12.2 Assignment ~ Term Project

In [1]:
```
# import necessary packages

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import thinkstats2
import thinkplot
from colorspacious import cspace_converter
import scipy.stats
import statsmodels.formula.api as smf

%matplotlib inline
plt.style.use('ggplot')
```

In [2]:
```
df = pd.read_csv('/Users/aliss/OneDrive - Bellevue University/DSC530/Final Project/
                 'GlobalTemperatures.csv')
#df = df.dropna()
df['dt'] = pd.to_datetime(df['dt'])

# convert temps from celsius to farenheit
df['LandAverageTemperature'] = df['LandAverageTemperature']*1.8+32
df['LandMaxTemperature'] = df['LandMaxTemperature']*1.8+32
df['LandMinTemperature'] = df['LandMinTemperature']*1.8+32
df['LandAndOceanAverageTemperature'] = df['LandAndOceanAverageTemperature']*1.8+32

df.head()
```

Out[2]:

	dt	LandAverageTemperature	LandAverageTemperatureUncertainty	LandMaxTemperature	LandM
0	1750-01-01	37.4612	3.574	NaN	
1	1750-02-01	37.5494	3.702	NaN	
2	1750-03-01	42.1268	3.076	NaN	
3	1750-04-01	47.2820	2.451	NaN	
4	1750-05-01	52.8314	2.072	NaN	

Select a minimum of 5 variables in your dataset used during your analysis. Consider what you think could have an impact on your question, and describe what the 5 variables mean in the dataset (Chapter 1).

dt is the date each temperature was recorded (year-month-day).

LandAverageTemperature is the average land temperature (°F).

LandAverageTemperatureUncertainty is the uncertainty of each temperature (%).

LandMaxTemperature is the maximum temperature recorded (°F).

LandMinTemperature is the minimum temperature recorded (°F).

LandAndOceanAverageTemperature is the average land and ocean temperature (°F).

In [3]:
```
#df['Year'] = df['dt'].dt.strftime('%Y')
temp_df = df[['dt','LandAverageTemperature', 'LandAverageTemperatureUncertainty',
       'LandMaxTemperature',
       'LandMinTemperature',
       'LandAndOceanAverageTemperature',]]

temp_df.head()
```

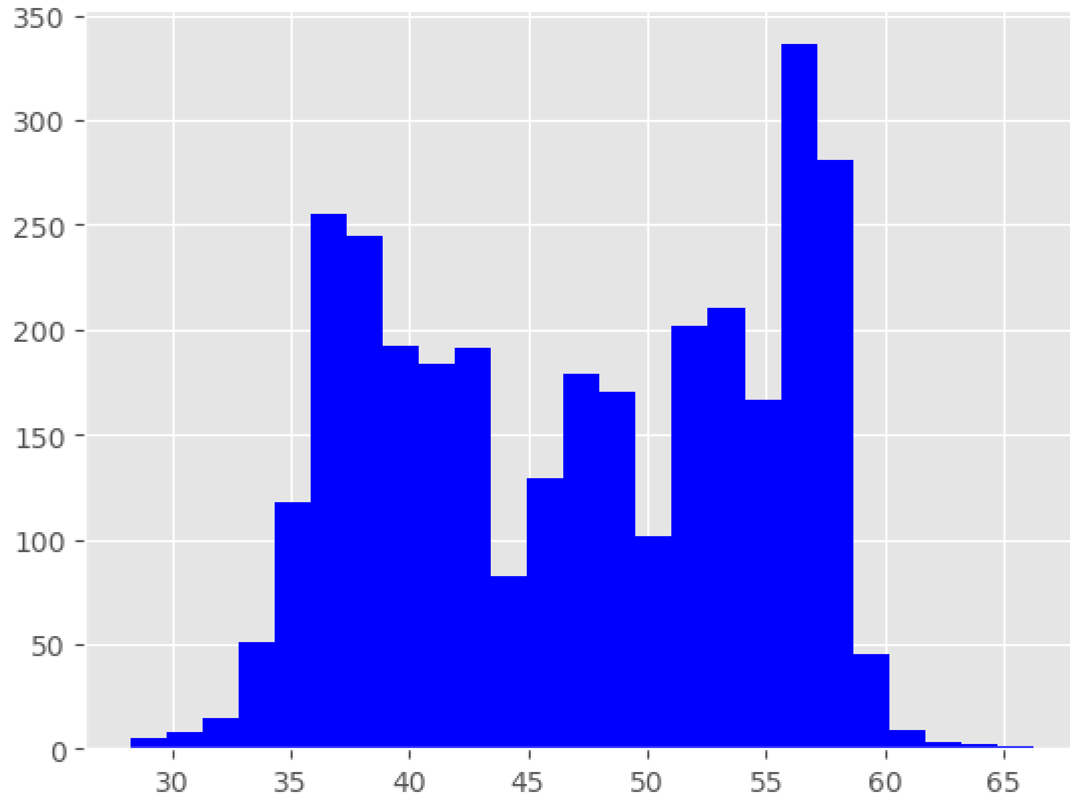
Out[3]:

	dt	LandAverageTemperature	LandAverageTemperatureUncertainty	LandMaxTemperature	LandM
0	1750-01-01	37.4612	3.574	NaN	
1	1750-02-01	37.5494	3.702	NaN	
2	1750-03-01	42.1268	3.076	NaN	
3	1750-04-01	47.2820	2.451	NaN	
4	1750-05-01	52.8314	2.072	NaN	

Include a histogram of each of the 5 variables – in your summary and analysis, identify any outliers and explain the reasoning for them being outliers and how you believe they should be handled (Chapter 2).

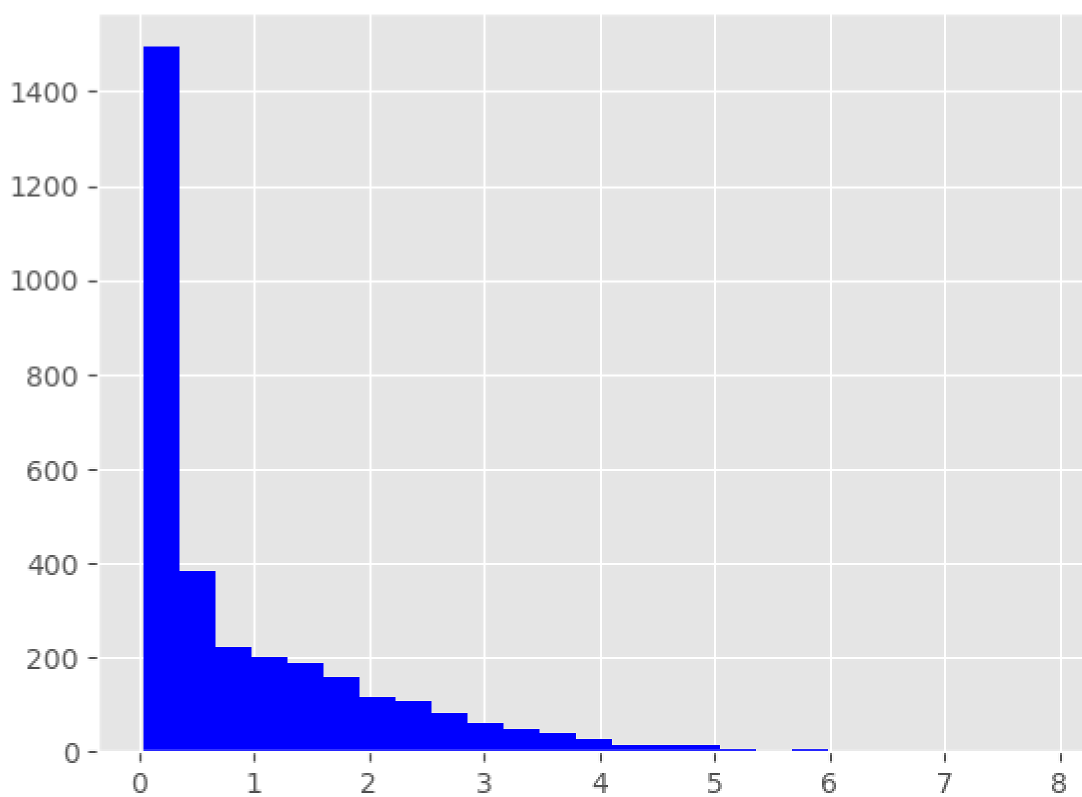
In [4]:
```
temp_df.LandAverageTemperature.hist(bins=25,color='blue')
```

