In [1]:
```
# import libraries / modules
import pandas as pd
import numpy as np
import thinkstats2
import thinkplot
import statsmodels.formula.api as smf
from thinkstats2 import Mean, MeanVar, Var, Std, Cov

# thinkstats, thinkstats2, referenced from: Downey, A. (2014).  Think Stats: Expl
```

In [2]:
```
# import data
df=pd.read_csv("DSM2019.csv")
```

In [3]:
```
# brief check of data to confirm import
df.head()
```

Out[3]:

	PLACE	FNAME	LNAME	DIV	DIV PL	10K	HALF	20MI	LAST_10K	PACE	TIME
0	1	William	Mutai	M3539	1/137	0:33:05	1:10:23	1:49:02	0:33:59	0:05:28	2:23:01
1	2	Sammy	Rotich	M3034	1/124	0:33:06	1:10:23	1:48:57	0:34:30	0:05:29	2:23:26
2	3	Steve	Froeschle	M2529	1/95	0:34:23	1:12:56	1:51:54	0:35:10	0:05:37	2:27:04
3	4	Dan	Froeschle	M2529	2/95	0:34:22	1:12:55	1:53:38	0:37:06	0:05:46	2:30:44
4	5	David	Tuwei	M4044	1/99	0:34:28	1:14:27	1:57:13	0:36:07	0:05:52	2:33:20

In [4]:
```
# determine imported data types
df.dtypes
```

Out[4]:
```
PLACE        int64
FNAME       object
LNAME       object
DIV         object
DIV PL      object
10K         object
HALF        object
20MI        object
LAST_10K    object
PACE        object
TIME        object
dtype: object
```

In [5]:
```
# change the time fields to read as time
df[["10K","HALF","20MI","LAST_10K","PACE","TIME"]] = df[["10K","HALF","20MI","LAS
```

In [6]:
```
# confirm changes, get more info on data frame
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1276 entries, 0 to 1275
Data columns (total 11 columns):
PLACE       1276 non-null int64
FNAME       1276 non-null object
LNAME       1276 non-null object
DIV         1275 non-null object
DIV PL      1276 non-null object
10K         1276 non-null timedelta64[ns]
HALF        1276 non-null timedelta64[ns]
20MI        1276 non-null timedelta64[ns]
LAST_10K    1276 non-null timedelta64[ns]
PACE        1276 non-null timedelta64[ns]
TIME        1276 non-null timedelta64[ns]
dtypes: int64(1), object(4), timedelta64[ns](6)
memory usage: 109.8+ KB
```

A minimum of 5 variables in your dataset used during your analysis (for help with selecting, the author made his selection on page 6 of your book). Consider what you think could have an impact on your question – remember this is never perfect, so don't be worried if you miss one (Chapter 1). Describe what the 5 variables mean in the dataset (Chapter 1).

In [7]:
```
# variable creation, description noted below

df['SHALF'] = df['TIME']-df['HALF'] # calculates time for second half of race
df['AVGPCE'] = df['PACE'] / np.timedelta64(1, 's') # converts average pace for e
df['FSTPCE'] = (df['HALF']/13.1) / np.timedelta64(1, 's') # converts average pac
df['SNDPCE'] = (df['SHALF']/13.1) / np.timedelta64(1, 's') # calculates average 
df['DIFF'] = df['SNDPCE']-df['FSTPCE'] #difference between 1st half pace and 2nd
df['FSTQ'] = (df['10K']/6.21371) / np.timedelta64(1, 's') # converts average pac
df['SNDQ'] = ((df['HALF']-df['10K'])/(13.1-6.21371)) / np.timedelta64(1, 's') # 
df['TRDQ'] = ((df['20MI']-df['HALF'])/(20-13.1)) / np.timedelta64(1, 's') # calc
df['FTHQ'] = ((df['TIME']-df['20MI'])/(6.21371)) / np.timedelta64(1, 's') # calc
df['PACING'] = np.where(df['FSTPCE']>=df['SNDPCE'],'Neg','Pos') # adds a categor
```

In [8]:
```
# confirm variable creation
df.head()
```

Out[8]:

	PLACE	FNAME	LNAME	DIV	DIV PL	10K	HALF	20MI	LAST_10K	PACE	.
0	1	William	Mutai	M3539	1/137	00:33:05	01:10:23	01:49:02	00:33:59	00:05:28	.
1	2	Sammy	Rotich	M3034	1/124	00:33:06	01:10:23	01:48:57	00:34:30	00:05:29	.
2	3	Steve	Froeschle	M2529	1/95	00:34:23	01:12:56	01:51:54	00:35:10	00:05:37	.
3	4	Dan	Froeschle	M2529	2/95	00:34:22	01:12:55	01:53:38	00:37:06	00:05:46	.
4	5	David	Tuwei	M4044	1/99	00:34:28	01:14:27	01:57:13	00:36:07	00:05:52	.

