Week 8 - Assignment 9.1

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In [1]: #9.1 As sample size increases, the power of a hypothesis test increases, which mean
        #more likely to be positive if the effect is real. Conversely, as sample size decre
        #test is less likely to be positive even if the effect is real.
        #To investigate this behavior, run the tests in this chapter with different subsets
        #NSFG data. You can use thinkstats2.SampleRows to select a random subset of the row
        #What happens to the p-values of these tests as the sample size decreases? What is
        #smallest sample size that yields a positive test?
In [7]: import thinkplot
        import thinkstats2
        import numpy as np
        import random
        import nsfg
        import hypothesis as hp
In [3]: from os.path import basename, exists
        def download(url):
            filename = basename(url)
            if not exists(filename):
                from urllib.request import urlretrieve
                local, = urlretrieve(url, filename)
                print("Downloaded " + local)
        download("https://github.com/AllenDowney/ThinkStats2/raw/master/code/2002FemPreg.dc
        download("https://github.com/AllenDowney/ThinkStats2/raw/master/code/2002FemPreg.da
        download("https://github.com/AllenDowney/ThinkStats2/raw/master/code/brfss.py")
        download("https://github.com/AllenDowney/ThinkStats2/raw/master/code/CDBRFS08.ASC.g
In [5]: class DiffMeansResample(hp.DiffMeansPermute):
            """Tests a difference in means using resampling."""
            def RunModel(self):
                """Run the model of the null hypothesis.
                returns: simulated data
                group1 = np.random.choice(self.pool, self.n, replace=True)
                group2 = np.random.choice(self.pool, self.m, replace=True)
                return group1, group2
In [6]: def RunResampleTest(firsts, others):
            """Tests differences in means by resampling.
            firsts: DataFrame
            others: DataFrame
            data = firsts.prglngth.values, others.prglngth.values
```

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ht = DiffMeansResample(data)
            p_value = ht.PValue(iters=10000)
            print('\ndiff means resample preglength')
            print('p-value =', p_value)
            print('actual =', ht.actual)
            print('ts max =', ht.MaxTestStat())
            data = (firsts.totalwgt_lb.dropna().values,
                    others.totalwgt lb.dropna().values)
            ht = hp.DiffMeansPermute(data)
            p_value = ht.PValue(iters=10000)
            print('\ndiff means resample birthweight')
            print('p-value =', p_value)
            print('actual =', ht.actual)
            print('ts max =', ht.MaxTestStat())
In [7]: #import first
        #live, firsts, others = first.MakeFrames()
        df_nsfg = nsfg.ReadFemPreg()
        not_live = df_nsfg[df_nsfg.outcome != 1]