Out[4]: <AxesSubplot: >



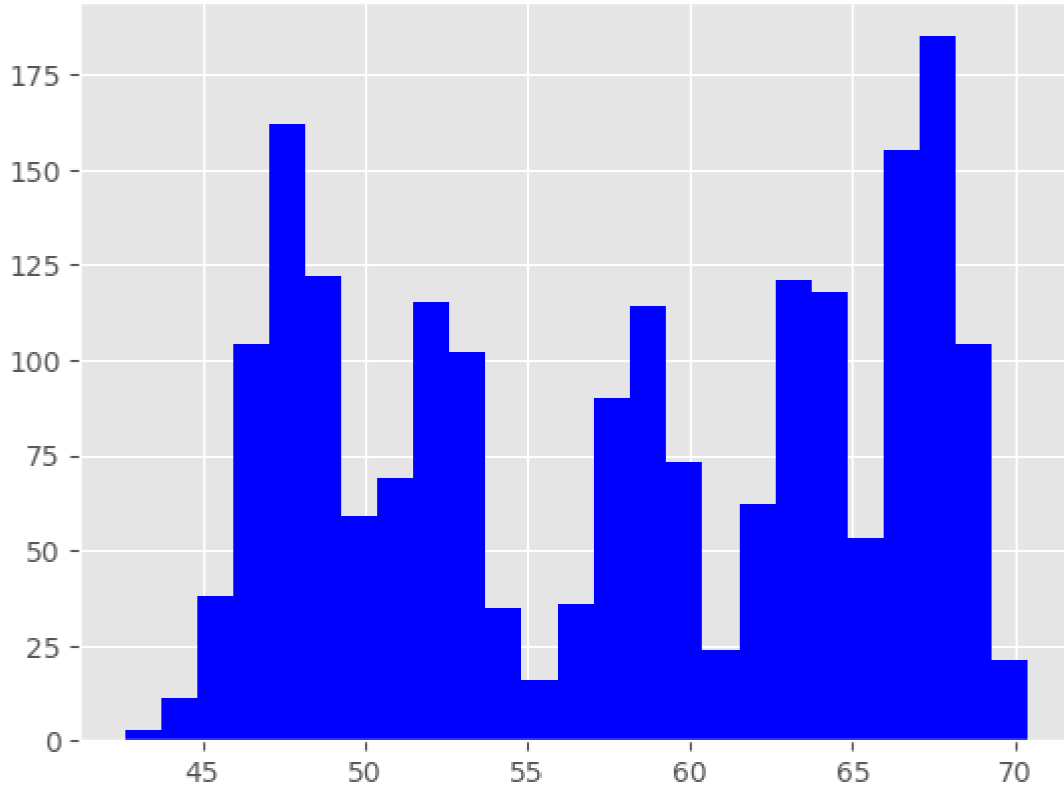
In [5]:
```
temp_df.LandAverageTemperatureUncertainty.hist(bins=25,color='blue')
```

Out[5]: <AxesSubplot: >



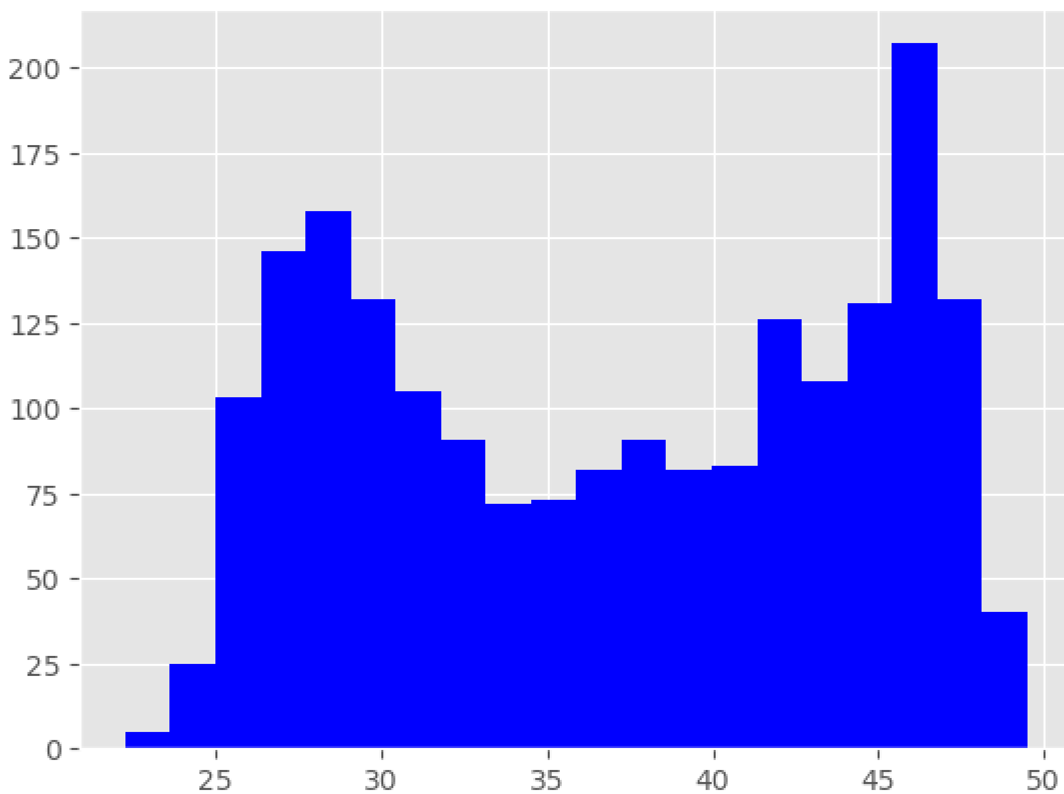
In [6]:
```
temp_df.LandMaxTemperature.hist(bins=25,color='blue')
```

Out[6]: <AxesSubplot: >



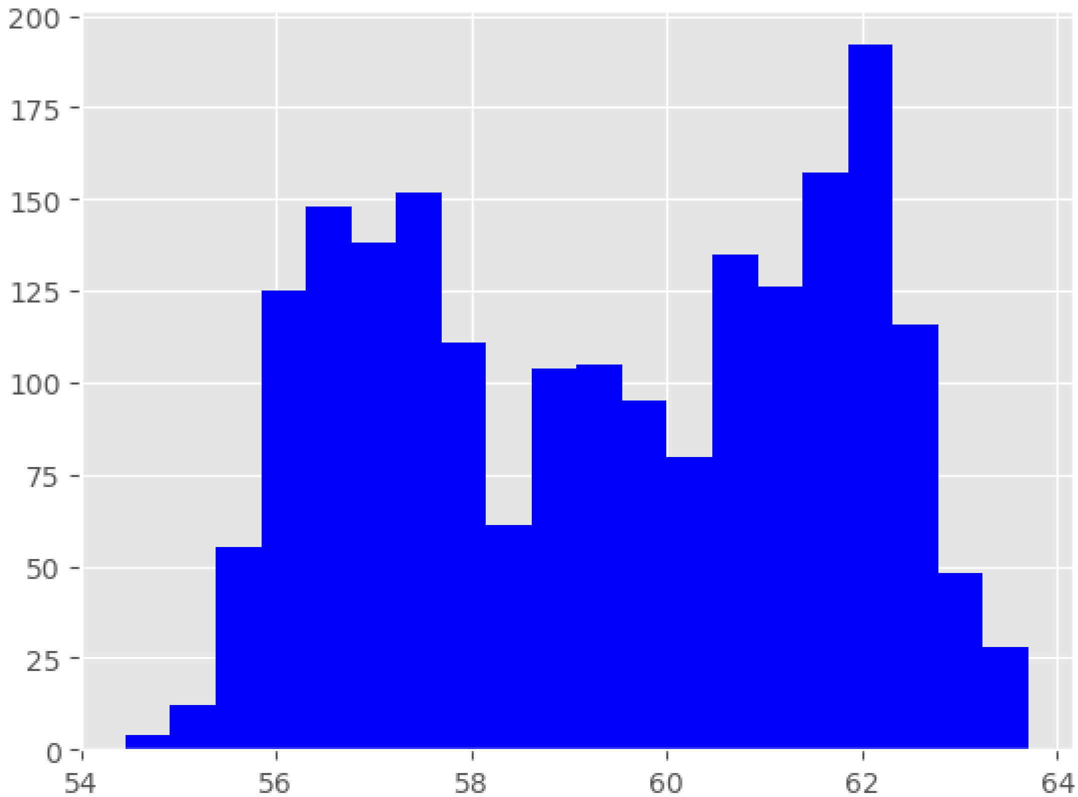
In [7]:
```
temp_df.LandMinTemperature.hist(bins=20,color='blue')
```