5 rows × 21 columns

In [9]:
```
#Create two dataframes based on Positive and Negative from 'Pacing' column
dfp = df[df.PACING == 'Pos']
dfn = df[df.PACING == 'Neg']
```

In [10]:
```
# positive split DF
dfp.head()
```

Out[10]:

	PLACE	FNAME	LNAME	DIV	DIV PL	10K	HALF	20MI	LAST_10K	PACE	...
0	1	William	Mutai	M3539	1/137	00:33:05	01:10:23	01:49:02	00:33:59	00:05:28	...
1	2	Sammy	Rotich	M3034	1/124	00:33:06	01:10:23	01:48:57	00:34:30	00:05:29	...
2	3	Steve	Froeschle	M2529	1/95	00:34:23	01:12:56	01:51:54	00:35:10	00:05:37	...
3	4	Dan	Froeschle	M2529	2/95	00:34:22	01:12:55	01:53:38	00:37:06	00:05:46	...
4	5	David	Tuwei	M4044	1/99	00:34:28	01:14:27	01:57:13	00:36:07	00:05:52	...

5 rows × 21 columns

In [11]:
```
# negative split DF
dfn.head()
```

Out[11]:

	PLACE	FNAME	LNAME	DIV	DIV PL	10K	HALF	20MI	LAST_10K	PACE	...
5	6	Justin	Vitale	M4044	2/99	00:40:11	01:23:13	02:01:23	00:33:35	00:05:55	...
7	8	Clay	Musial	M2024	2/80	00:37:16	01:19:12	02:01:29	00:35:46	00:06:01	...
13	14	Hiram	Marquez	M2024	5/80	00:39:45	01:22:46	02:05:51	00:37:39	00:06:15	...
14	15	Ethan	Smith	M2024	6/80	00:39:46	01:22:46	02:05:51	00:38:58	00:06:18	...
15	16	Ben	Kipp	M3539	2/137	00:39:46	01:22:47	02:07:08	00:38:25	00:06:20	...

5 rows × 21 columns

In [12]:
```
# HARDLY ANYONE NEGATIVE SPLITS
df['PACING'].value_counts()
```

Out[12]:
```
Pos    1137
Neg     139
Name: PACING, dtype: int64
```

In [13]:
```
# determine the mean pace for the groups
df.groupby('PACING')['AVGPCE'].mean()
```

Out[13]:
```
PACING
Neg    528.769784
Pos    618.792436
Name: AVGPCE, dtype: float64
```

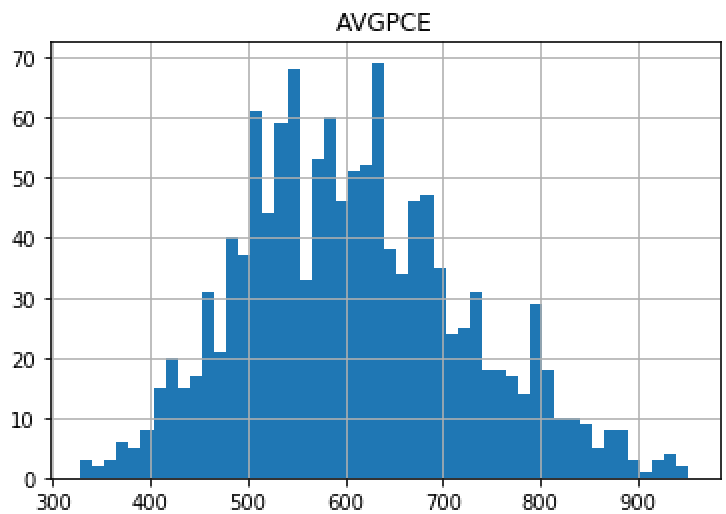
In [14]:
```
# check data types after variable creation
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1276 entries, 0 to 1275
Data columns (total 21 columns):
PLACE       1276 non-null int64
FNAME       1276 non-null object
LNAME       1276 non-null object
DIV         1275 non-null object
DIV PL      1276 non-null object
10K         1276 non-null timedelta64[ns]
HALF        1276 non-null timedelta64[ns]
20MI        1276 non-null timedelta64[ns]
LAST_10K    1276 non-null timedelta64[ns]
PACE        1276 non-null timedelta64[ns]
TIME        1276 non-null timedelta64[ns]
SHALF       1276 non-null timedelta64[ns]
AVGPCE      1276 non-null float64
FSTPCE      1276 non-null float64
SNDPCE      1276 non-null float64
DIFF        1276 non-null float64
FSTQ        1276 non-null float64
SNDQ        1276 non-null float64
TRDQ        1276 non-null float64
FTHQ        1276 non-null float64
PACING      1276 non-null object
dtypes: float64(8), int64(1), object(5), timedelta64[ns](7)
memory usage: 209.5+ KB
```

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 [15]:
```
# create histograms
df.hist(column='AVGPCE',bins=50)
df.hist(column='FSTPCE',bins=50)
df.hist(column='SNDPCE',bins=50)
df.hist(column='FSTQ',bins=50)
df.hist(column='SNDQ',bins=50)
df.hist(column='TRDQ',bins=50)
df.hist(column='FTHQ',bins=50)
# avg pace of negative and positive splitters
dfn.hist(column='AVGPCE',bins=50)
dfp.hist(column='AVGPCE',bins=50)
```