        live = df_nsfg[df_nsfg.outcome == 1]
        live_first_born = live[live.birthord ==1]
        live_other_born = live[live.birthord!=1]
        live_subs = live.dropna(subset=['agepreg', 'totalwgt_lb'])
        data = live_first_born.prglngth.values, live_other_born.prglngth.values
        RunResampleTest(live_first_born, live_other_born)
        diff means resample preglength
        p-value = 0.1608
        actual = 0.07803726677754952
        ts max = 0.21706913264567618
        diff means resample birthweight
        p-value = 0.0
        actual = 0.12476118453549034
        ts max = 0.11767152317556118
In [8]: n = len(live)
        cnt=0
                 ', 'p1 ', 'p2 ', 'p3 ', 'p4')
        print('n
        iters = 1000
        for _ in range(10):
            sample = thinkstats2.SampleRows(live, n)
            first_born = sample[sample.birthord == 1]
            other_born = sample[sample.birthord != 1]
            # compare pregnancy lengths
            preg_lengths_data = first_born.prglngth.values, other_born.prglngth.values
            ht = hp.DiffMeansPermute(preg_lengths_data)
            p1 = ht.PValue(iters=1000)
            # compare birthweights
            birthweights_data = (first_born.totalwgt_lb.dropna().values,
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other_born.totalwgt_lb.dropna().values)
   ht = hp.DiffMeansPermute(birthweights_data)
   p2 = ht.PValue(iters=iters)
   # test correlation of mother's age and child's birth weight
   live_corr = sample.dropna(subset=['agepreg', 'totalwgt_lb'])
   preg_lengths_data = live_corr.agepreg.values, live_corr.totalwgt_lb.values
   ht = hp.CorrelationPermute(preg_lengths_data)
   p3 = ht.PValue(iters=iters)
   # compare pregnancy Lengths (chi-squared)
   chi_preg_lengths_data = first_born.prglngth.values, other_born.prglngth.values
   ht = hp.PregLengthTest(chi_preg_lengths_data)
   np.seterr(invalid='ignore')
   p4 = ht.PValue(iters=iters)
   print('%d\t%0.2f\t%0.2f\t%0.2f\t%0.2f' % (n, p1, p2, p3, p4))
   n //= 2
n
               p2
       p1
                      р3
                             p4
       0.17
              0.00 0.00
                             0.00
9148
       0.48 0.00 0.00
4574
                             0.00
2287
       0.93 0.10 0.00 0.00
1143 0.46 0.00 0.00 0.03
571
     0.23 0.56 0.10 0.58
285
     0.40 0.58 0.14 0.39
      0.97 0.67 0.31
142
                             0.66
71
     0.43 0.10 0.02 0.00
       0.19 0.46 0.01
35
                            0.00
17
       0.66 0.34 0.63 0.00
My results:
p1: difference in mean pregnancy length
p2: difference in mean birth weight
p3: correlation of mother's age and birth weight
p4: chi-square test of pregnancy length
Diff means resample preglength
p-value = 0.1608
actual = 0.07803726677754952
ts max = 0.21706913264567618
```

```
Diff means resample birthweight
```

```
p-value = 0.0
actual = 0.12476118453549034
ts max = 0.11767152317556118
```