Out[7]: <AxesSubplot: >



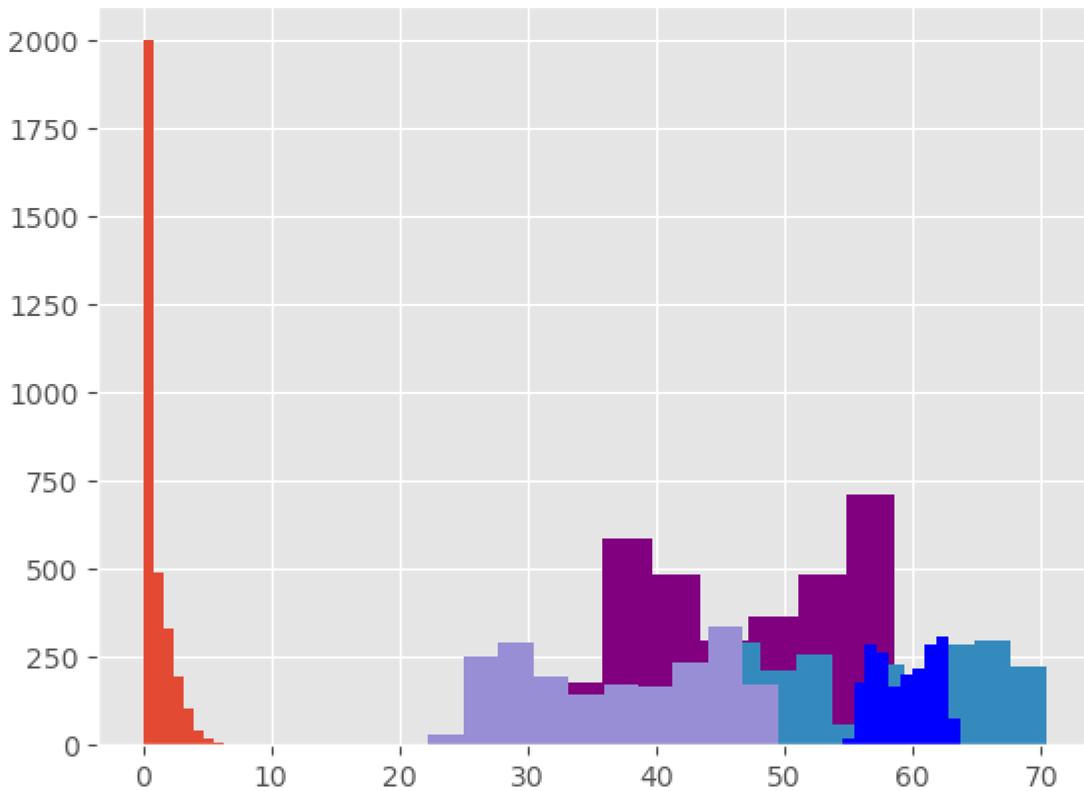
In [8]:
```
temp_df.LandAndOceanAverageTemperature.hist(bins=20,color='blue')
```

Out[8]: <AxesSubplot: >



In [9]:
```
temp_df.LandAverageTemperature.hist(color='purple')
temp_df.LandAverageTemperatureUncertainty.hist()
temp_df.LandMaxTemperature.hist()
temp_df.LandMinTemperature.hist()
temp_df.LandAndOceanAverageTemperature.hist(color='blue')
```

Out[9]: <AxesSubplot: >



Include the other descriptive characteristics about the variables: Mean, Mode, Spread, and Tails (Chapter 2).

In [10]:
```
mean = temp_df.LandAverageTemperature.mean()
mode = temp_df.LandAverageTemperature.mode()
spread = temp_df.LandAverageTemperature.var()
tails = temp_df.LandAverageTemperature.skew()
print("mean = " + str(round(mean, 2)), "\nmode = " + str(mode),
      "\nspread = " + str(round(spread,2)), "\ntails = " + str(round(tails,2)))
```

```
mean = 47.07
mode = 0    55.9274
1    56.7770
Name: LandAverageTemperature, dtype: float64
spread = 62.19
tails = -0.08
```

In [11]:
```
mean = temp_df.LandAverageTemperatureUncertainty.mean()
mode = temp_df.LandAverageTemperatureUncertainty.mode()
spread = temp_df.LandAverageTemperatureUncertainty.var()
tails = temp_df.LandAverageTemperatureUncertainty.skew()
print("mean = " + str(round(mean, 2)), "\nmode = " + str(mode),
      "\nspread = " + str(round(spread,2)), "\ntails = " + str(round(tails,2)))
```

```
mean = 0.94
mode = 0    0.087
Name: LandAverageTemperatureUncertainty, dtype: float64
spread = 1.2
tails = 1.78
```

In [12]:
```
mean = temp_df.LandMaxTemperature.mean()
mode = temp_df.LandMaxTemperature.mode()
spread = temp_df.LandMaxTemperature.var()
```

```python
tails = temp_df.LandMaxTemperature.skew()
print("mean = " + str(round(mean, 2)), "\nmode = " + str(mode),
      "\nspread = " + str(round(spread,2)), "\ntails = " + str(round(tails,2)))
```

```
mean = 57.83
mode = 0     47.3990
1     51.4058
2     52.5398
3     62.9528
4     63.1202
5     63.8834
6     66.8480
7     67.3304
8     67.5554
9     67.7300
10    67.9766
11    68.0666
Name: LandMaxTemperature, dtype: float64
spread = 60.17
tails = -0.1
```

In [13]:

```python
mean = temp_df.LandMinTemperature.mean()
mode = temp_df.LandMinTemperature.mode()
spread = temp_df.LandMinTemperature.var()
tails = temp_df.LandMinTemperature.skew()
print("mean = " + str(round(mean, 2)), "\nmode = " + str(mode),
      "\nspread = " + str(round(spread,2)), "\ntails = " + str(round(tails,2)))
```

```
mean = 36.94
mode = 0    46.7312
Name: LandMinTemperature, dtype: float64
spread = 55.96
tails = -0.05
```

In [14]:

```python
mean = temp_df.LandAndOceanAverageTemperature.mean()
mode = temp_df.LandAndOceanAverageTemperature.mode()
spread = temp_df.LandAndOceanAverageTemperature.var()
tails = temp_df.LandAndOceanAverageTemperature.skew()
print("mean = " + str(round(mean, 2)), "\nmode = " + str(mode),
      "\nspread = " + str(round(spread,2)), "\ntails = " + str(round(tails,2)))
```

```
mean = 59.38
mode = 0    59.009
Name: LandAndOceanAverageTemperature, dtype: float64
spread = 5.26
tails = -0.06
```

In [15]:

```python
temp_df.describe()
```

Out[15]:

	LandAverageTemperature	LandAverageTemperatureUncertainty	LandMaxTemperature	LandMin
count	3180.000000	3180.000000	1992.000000	
mean	47.074516	0.938468	57.831082	
std	7.886358	1.096440	7.757242	
min	28.256000	0.034000	42.620000	
25%	39.761600	0.186750	50.381600	
50%	47.498900	0.392000	58.568000	
75%	54.586850	1.419250	65.212700	
max	66.237800	7.880000	70.376000	

In [16]:

```
tails = temp_df.skew(numeric_only=True)
tails
```

Out[16]:

```
LandAverageTemperature              -0.081426
LandAverageTemperatureUncertainty    1.780597
LandMaxTemperature                  -0.096938
LandMinTemperature                  -0.050255
LandAndOceanAverageTemperature      -0.056049
dtype: float64
```

Using pg. 29 of your text as an example, compare two scenarios in your data using a PMF. Reminder, this isn't comparing two variables against each other – it is the same variable, but a different scenario, almost like a filter (Chapter 3).

In [17]:

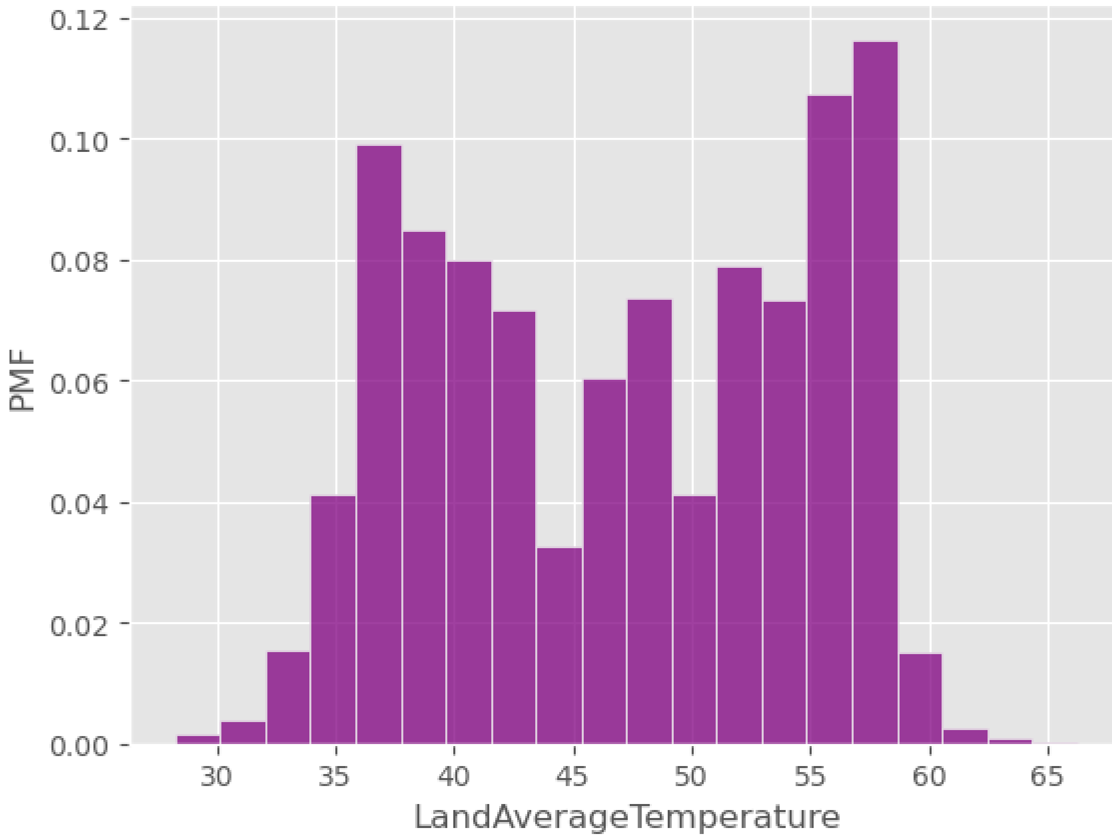
```
pmf = thinkstats2.Pmf(temp_df.LandAverageTemperature)
pmf.Total(), pmf.Mean()
```