Out[15]:
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x00000110C000C808
>]],
      dtype=object)
```



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

In [16]:
```
df['TIME'].mean(), df['TIME'].var(), df['TIME'].std(), df['TIME'].mode()
```

Out[16]:
```
(Timedelta('0 days 04:25:42.725705'),
 9.260732252546563e+24,
 Timedelta('0 days 00:50:43.145125'),
 0   03:46:59
 1   04:13:17
 2   04:38:41
 3   04:51:20
 4   04:59:31
 5   05:01:58
 dtype: timedelta64[ns])
```

In [17]:
```
df['AVGPCE'].mean(), df['AVGPCE'].var(), df['AVGPCE'].std(), df['AVGPCE'].mode()
```

Out[17]:
```
(608.9858934169279, 13489.850781240375, 116.14581689083931, 0    543.0
 1    546.0
 dtype: float64)
```

In [18]:
```
df['FSTPCE'].mean(), df['FSTPCE'].var(), df['FSTPCE'].std(), df['FSTPCE'].mode()
```

Out[18]:
```
(572.0013639948173, 10359.362043814128, 101.78095128173113, 0    412.213740
 1    412.366412
 2    412.442748
 3    493.282443
 4    532.519084
 5    533.664122
 6    540.381679
 7    579.160305
 dtype: float64)
```

In [19]:
```
df['SNDPCE'].mean(), df['SNDPCE'].var(), df['SNDPCE'].std(), df['SNDPCE'].mode()
```

Out[19]:
```
(645.0005982430721, 19327.78075650816, 139.02438907079636, 0    545.496183
 1    724.580153
 dtype: float64)
```

In [20]:
```
df['FSTQ'].mean(), df['FSTQ'].var(), df['FSTQ'].std(), df['FSTQ'].mode()
```

Out[20]:
```
(564.9948178849833, 9521.532919059397, 97.57834246931742, 0    411.670323
 dtype: float64)
```

In [21]:
```
df['SNDQ'].mean(), df['SNDQ'].var(), df['SNDQ'].std(), df['SNDQ'].mode()
```

Out[21]:
```
(578.3235847592618, 11544.363007856986, 107.44469743945946, 0    412.994515
 1    489.813818
 2    548.045464
 dtype: float64)
```

In [22]:
```
df['TRDQ'].mean(), df['TRDQ'].var(), df['TRDQ'].std(), df['TRDQ'].mode()
```

Out[22]:
```
(631.0082458765636, 21008.008477859014, 144.94139670176708, 0    467.826087
 1    516.521739
 2    537.971014
 3    647.101449
 4    784.927536
 dtype: float64)
```

In [23]:
```