Conclusion: Tests that are positive with large sample sizes become negative as data reduces. Test pattern is not consistent and is erratic. We can see positive tests for small data sample as well.

Week 8 - Assignment 10.1

In [4]: #10.1 Using the data from the BRFSS, compute the linear least squares fit for log(w #versus height. How would you best present the estimated parameters for a model lik #this where one of the variables is log-transformed? If you were trying to guess so #weight, how much would it help to know their height?

#Like the NSFG, the BRFSS oversamples some groups and provides a sampling weight #for each respondent. In the BRFSS data, the variable name for these weights is #totalwt. Use resampling, with and without weights, to estimate the mean height of #respondents in the BRFSS, the standard error of the mean, and a 90% confidence int #How much does correct weighting affect the estimates?

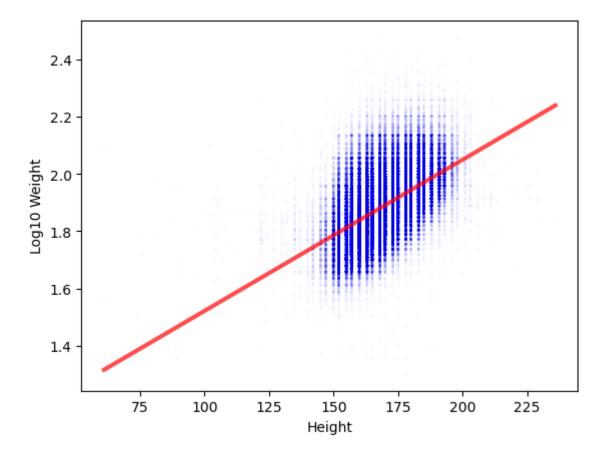
```
In [8]: import brfss
In [9]: brfss_df = brfss.ReadBrfss(nrows=None)
    brfss_df = brfss_df.dropna(subset=['htm3', 'wtkg2'])
    heights, weights = brfss_df.htm3, brfss_df.wtkg2
    weights_log = np.log10(weights)

In [10]: inter, slope = thinkstats2.LeastSquares(heights, weights_log)
    inter, slope

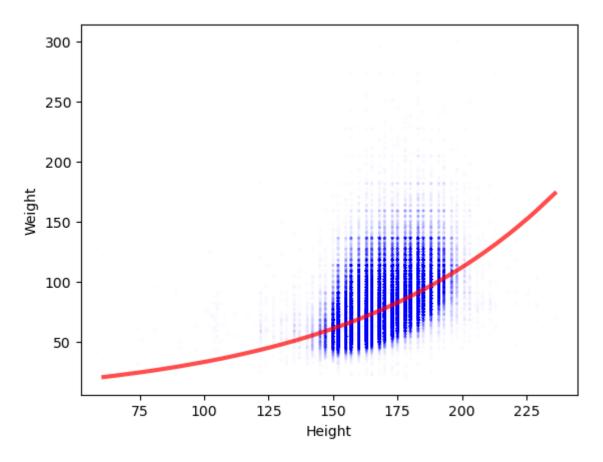
Out[10]: (0.9930804163918192, 0.005281454169417767)

In [11]: #Make a scatter plot of the data and show the fitted line.
```

```
In [11]: #Make a scatter plot of the data and show the fitted line.
fit_xs, fit_ys = thinkstats2.FitLine(heights, inter, slope)
thinkplot.Scatter(heights, weights_log, alpha=0.01, s=5)
thinkplot.Plot(fit_xs, fit_ys, color='red')
thinkplot.Config(xlabel='Height', ylabel='Log10 Weight', legend=False)
```



In [12]: #Same plot but applying the inverse transform to show weights on a linear scale.
f_xs, f_ys = thinkstats2.FitLine(heights, inter, slope)
thinkplot.Scatter(heights, weights, alpha=0.01, s=5)
thinkplot.Plot(f_xs, 10**f_ys, color='red')
thinkplot.Config(xlabel='Height', ylabel='Weight', legend=False)

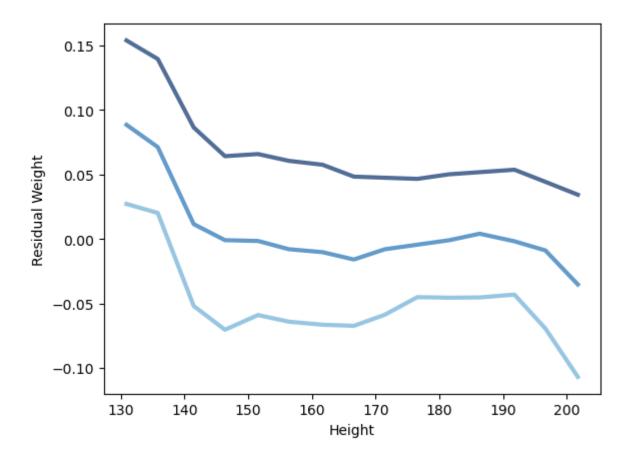


```
In [13]: #Plot percentiles of the residuals.
# Solution goes here
residuals=thinkstats2.Residuals(heights,weights_log,inter,slope)
brfss_df['residual']=residuals
bins=np.arange(130,210,5)
ind=np.digitize(brfss_df.htm3,bins)
grps=brfss_df.groupby(ind)

means=[grp.htm3.mean() for i, grp in grps][1:-1]
cdfs=[thinkstats2.Cdf(grp.residual) for i, grp in grps][1:-1]

thinkplot.PrePlot(3)
for percent in [75,50,25]:
    y=[cdf.Percentile(percent) for cdf in cdfs]
    label='%dth' % percent
    thinkplot.Plot(means,y,label=label)

thinkplot.Config(xlabel='Height',ylabel='Residual Weight')
```