Out[17]:

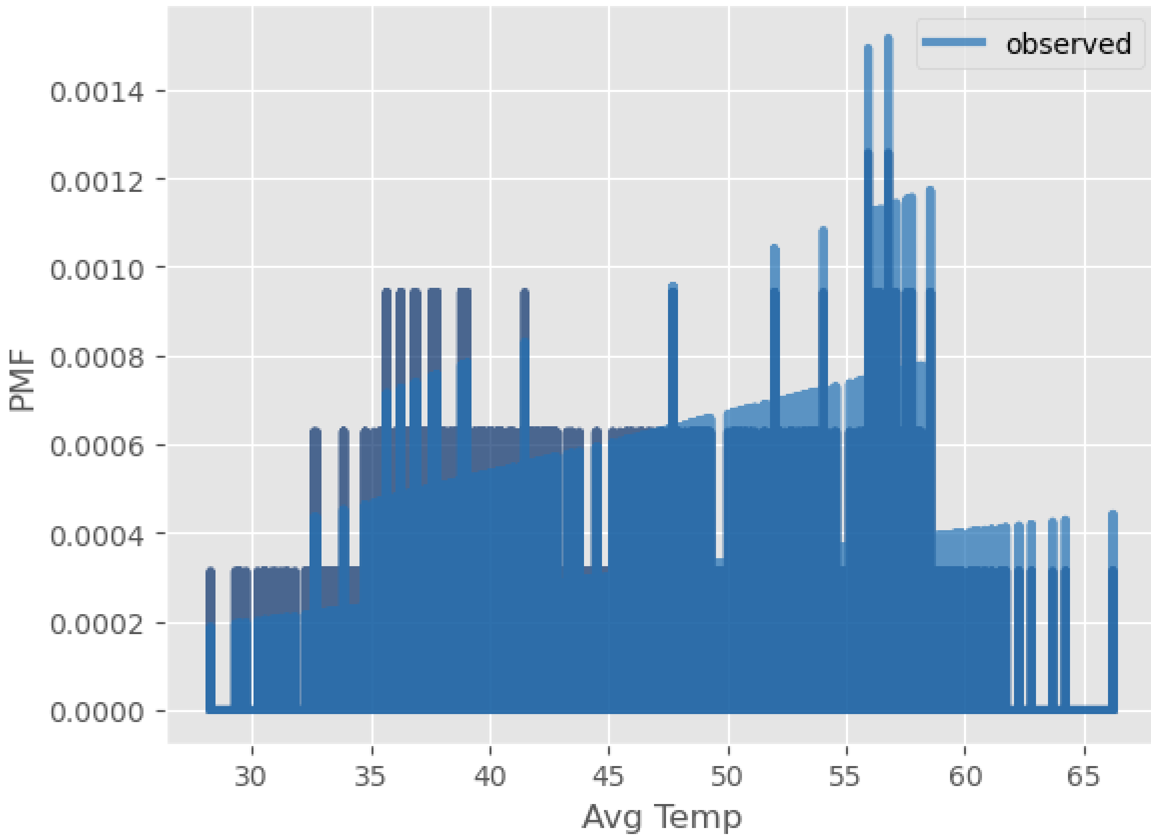
```
(1.000000000000088, 47.074516037736)
```

In [18]:

```
plt.ylabel('PMF')
sns.histplot(temp_df.LandAverageTemperature, stat='probability', color='purple',
             bins=20);
```



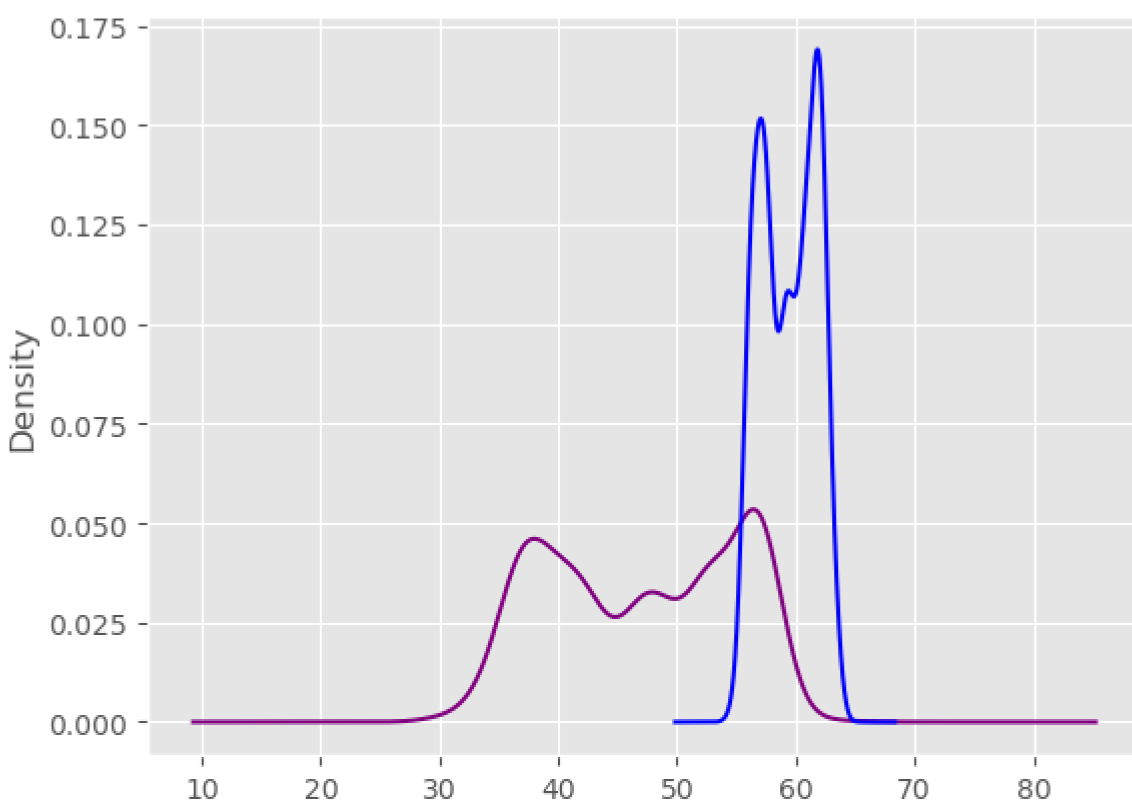
In [19]:
```
def BiasPmf(pmf, label):
    new_pmf = pmf.Copy(label=label)
    for x, p in pmf.Items():
        new_pmf.Mult(x, x)
    new_pmf.Normalize()
    return new_pmf

biased_pmf = BiasPmf(pmf, label='observed')
thinkplot.Pmfs([pmf, biased_pmf])
thinkplot.Show(xlabel='Avg Temp', ylabel='PMF')
```



