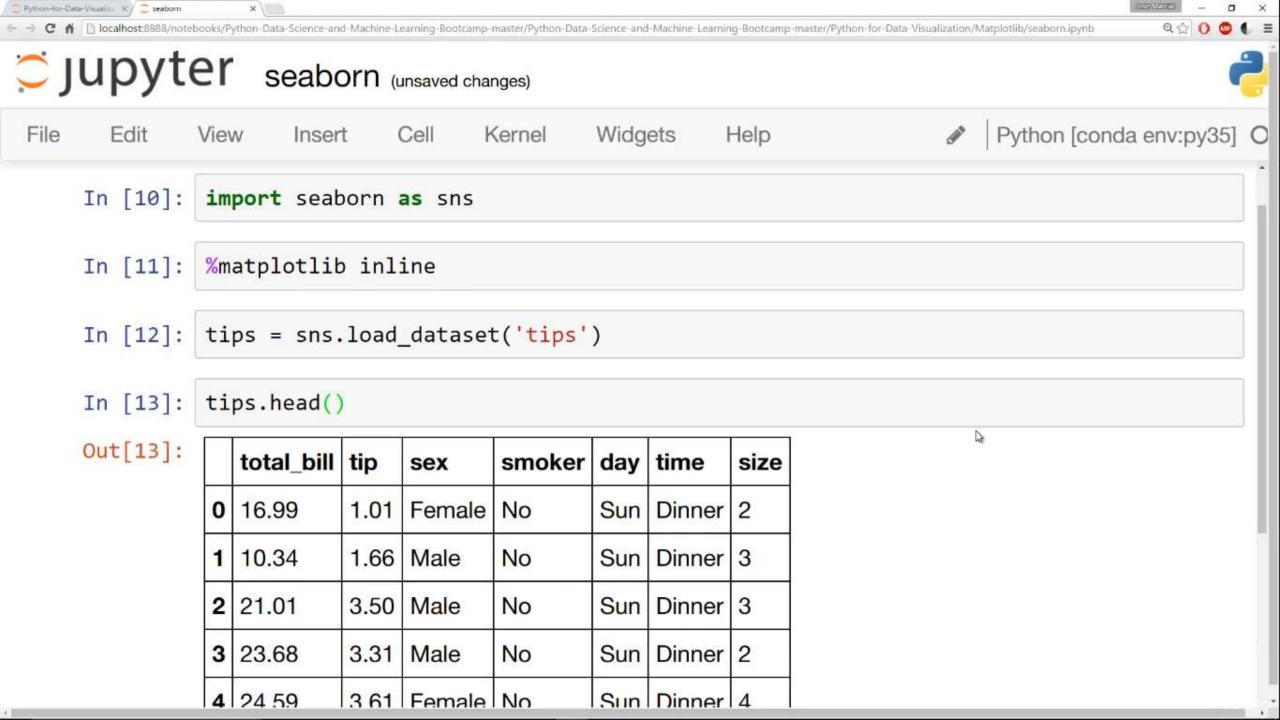
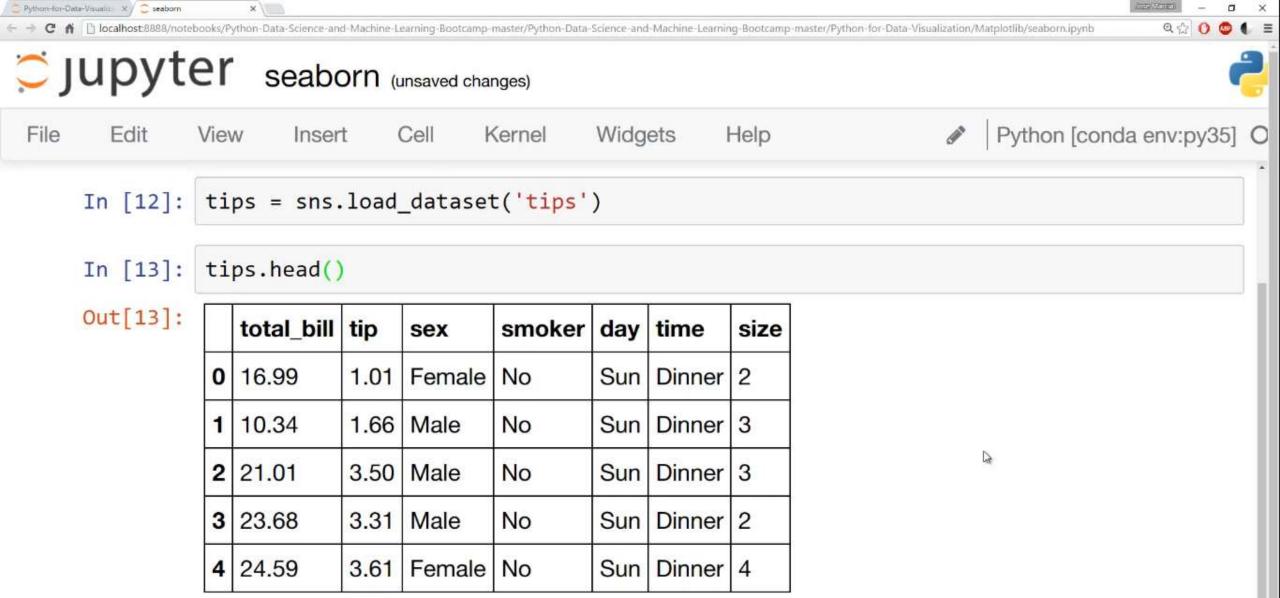