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In [14]: #Compute Correlation
ht_wt_correlation = thinkstats2.Corr(heights, weights_log)
ht_wt_correlation
```

Out[14]: 0.5317282605983424

In [15]: #Compute coefficient of determination
 coefficient=thinkstats2.CoefDetermination(weights_log,residuals)
 coefficient

Out[15]: 0.28273494311893876

In [20]: #Confirm that R2=\rho2
ht_wt_correlation**2-coefficient,np.isclose(ht_wt_correlation**2, coefficient)
#np.isclose - Returns a boolean array where two arrays are element-wise equal withi

Out[20]: (0.0, True)

In [21]: #Compute Std(ys), which is the RMSE of predictions that don't use height.
ys_std=thinkstats2.Std(weights_log)
ys_std

Out[21]: 0.10320725030004886

In [22]: #Compute Std(res), the RMSE of predictions that do use height.
res_std=thinkstats2.Std(residuals)
res_std

```
Out[22]: 0.0874077708041609
In [23]: #How much does height information reduce RMSE?
         1-(res_std/ys_std)
Out[23]: 0.1530849765879334
In [24]:
         #Use resampling to compute sampling distributions for inter and slope.
         estimate_list=[]
         for i in range(100):
             sample=thinkstats2.ResampleRows(brfss_df)
             est=thinkstats2.LeastSquares(sample.htm3,np.log10(sample.wtkg2))
             estimate_list.append(est)
         inter,slope=zip(*estimate_list)
         #inter, slope
In [25]: #Plot the sampling distribution of slope.
         cdf=thinkstats2.Cdf(slope)
         thinkplot.Cdf(cdf)
Out[25]: {'xscale': 'linear', 'yscale': 'linear'}
          1.0
          0.8
          0.6
          0.4
          0.2
          0.0
                 0.005250.005260.005270.005280.005290.005300.005310.00532
In [26]: #Compute the p-value of the slope.
         pvalue=cdf[0]
         pvalue
```

Out[26]: 0

```
In [27]: #Compute the 90% confidence interval of slope.
         confidence_interval=cdf.Percentile(5),cdf.Percentile(95)
         confidence interval
Out[27]: (0.005259348105154235, 0.005302822447494455)
In [28]: #Compute the mean of the sampling distribution.
         mean=thinkstats2.Mean(slope)
         mean
Out[28]: 0.005281327462938837
In [29]: #Compute the standard deviation of the sampling distribution, which is the standard
         std error=thinkstats2.Std(slope)
         std_error
Out[29]: 1.4508136293916886e-05
In [30]: #Resample rows without weights, compute mean height, and summarize results.
         est_without_weight=[thinkstats2.ResampleRows(brfss_df).htm3.mean() for i in range(1
         print("Mean Height",thinkstats2.Mean(est_without_weight))
         print('Standard error',thinkstats2.Std(est_without_weight))
         cdf=thinkstats2.Cdf(est_without_weight)
         ci=cdf.Percentile(5),cdf.Percentile(95)
         print('Confidence Interval',ci)
         Mean Height 168.95528600517392
         Standard error 0.015423644516628907
         Confidence Interval (168.92803007336445, 168.97904919258676)
In [31]: #Resample rows with weights. Note that the weight column in this dataset is called
         weight=brfss_df['finalwt']
         cdf=thinkstats2.Cdf(dict(weight))
         indices=cdf.Sample(len(weight))
         sample=brfss_df.loc[indices]
         est_with_weight=[sample.htm3.mean() for i in range(100)]
         print("Mean",thinkstats2.Mean(est_with_weight))
         print('Standard error',thinkstats2.Std(est_with_weight))
         cdf=thinkstats2.Cdf(est with weight)
         ci=cdf.Percentile(5),cdf.Percentile(95)
         print('Confidence Interval',ci)
         Mean 170.50511328038155
```

Mean 170.50511328038155 Standard error 2.842170943040401e-14 Confidence Interval (170.50511328038158, 170.50511328038158)