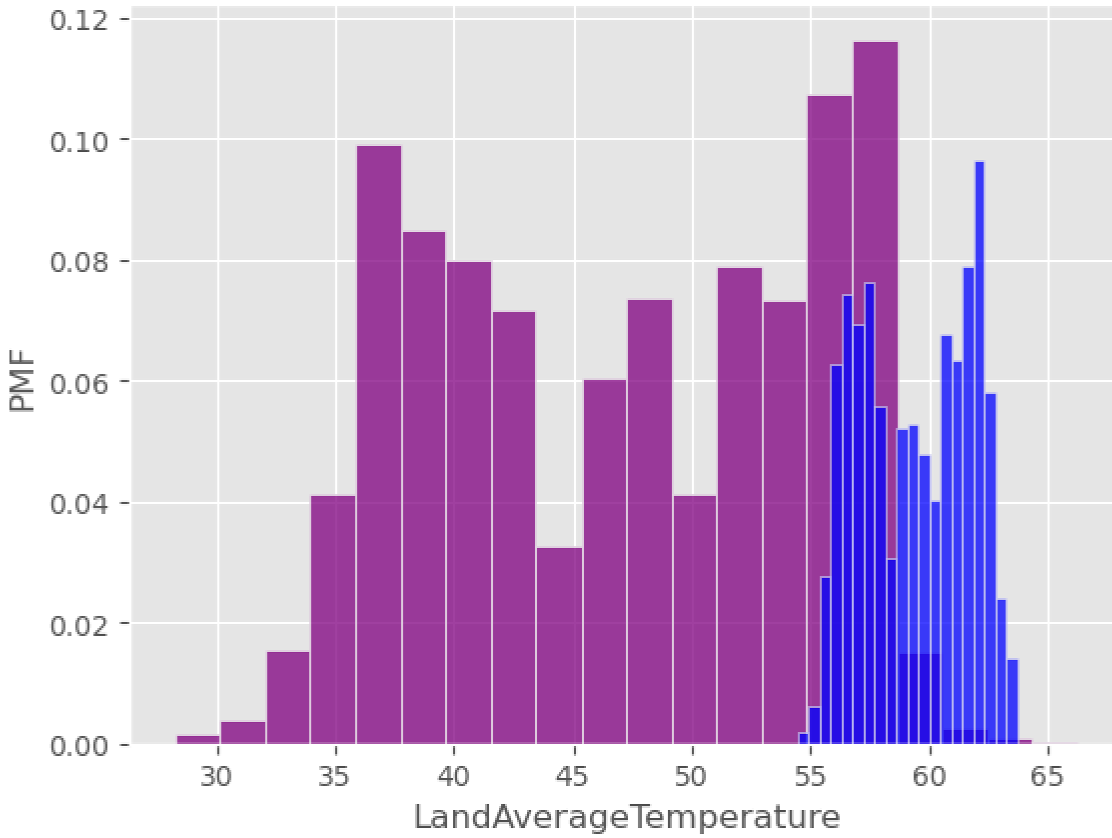
<Figure size 800x600 with 0 Axes>

In [20]:
```
temp_df.LandAverageTemperature.plot(kind="density", color='purple')
temp_df.LandAndOceanAverageTemperature.plot(kind="density", color='blue')
```

Out[20]: <AxesSubplot: ylabel='Density'>



In [21]:
```
plt.ylabel('PMF')
sns.histplot(temp_df.LandAverageTemperature, stat='probability', color='purple',
             bins=20)
sns.histplot(temp_df.LandAndOceanAverageTemperature, stat='probability', color='blue',
             bins=20);
```

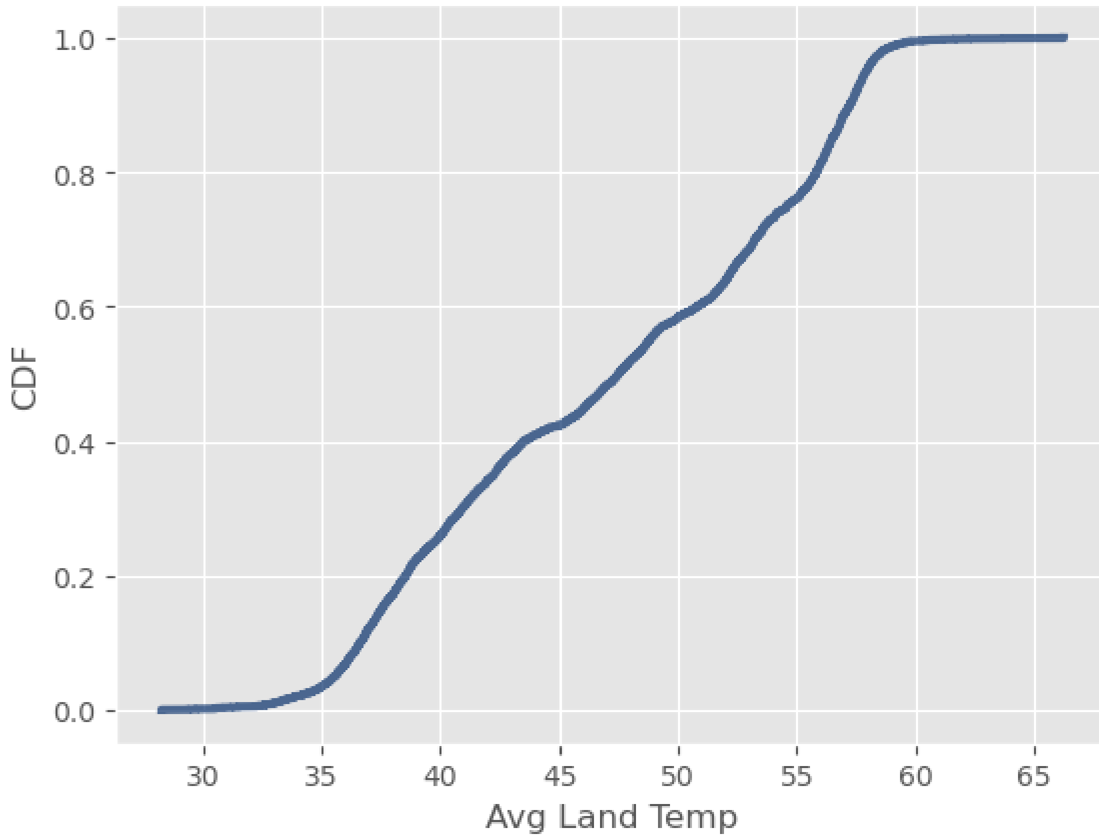


Create 1 CDF with one of your variables, using page 41-44 as your guide, what does this tell you about your variable and how does it address the question you are trying to answer (Chapter 4).

In [22]:
```
land_temp = temp_df.LandAverageTemperature
land_temp_dropna = land_temp.dropna()
print(len(land_temp), len(land_temp_dropna))

temp_pmf = thinkstats2.Pmf(land_temp_dropna)
```

```
3192 3180
```

In [23]:
```
def EvalCdf(temp_df, LandAverageTemperature):
    count = 0.0
    for value in sample:
        if value <= x:
            count += 1
    prob = count / len(sample)
    return prob

cdf = thinkstats2.Cdf(temp_df.LandAverageTemperature)
thinkplot.Cdf(cdf)
thinkplot.Show(xlabel='Avg Land Temp', ylabel='CDF')
```

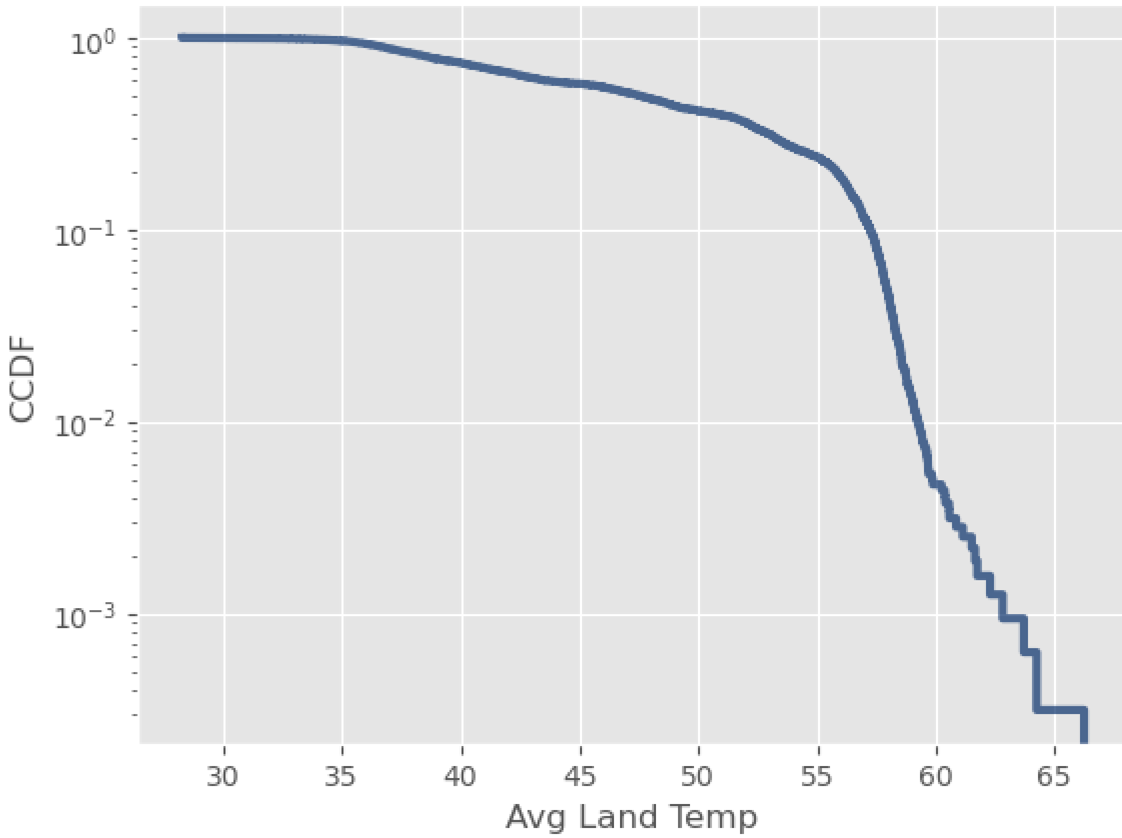



```
<Figure size 800x600 with 0 Axes>
```

This CDF of average land temperature shows us that there are few values lower than 35 degrees F or higher than 58 degrees F. The mode between 55 and 56 degrees F is also apparent.