df['FTHQ'].mean(), df['FTHQ'].var(), df['FTHQ'].std(), df['FTHQ'].mode()
```

Out[23]:
```
(659.1152371828987, 20411.422783022204, 142.868550713662, 0    570.190756
 1    701.513267
 dtype: float64)
```

In [24]:
```
df.groupby(['PACING']).groups.keys()
```

Out[24]:
```
dict_keys(['Neg', 'Pos'])
```

In [25]:
```
df['AVGPCE'][df['PACING'] == 'Neg'].mean(), df['AVGPCE'][df['PACING'] == 'Neg'].
```

Out[25]:
```
(528.7697841726618, 8835.091544155985, 93.99516766385379, 0    408.0
 1    412.0
 2    464.0
 3    483.0
 4    524.0
 5    527.0
 6    541.0
 dtype: float64)
```

In [26]:
```
df['AVGPCE'][df['PACING'] == 'Pos'].mean(), df['AVGPCE'][df['PACING'] == 'Pos'].
```

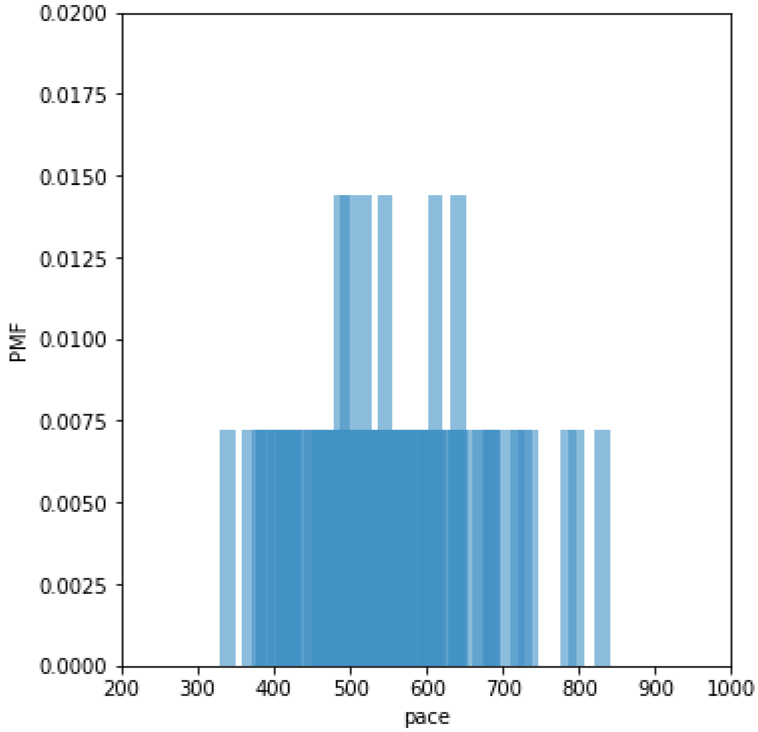
Out[26]:
```
(618.792436235708, 13183.592442739113, 114.81982600029976, 0    646.0
 dtype: float64)
```

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. The example in the book is first babies compared to all other babies, it is still the same variable, but breaking the data out based on criteria we are exploring (Chapter 3).

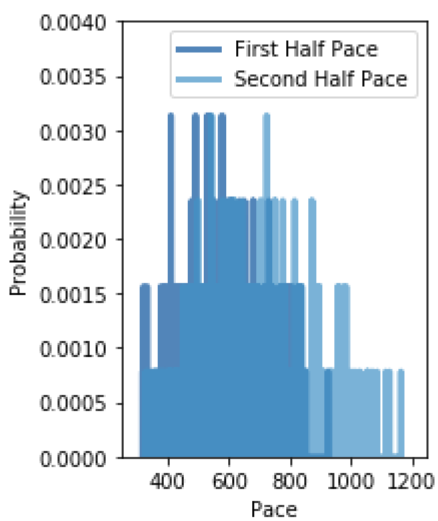
In [27]:
```
pmfA = thinkstats2.Pmf(dfn['FSTPCE'])
pmfB = thinkstats2.Pmf(dfn['SNDPCE'])
```

In [28]:
```
pmf1st = thinkstats2.Pmf(df['FSTPCE'], label='First Half Pace')
pmf2nd = thinkstats2.Pmf(df['SNDPCE'], label='Second Half Pace')
```

In [29]:
```
width=20
axis = [200, 1000, 0, 0.02]
thinkplot.PrePlot(2, cols=2)
thinkplot.Hist(pmfA, align='right')
thinkplot.Hist(pmfB, align='left',width=width)
thinkplot.Config(xlabel='pace',ylabel='PMF',axis=axis)
```



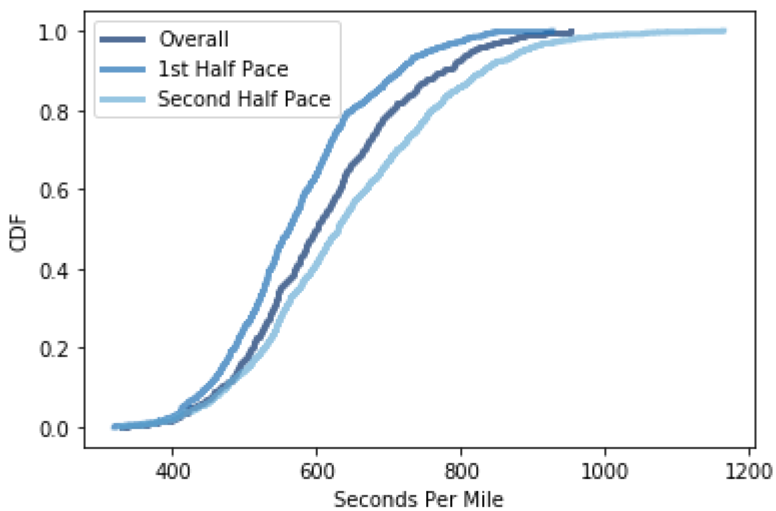
In [30]:
```
axis = [250, 1250, 0, .004]
thinkplot.PrePlot(2)
thinkplot.SubPlot(2)
thinkplot.Pmfs([pmf1st, pmf2nd])
thinkplot.Config(xlabel='Pace',ylabel='Probability', axis=axis)
```



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 [31]:
```
# Create CDF
overall_pace=df['AVGPCE']
overall_pace=df['AVGPCE'].dropna()
overall_cdf=thinkstats2.Cdf(overall_pace, label='Overall')

