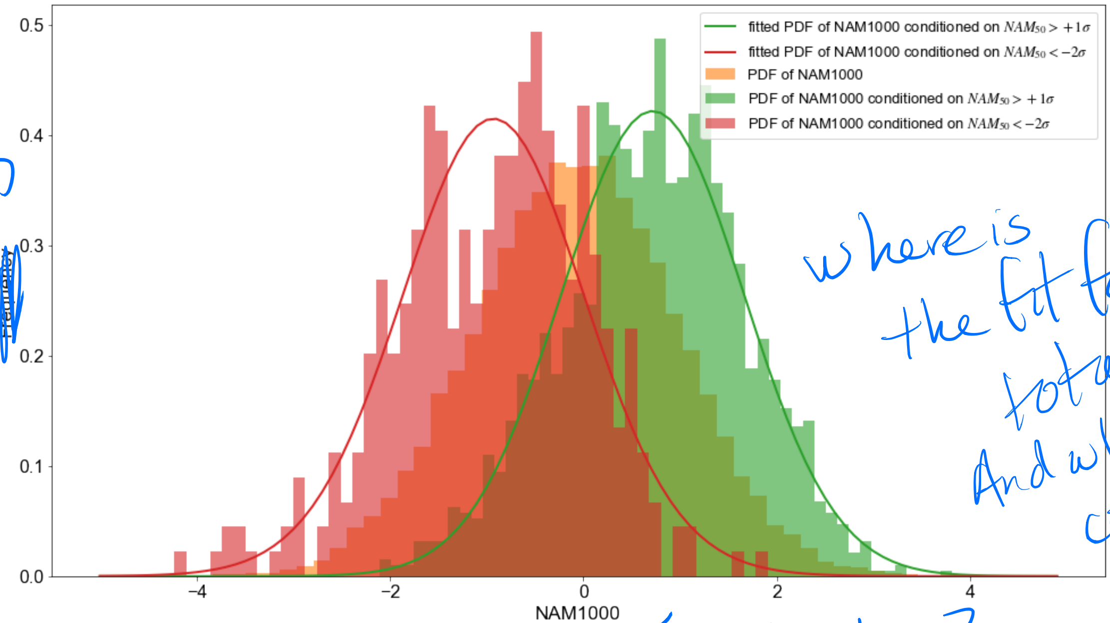
why not normal/Gaussian fit?

Assume the degree of freedom for each case is the sample size.

```
In [521]: paramsPos= stats.t.fit(posClimNAM1000.values, len(posClimNAM1000)-1)
          paramsNeg= stats.t.fit(negClimNAM1000.values, len(negClimNAM1000)-1)
```

Sample sizes for each PDF?

```
In [522]: posDist= stats.t(*paramsPos)
          negDist= stats.t(*paramsNeg)

In [532]: fig, ax= plt.subplots(1,1, figsize=(14,8))
          ax.plot(np.arange(-5,5,0.1), posDist.pdf(np.arange(-5,5,0.1)),color= 'C2',
                  label='fitted PDF of NAM1000 conditioned on $NAM_{50}>+1\sigma$')
          ax.plot(np.arange(-5,5,0.1), negDist.pdf(np.arange(-5,5,0.1)),color= 'C3',
                  label='fitted PDF of NAM1000 conditioned on $NAM_{50}<-2\sigma$')
          climNAM1000.iloc[:,-1].plot.hist(alpha=.6, bins=50, density=True,
                                         label='PDF of NAM1000', color= 'C1')
          posClimNAM1000.plot.hist(alpha=.6, bins=50, density=True, color= 'C2',
                                   label='PDF of NAM1000 conditioned on $NAM_{50}>+1\sigma$')
          negClimNAM1000.plot.hist(alpha=.6,bins=50, density=True,color= 'C3',
                                   label='PDF of NAM1000 conditioned on $NAM_{50}<-2\sigma$')
          ax.set_xlabel('NAM1000')
          plt.legend();
```



where is the fit for the total NDJFM? And why change colors?

Figure caption?

I cannot see the answers

```
In [546]: print('probability that $NAM_{1000}$ smaller than $-1\sigma$ conditioned on $NAM_{50}
          '%(posDist.cdf(-np.std(posClimNAM1000.values))))

probability that $NAM_{1000}$ smaller than $-1\sigma$ conditioned on $NAM_{50}>+1\sigma$is: 0.0
```

```
In [547]: print('probability that $NAM_{1000}$ smaller than $-1\sigma$ conditioned on $NAM_{50}
          '%(negDist.cdf(-np.std(negClimNAM1000.values))))

probability that $NAM_{1000}$ smaller than $-1\sigma$ conditioned on $NAM_{50}<-2\sigma$is: 0.4
```

your answers didn't print

K-S test

```
In [559]: stats.ks_2samp(posDist.rvs(size=100), negDist.rvs(size=100))

Out[559]: Ks_2sampResult(statistic=0.63, pvalue=6.314161651442317e-19)
```

From the K-S test results, we can reject the null hypothesis that two samples are identical with almost 100% confidence.

The NAM_{50} (stratospheric polar vortex) is a good indicator to describe northern hemisphere surface weather since is has distinct behavior (from the PDFs) among positive NAM_{50} and negative NAM_{50}. Basically, positive NAM_{50} pushes NAM_{1000} more towards positive and negative NAM_{50} pushes NAM_{1000} towards negative. Hence, it could be an indicator to predict northern hemisphere surface weather.

Nice interpretation of the stats and statistical test.

Q1: 29/35

Q2: 30/30

Q3: 29/35

No figure captions: -6

Total: 82%