Plot 1 analytical distribution and provide your analysis on how it applies to the dataset you have chosen (Chapter 5).

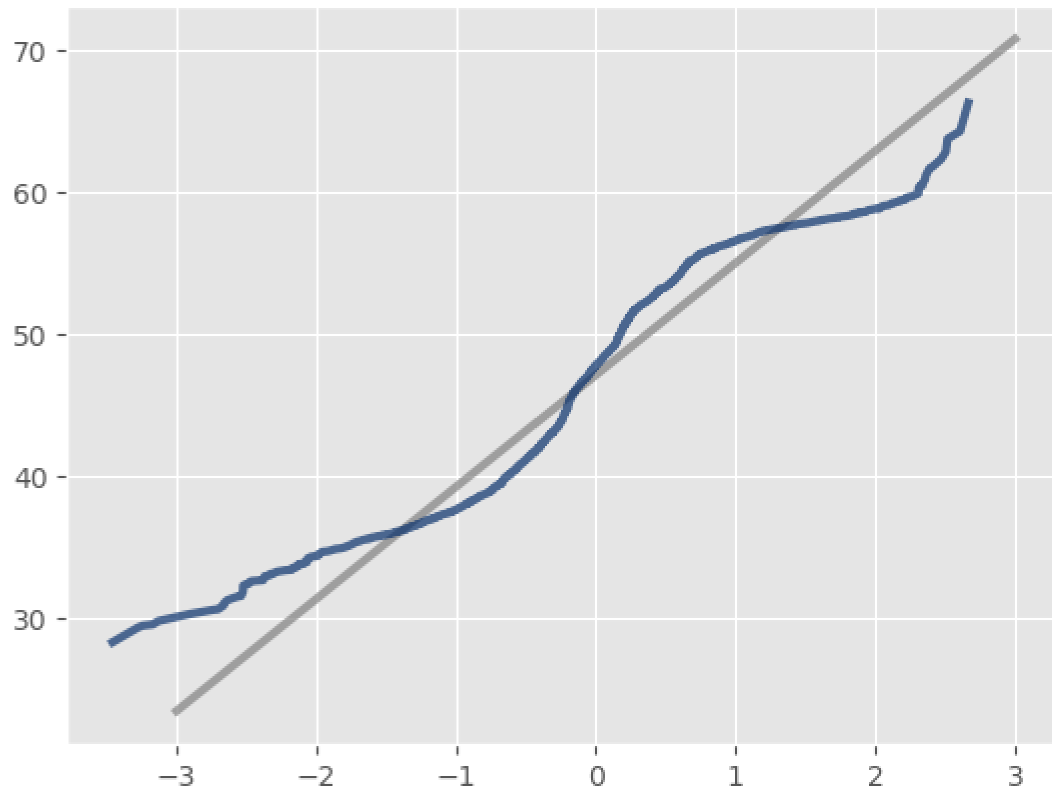
In [24]:
```
thinkplot.Cdf(cdf, complement=True)
thinkplot.Show(xlabel='Avg Land Temp', ylabel='CCDF', yscale='log')
```



<Figure size 800x600 with 0 Axes>

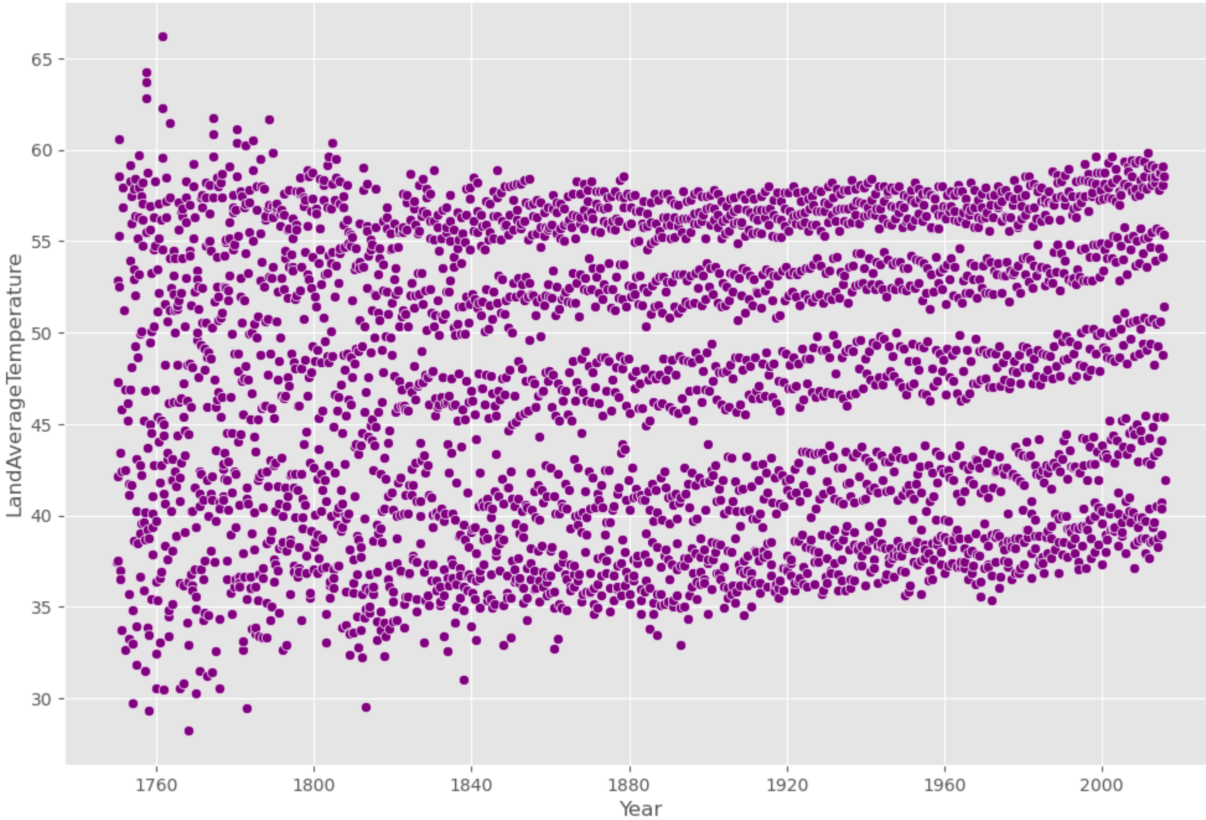
We can plot the complementary CDF, which is 1 − CDF(x), on a log-y scale to check the data for an exponential distribution. If so, the result is a straight line. Since this is not a straight line, we can make the assumption that temperatures did not increase at an exponential rate, and the exponential distribtion is not a perfect model for this data.

In [25]:
```
def MakeNormalPlot(x):
    mean = temp_df.LandAverageTemperature.mean()
    std = temp_df.LandAverageTemperature.std()

    xs = [-3, 3]
    fxs, fys = thinkstats2.FitLine(xs, inter=mean, slope=std)
    thinkplot.Plot(fxs, fys, color='gray', label='model')

    xs, ys = thinkstats2.NormalProbability(temp_df.LandAverageTemperature)
    thinkplot.Plot(xs, ys, label='Avg Temp')

MakeNormalPlot(temp_df.LandAverageTemperature)
```