FSTPCE_pace=df['FSTPCE']
FSTPCE_pace=df['FSTPCE'].dropna()
FSTPCE_cdf=thinkstats2.Cdf(FSTPCE_pace, label='1st Half Pace')

SNDPCE_pace=df['SNDPCE']
SNDPCE_pace=df['SNDPCE'].dropna()
SNDPCE_cdf=thinkstats2.Cdf(SNDPCE_pace, label='Second Half Pace')
```

In [32]:
```
# Plot CDF
thinkplot.PrePlot(3)
thinkplot.Cdfs([overall_cdf,FSTPCE_cdf,SNDPCE_cdf])
thinkplot.Show(xlabel='Seconds Per Mile',ylabel='CDF')
```




```
<Figure size 576x432 with 0 Axes>
```

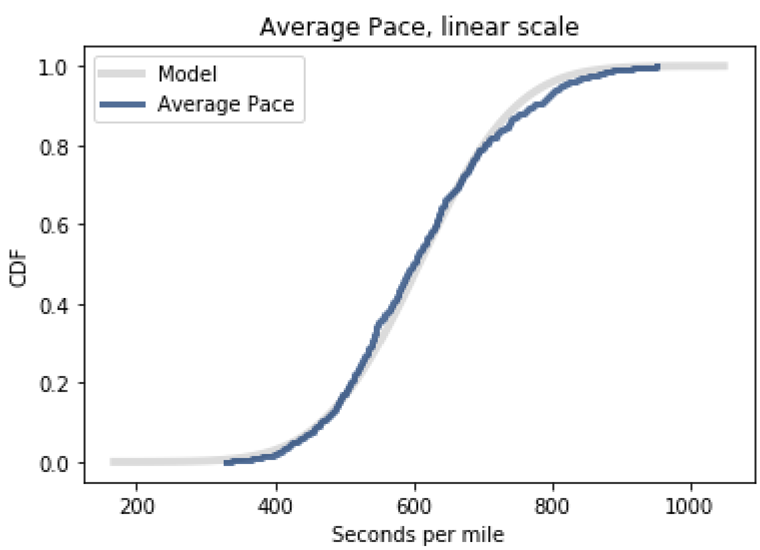
Plot 1 analytical distribution and provide your analysis on how it applies to the dataset you have chosen.

Used Lognormal model, explained on page 56 https://en.wikipedia.org/wiki/Log-normal_distribution (https://en.wikipedia.org/wiki/Log-normal_distribution)

In [33]:
```
# The following function estimates the parameters of a normal distribution and
# plots the data and a normal model.

avgpace=df['AVGPCE']

def MakeNormalModel(avgpace):
    cdf = thinkstats2.Cdf(avgpace, label='Average Pace')

    mean, var = thinkstats2.TrimmedMeanVar(avgpace)
    std = np.sqrt(var)
    print('n, mean, std', len(avgpace), mean, std)

    xmin = mean - 4 * std
    xmax = mean + 4 * std

    xs, ps = thinkstats2.RenderNormalCdf(mean, std, xmin, xmax)
    thinkplot.Plot(xs, ps, label='Model', linewidth=4, color='0.8')
    thinkplot.Cdf(cdf)
```

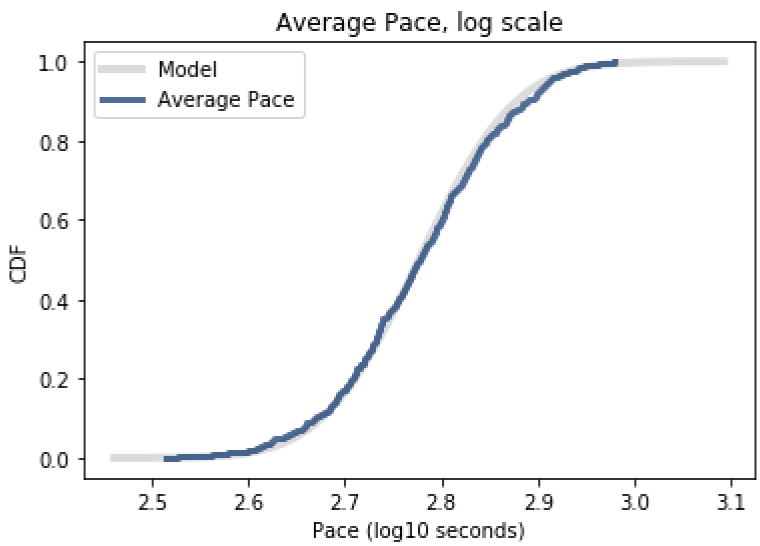
In [34]:
```
#Here's the distribution of average pace and a normal model,

MakeNormalModel(avgpace)
thinkplot.Config(title='Average Pace, linear scale', xlabel='Seconds per mile',
                 ylabel='CDF', loc='upper left')
```

```
n, mean, std 1276 608.388178913738 110.18176728067392
```



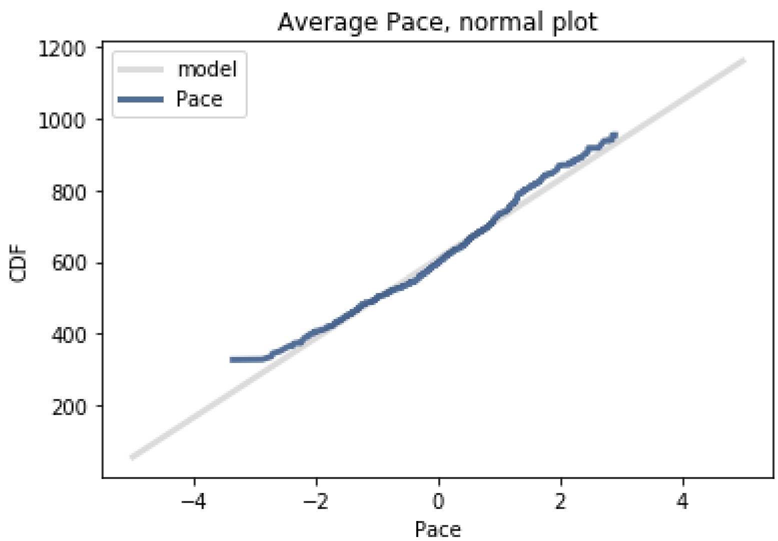
In [35]:
```
# distribution of average pace and a lognormal model,
# plotted on a log-x scale. The model is a better fit for the data,
# although the slower runners are slower than the model expects.