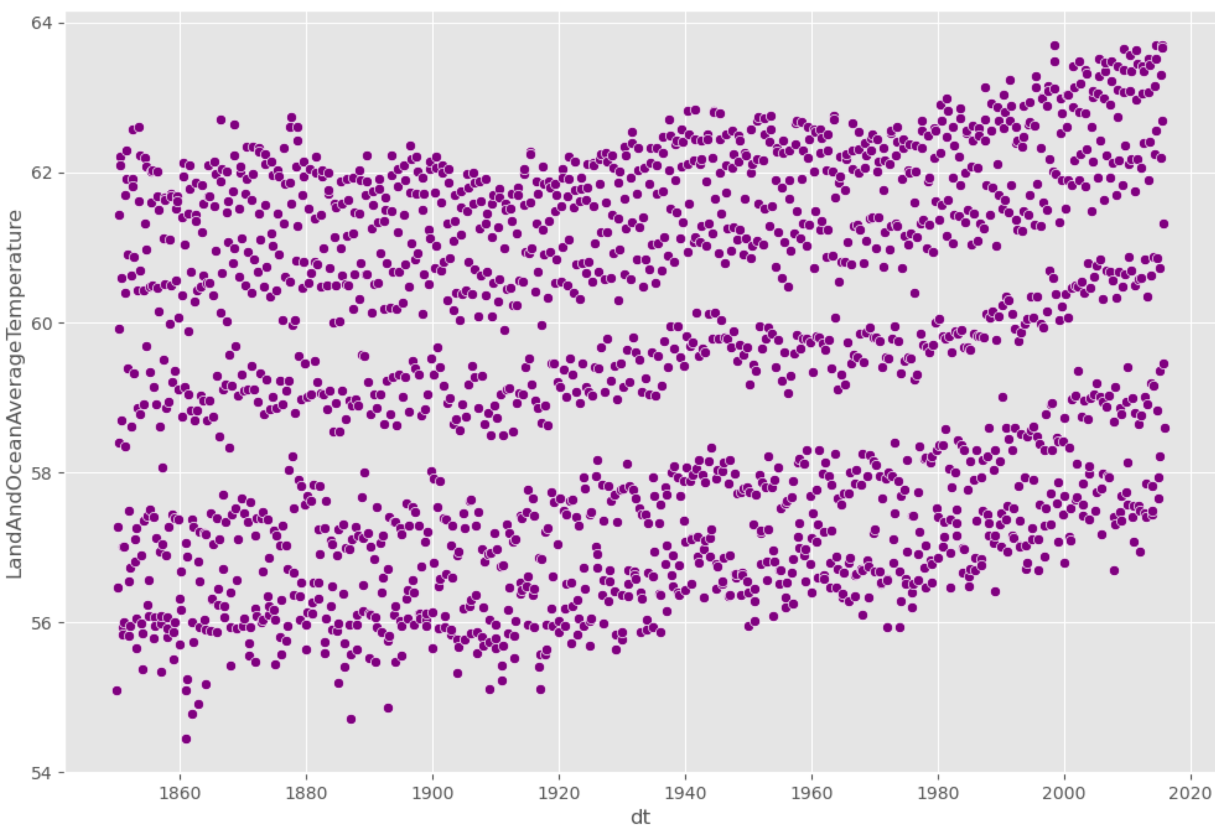


Create two scatter plots comparing two variables and provide your analysis on correlation and causation. Remember, covariance, Pearson's correlation, and Non-Linear Relationships should also be considered during your analysis (Chapter 7).

In [26]:
```
plt.figure(figsize=(12,8))

sns.scatterplot(data=df, x='dt', y='LandAverageTemperature', color='purple')

plt.xlabel('Year')
plt.show()
```

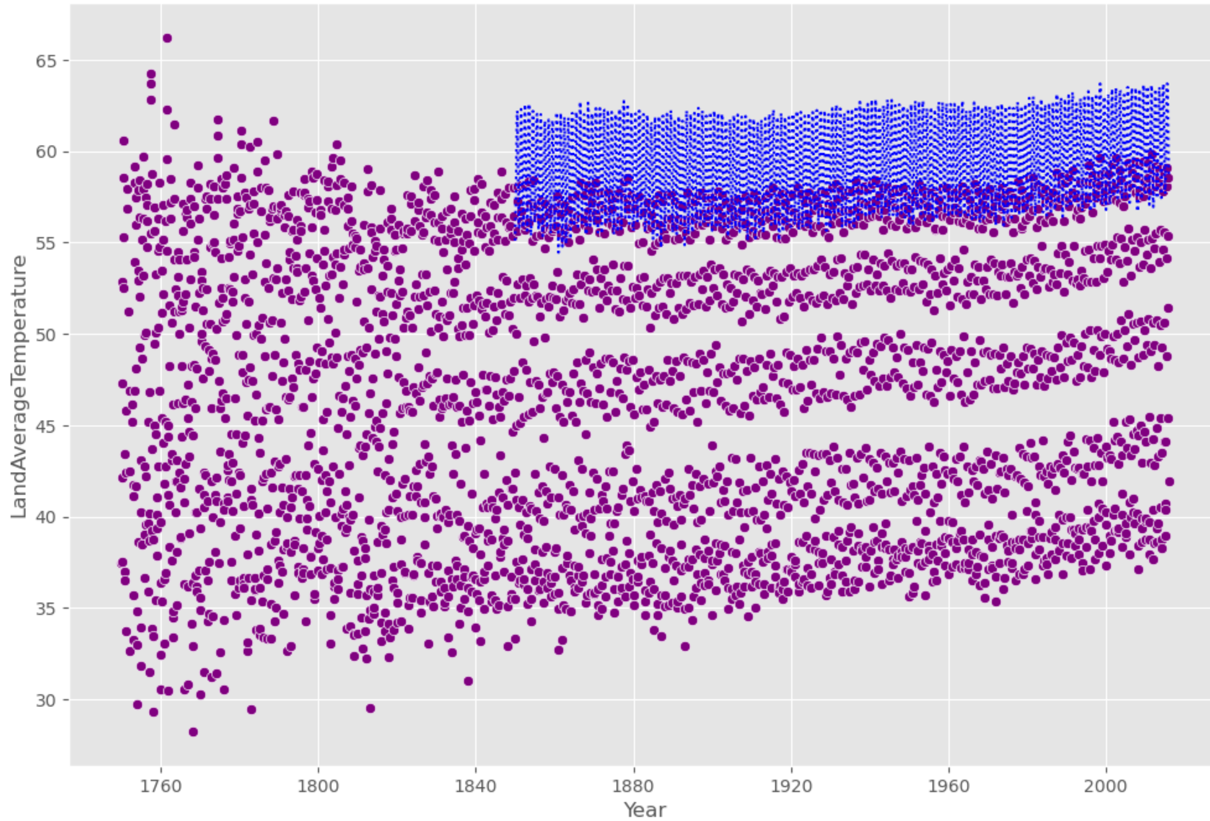


In [27]:
```
plt.figure(figsize=(12,8))
sns.scatterplot(data=df, x='dt', y='LandAndOceanAverageTemperature', color='purple')
plt.show()
```



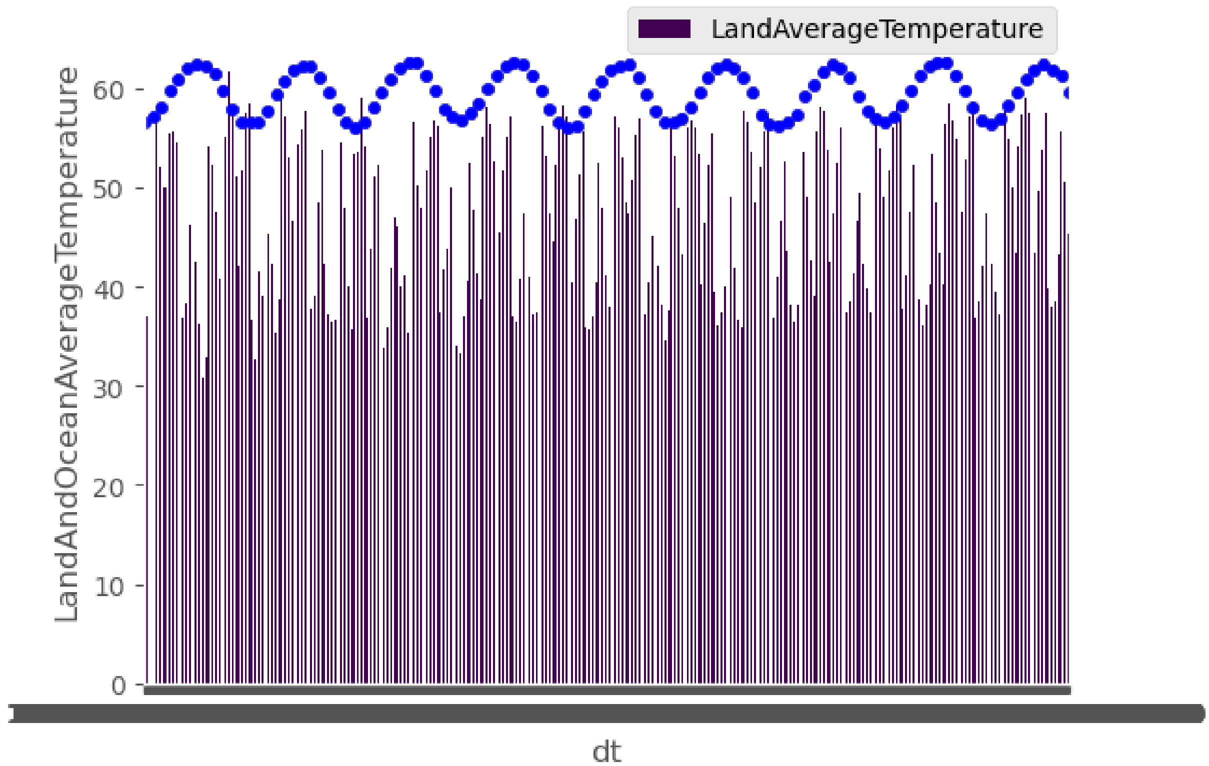
In [28]:
```
plt.figure(figsize=(12,8))
```

```python
sns.scatterplot(data=df, x='dt', y='LandAverageTemperature', color='purple')
sns.lineplot(data=df, x='dt', y='LandAndOceanAverageTemperature', color='Blue',
             linestyle=':')

plt.xlabel('Year')
plt.show()
```



In [29]:
```python
ax = plt.gca()

temp_df.plot(kind='bar',x='dt',y='LandAverageTemperature', cmap='viridis', ax=ax)
temp_df.plot(kind='scatter',x='dt',y='LandAndOceanAverageTemperature', color=
             'blue', ax=ax)

plt.show()
```

```
C:\Users\aliss\anaconda3\lib\site-packages\pandas\plotting\_matplotlib\core.py:1114:
UserWarning: No data for colormapping provided via 'c'. Parameters 'cmap' will be ign
ored
  scatter = ax.scatter(
```



In [30]:
```
temp_df = temp_df.dropna()

print("Covariance:")
np.cov(temp_df.LandAverageTemperature, temp_df.LandAndOceanAverageTemperature)
```

Out[30]:
```
Covariance:
array([[58.88639021, 17.38868956],
       [17.38868956,  5.25953366]])
```

In [31]:
```
print("Pearson Correlation Coefficient:")
scipy.stats.pearsonr(temp_df.LandAverageTemperature,
                     temp_df.LandAndOceanAverageTemperature)
```

Out[31]:
```
Pearson Correlation Coefficient:
PearsonRResult(statistic=0.988065575554971, pvalue=0.0)
```

Conduct a test on your hypothesis using one of the methods covered in Chapter 9.

In [32]:
```
class HypothesisTest(object):

    def __init__(self, data):
        self.data = data
        self.MakeModel()
        self.actual = self.TestStatistic(data)

    def PValue(self, iters=1000):
        self.test_stats = [self.TestStatistic(self.RunModel())
                           for _ in range(iters)]

        count = sum(1 for x in self.test_stats if x >= self.actual)
        return count / iters
```

```python
    def TestStatistic(self, data):
        raise UnimplementedMethodException()

    def MakeModel(self):
        pass

    def RunModel(self):
        raise UnimplementedMethodException()

class DiffMeansPermute(thinkstats2.HypothesisTest):

    def TestStatistic(self, data):
        group1, group2 = data
        test_stat = abs(group1.mean() - group2.mean())
        return test_stat

    def MakeModel(self):
        group1, group2 = self.data
        self.n, self.m = len(group1), len(group2)
        self.pool = np.hstack((group1, group2))

    def RunModel(self):
        np.random.shuffle(self.pool)
        data = self.pool[:self.n], self.pool[self.n:]
        return data

data = temp_df.LandAverageTemperature.values,
       temp_df.LandAndOceanAverageTemperature.values
ht = DiffMeansPermute(data)
pvalue = ht.PValue()
pvalue
```

Out[32]:
```
0.0
```

In [33]:
```python
class CorrelationPermute(thinkstats2.HypothesisTest):

    def TestStatistic(self, data):
        xs, ys = data
        test_stat = abs(thinkstats2.Corr(xs, ys))
        return test_stat

    def RunModel(self):
        xs, ys = self.data
        xs = np.random.permutation(xs)
        return xs, ys

cleaned = temp_df.dropna(subset=['LandAverageTemperature',
                                 'LandAndOceanAverageTemperature'])
data = cleaned.LandAverageTemperature.values,
       cleaned.LandAndOceanAverageTemperature.values
ht = CorrelationPermute(data)
pvalue = ht.PValue()
pvalue
```

Out[33]:
```
0.0
```

In [34]:
```python
ht.actual, ht.MaxTestStat()
```

Out[34]:

```
(0.9880655755549708, 0.06486833760459351)
```

In [35]:

```
def FalseNegRate(data, num_runs=1000):
    """Computes the chance of a false negative based on resampling.

    data: pair of sequences
    num_runs: how many experiments to simulate

    returns: float false negative rate
    """
    group1, group2 = data
    count = 0

    for i in range(num_runs):
        sample1 = thinkstats2.Resample(group1)
        sample2 = thinkstats2.Resample(group2)
        ht = DiffMeansPermute((sample1, sample2))
        p_value = ht.PValue(iters=101)
        if p_value > 0.05:
            count += 1

    return count / num_runs

neg_rate = FalseNegRate(data)
neg_rate
```

Out[35]:

```
0.0
```

Conduct a regression analysis on either one dependent and one explanatory variable, or multiple explanatory variables (Chapter 10 & 11).

In [39]:

```
formula = 'LandAverageTemperature ~ LandAndOceanAverageTemperature'
model = smf.ols(formula, data=temp_df)
results = model.fit()
results.summary()
```

Out[39]:

OLS Regression Results

Dep. Variable:	LandAverageTemperature	**R-squared:**	0.976
Model:	OLS	**Adj. R-squared:**	0.976
Method:	Least Squares	**F-statistic:**	8.188e+04
Date:	Sat, 04 Mar 2023	**Prob (F-statistic):**	0.00
Time:	15:50:42	**Log-Likelihood:**	-3159.1
No. Observations:	1992	**AIC:**	6322.
Df Residuals:	1990	**BIC:**	6333.
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	-148.8977	0.687	-216.861	0.000	-150.244	-147.551
LandAndOceanAverageTemperature	3.3061	0.012	286.152	0.000	3.283	3.329

Omnibus:	41.897	**Durbin-Watson:**	0.234
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	36.275
Skew:	-0.269	**Prob(JB):**	1.33e-08
Kurtosis:	2.615	**Cond. No.**	1.54e+03

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.54e+03. This might indicate that there are
strong multicollinearity or other numerical problems.

In [42]:

```
formula = 'LandAverageTemperature ~ LandAndOceanAverageTemperature + 
          'LandAverageTemperatureUncertainty'
results = smf.ols(formula, data=temp_df).fit()
results.summary()
```

Out[42]:

OLS Regression Results

Dep. Variable:	LandAverageTemperature	**R-squared:**	0.980
Model:	OLS	**Adj. R-squared:**	0.980
Method:	Least Squares	**F-statistic:**	4.960e+04
Date:	Sat, 04 Mar 2023	**Prob (F-statistic):**	0.00
Time:	15:56:14	**Log-Likelihood:**	-2971.7
No. Observations:	1992	**AIC:**	5949.
Df Residuals:	1989	**BIC:**	5966.
Df Model:	2		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	-152.2113	0.646	-235.589	0.000	-153.478	-150.944
LandAndOceanAverageTemperature	3.3515	0.011	311.647	0.000	3.330	3.373
LandAverageTemperatureUncertainty	2.2340	0.110	20.292	0.000	2.018	2.450

Omnibus:	7.999	**Durbin-Watson:**	0.335
Prob(Omnibus):	0.018	**Jarque-Bera (JB):**	7.187
Skew:	-0.096	**Prob(JB):**	0.0275
Kurtosis:	2.777	**Cond. No.**	1.59e+03

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.59e+03. This might indicate that there are
strong multicollinearity or other numerical problems.

Summary

Statistical/Hypothetical Question

Do increases in land or ocean temperatures drive the other? Are we able to gain any significant insight into climate change from the analysis?

Outcome of your EDA

Despite the uncertainty of early measurements, we can see notable increases in both land and ocean temperatures over time. However, in trying to determine correlation and causality, our hypothesis testing proved these variables to not be signficantly related statistically.

What do you feel was missed during the analysis?

There was very little data available in the data set regarding other outside factors that may contribute to the temperature increase or better link land and ocean temperatures together. There was also a lot of missing data throughout, specifically in available ocean temperatures.

Were there any variables you felt could have helped in the analysis?

Anything related to the land/air/ocean where measurements were taken, or possibly a deeper dive into related socioeconomic activities (Industrial Revolution, etc) that could've provided additional insight to outliers.

Were there any assumptions made you felt were incorrect?

I thought that the ocean temperature would be more significantly correlated to land temperature, as air movement and moisture from the ocean have significant effects on the surrounding areas.

What challenges did you face, what did you not fully understand?

Trying to link the two variables proved more challenging the more I manipulated and continued finding limitations in the available data. There was also very high multicollinearity between the variables, but I think this had more to do with a poor choice of data set than their actual relationships to each other. The only things this really tells us is that both temperatures have increased over time (not shocking).

Because our p values were all 0, we know none of the variables have statistically significant impacts on our models once included, as both land and ocean temperatures appear to convey basically the same thing, and the only other data we had to go off of was uncertainty and time.

In [ ]:

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