log_paces = np.log10(avgpace)
MakeNormalModel(log_paces)
thinkplot.Config(title='Average Pace, log scale', xlabel='Pace (log10 seconds)',
                 ylabel='CDF', loc='upper left')
```

```
n, mean, std 1276 2.7770564137582054 0.07887863035819541
```



In [36]:
```
#The following function generates a normal probability plot.
def MakeNormalPlot(avgpace):

    mean, var = thinkstats2.TrimmedMeanVar(avgpace, p=0.01)
    std = np.sqrt(var)

    xs = [-5, 5]
    xs, ys = thinkstats2.FitLine(xs, mean, std)
    thinkplot.Plot(xs, ys, color='0.8', label='model')

    xs, ys = thinkstats2.NormalProbability(avgpace)
    thinkplot.Plot(xs, ys, label='Pace')
```

In [37]:
```
# generate a normal probability plot with average, data deviate from the model

MakeNormalPlot(avgpace)
thinkplot.Config(title='Average Pace, normal plot', xlabel='Pace',
                 ylabel='CDF', loc='upper left')
```



In [38]:
```
# If we make a normal probability plot with log weights, the model fit
# the data well except in the tails, where the slowest people exceed
# expectations.
```

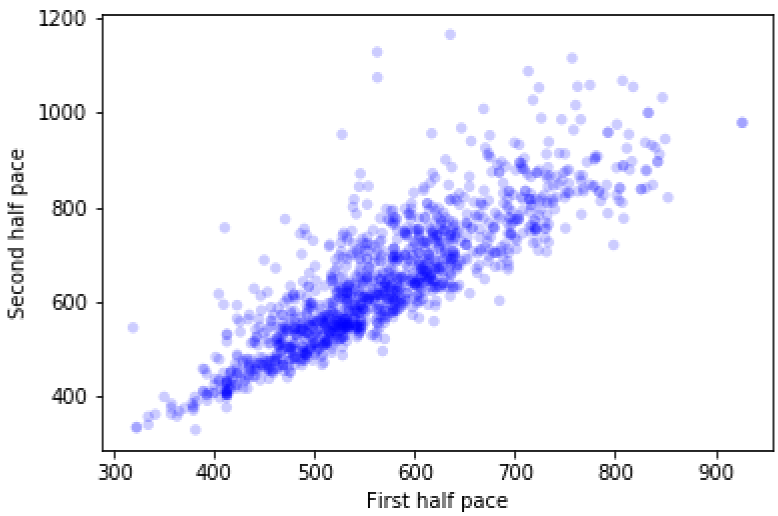
In [39]:
```
MakeNormalPlot(log_paces)
thinkplot.Config(title='Average Pace, lognormal plot', xlabel='Pace (log10 secon
                 ylabel='CDF', loc='upper left')
```

Create two scatter plots comparing two variables and provide your analysis on correlation and causation. Remember, covariance

analysis on correlation and causation. Remember, covariance, Pearson’s correlation, and Non-Linear Relationships should also be considered during your analysis (Chapter 7).

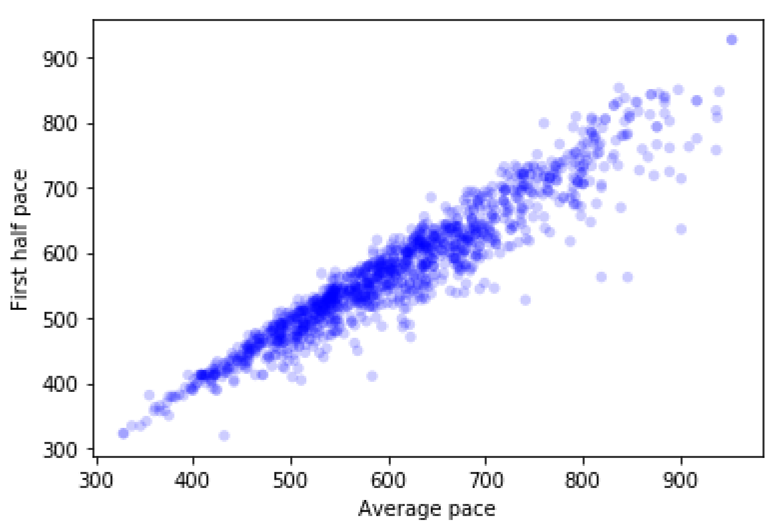
In [40]:

```
# Compare first and second half paces
FSTPCE=df['FSTPCE']
SNDPCE=df['SNDPCE']

thinkplot.Scatter(FSTPCE, SNDPCE, alpha=0.2)
thinkplot.Config(xlabel='First half pace',
                 ylabel='Second half pace')
```



In [41]:
```
#pg 84
def Cov(xs, ys, meanx=None, meany=None):
    xs = np.asarray(xs)
    ys = np.asarray(ys)

    if meanx is None:
        meanx = np.mean(xs)
    if meany is None:
        meany = np.mean(ys)

    cov = np.dot(xs-meanx, ys-meany) / len(xs)
    return cov

#pg 85
def Corr(xs, ys):
    xs = np.asarray(xs)
    ys = np.asarray(ys)

    meanx, varx = thinkstats2.MeanVar(xs)
    meany, vary = thinkstats2.MeanVar(ys)

    corr = Cov(xs, ys, meanx, meany) / np.sqrt(varx * vary)
    return corr

#pg 87
def SpearmanCorr(xs, ys):
    xranks = pd.Series(xs).rank()
    yranks = pd.Series(ys).rank()
    return Corr(xranks, yranks)
```

In [42]:
```
# Plot First half amd average pace
AVRGPCE=df['AVGPCE']
FSTPCE=df['FSTPCE']


thinkplot.Scatter(AVRGPCE, FSTPCE, alpha=0.2)
thinkplot.Config(xlabel='Average pace',
                    ylabel='First half pace')
```



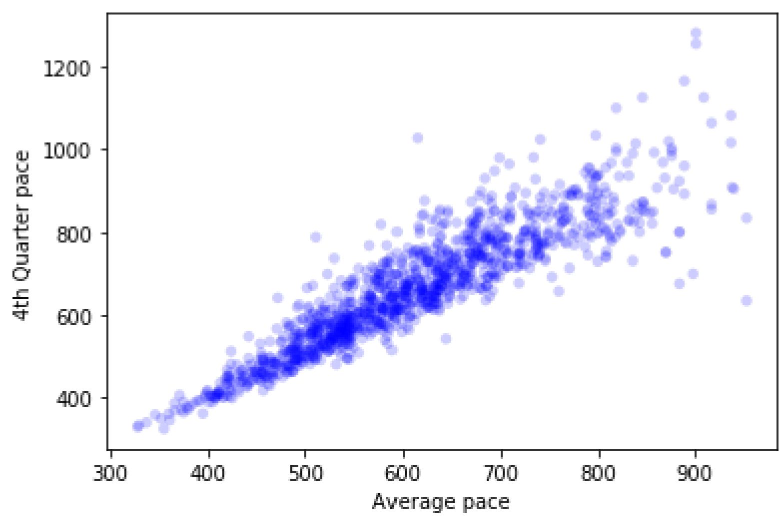
In [43]:
```
# First half comparison to average pace

Corr(FSTPCE, AVRGPCE)
```

Out[43]: 0.9515096654620224

In [44]:
```
SpearmanCorr(FSTPCE, AVRGPCE)
```

Out[44]: 0.9517187086911902

In [45]:
```
# Plot fourth quarter and average pace
FTHPCE=df['FTHQ']


thinkplot.Scatter(AVRGPCE, FTHPCE, alpha=0.2)
thinkplot.Config(xlabel='Average pace',
                    ylabel='4th Quarter pace')
```



In [46]:
```
# fourth comparison to average pace
Corr(FTHPCE, AVRGPCE)
```

Out[46]: 0.9031800951515844

In [47]:
```
SpearmanCorr(FTHPCE, AVRGPCE)
```

Out[47]: 0.9214131163196431

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

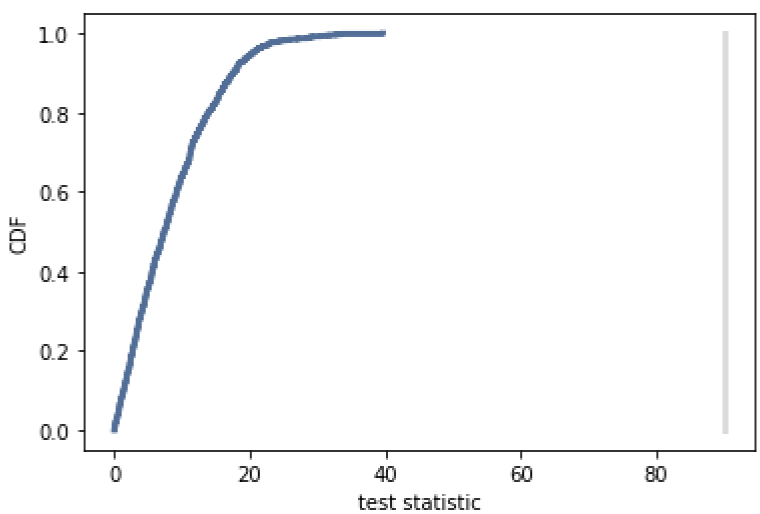
In [48]:
```
class DiffMeansPermute(thinkstats2.HypothesisTest):

    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
```

In [49]:
```
data1 = dfp.AVGPCE.values, dfn.AVGPCE.values
ht = DiffMeansPermute(data1)
pvalue = ht.PValue()
pvalue
```

Out[49]: 0.0

P is 0, conclude difference in average pace of the two groups is significant

In [50]:
```
ht.PlotCdf()
thinkplot.Show(xlabel='test statistic', ylabel='CDF')
```




```
<Figure size 576x432 with 0 Axes>
```

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

In [51]:
```
# dataframe, negative splitters
formula1 = 'AVGPCE ~ FSTPCE'
model = smf.ols(formula1, data=dfn)
results = model.fit()
print(results.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                 AVGPCE   R-squared:                       0.994
Model:                            OLS   Adj. R-squared:                  0.994
Method:                 Least Squares   F-statistic:                 2.231e+04
Date:                Wed, 26 Feb 2020   Prob (F-statistic):          1.41e-153
Time:                        09:05:40   Log-Likelihood:                -473.88
No. Observations:                 139   AIC:                             951.8
Df Residuals:                     137   BIC:                             957.6
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept      6.6314      3.551      1.867      0.064      -0.391      13.654
FSTPCE         0.9754      0.007    149.353      0.000       0.963       0.988
==============================================================================
Omnibus:                       63.500   Durbin-Watson:                   2.029
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              177.825
Skew:                          -1.850   Prob(JB):                     2.43e-39
Kurtosis:                       7.124   Cond. No.                     3.09e+03
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctl
y specified.
[2] The condition number is large, 3.09e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

In [52]:
```
# dataframe, negative splitters
formula2 = 'AVGPCE ~ SNDPCE'
model = smf.ols(formula2, data=dfn)
results = model.fit()
print(results.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                 AVGPCE   R-squared:                       0.993
Model:                            OLS   Adj. R-squared:                  0.993
Method:                 Least Squares   F-statistic:                 2.040e+04
Date:                Wed, 26 Feb 2020   Prob (F-statistic):          6.08e-151
Time:                        09:05:40   Log-Likelihood:                -480.03
No. Observations:                 139   AIC:                             964.1
Df Residuals:                     137   BIC:                             969.9
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept      0.9210      3.753      0.245      0.806      -6.499       8.341
SNDPCE         1.0124      0.007    142.846      0.000       0.998       1.026
==============================================================================
Omnibus:                       73.381   Durbin-Watson:                   2.052
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              247.471
Skew:                           2.076   Prob(JB):                     1.83e-54
Kurtosis:                       8.049   Cond. No.                     3.04e+03
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctl
y specified.
[2] The condition number is large, 3.04e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

In [53]:
```
# dataframe, positive splitters
model = smf.ols(formula1, data=dfp)
results = model.fit()
print(results.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                 AVGPCE   R-squared:                       0.910
Model:                            OLS   Adj. R-squared:                  0.910
Method:                 Least Squares   F-statistic:                 1.146e+04
Date:                Wed, 26 Feb 2020   Prob (F-statistic):               0.00
Time:                        09:05:40   Log-Likelihood:                -5638.0
No. Observations:                1137   AIC:                         1.128e+04
Df Residuals:                    1135   BIC:                         1.129e+04
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept     -2.7088      5.896     -0.459      0.646     -14.277       8.859
FSTPCE         1.0781      0.010    107.037      0.000       1.058       1.098
==============================================================================
Omnibus:                      445.070   Durbin-Watson:                   1.618
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             2215.191
Skew:                           1.768   Prob(JB):                         0.00
Kurtosis:                       8.853   Cond. No.                     3.37e+03
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctl
y specified.
[2] The condition number is large, 3.37e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

In [54]:
```
# dataframe, positive splitters
model = smf.ols(formula2, data=dfp)
results = model.fit()
print(results.summary())
```

```
                            OLS Regression Results                            
==============================================================================
Dep. Variable:                 AVGPCE   R-squared:                       0.950
Model:                            OLS   Adj. R-squared:                  0.950
Method:                 Least Squares   F-statistic:                 2.150e+04
Date:                Wed, 26 Feb 2020   Prob (F-statistic):               0.00
Time:                        09:05:40   Log-Likelihood:                -5304.7
No. Observations:                1137   AIC:                         1.061e+04
Df Residuals:                    1135   BIC:                         1.062e+04
Df Model:                           1                                         
Covariance Type:            nonrobust                                         
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept     76.4901      3.777     20.254      0.000      69.080      83.900
SNDPCE         0.8215      0.006    146.619      0.000       0.811       0.833
==============================================================================
Omnibus:                      192.990   Durbin-Watson:                   1.692
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              644.371
Skew:                          -0.815   Prob(JB):                    1.19e-140
Kurtosis:                       6.308   Cond. No.                     3.34e+03
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctl
y specified.
[2] The condition number is large, 3.34e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```