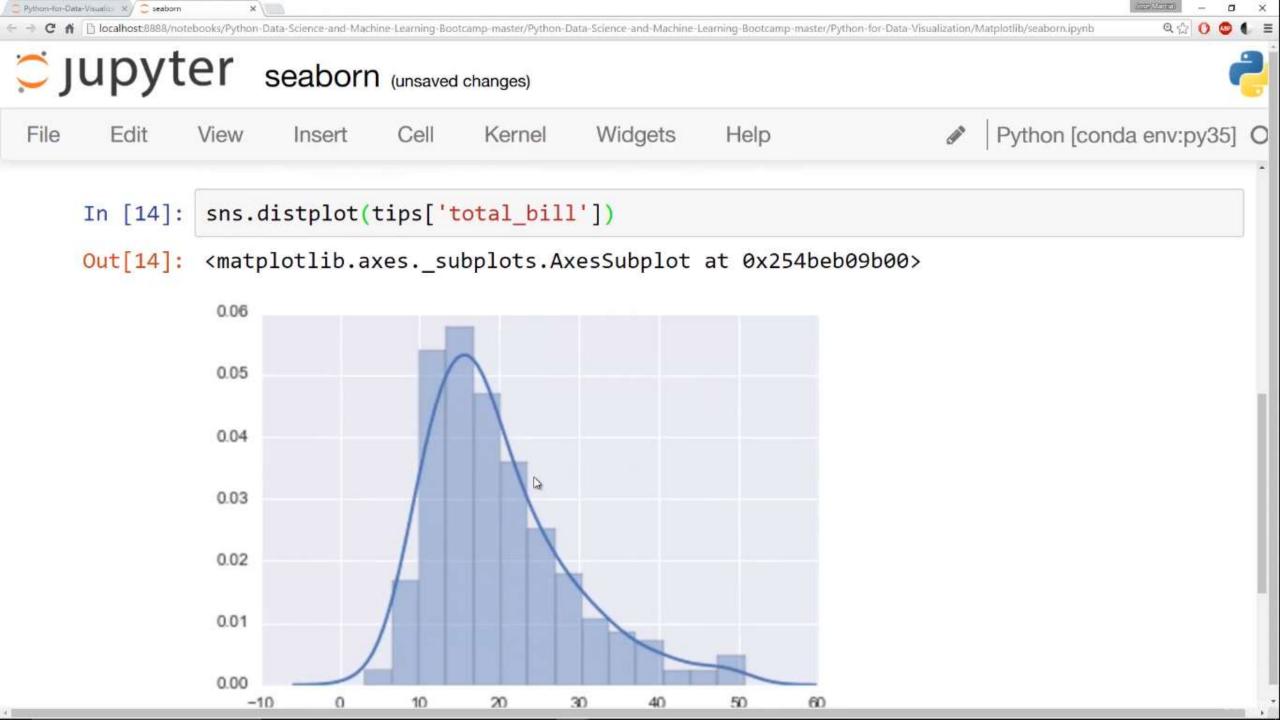
Distribution Plots

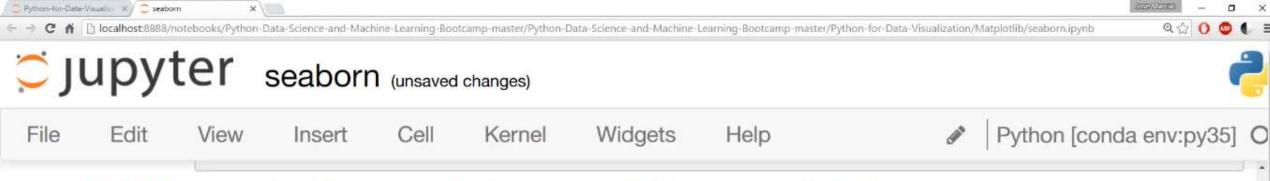


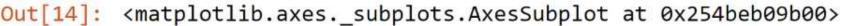


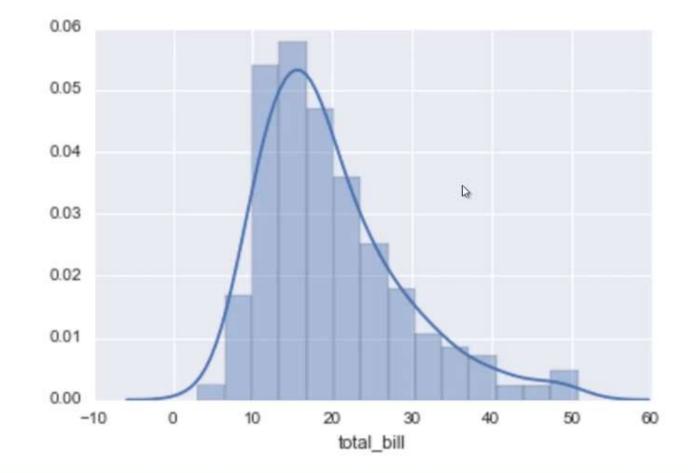


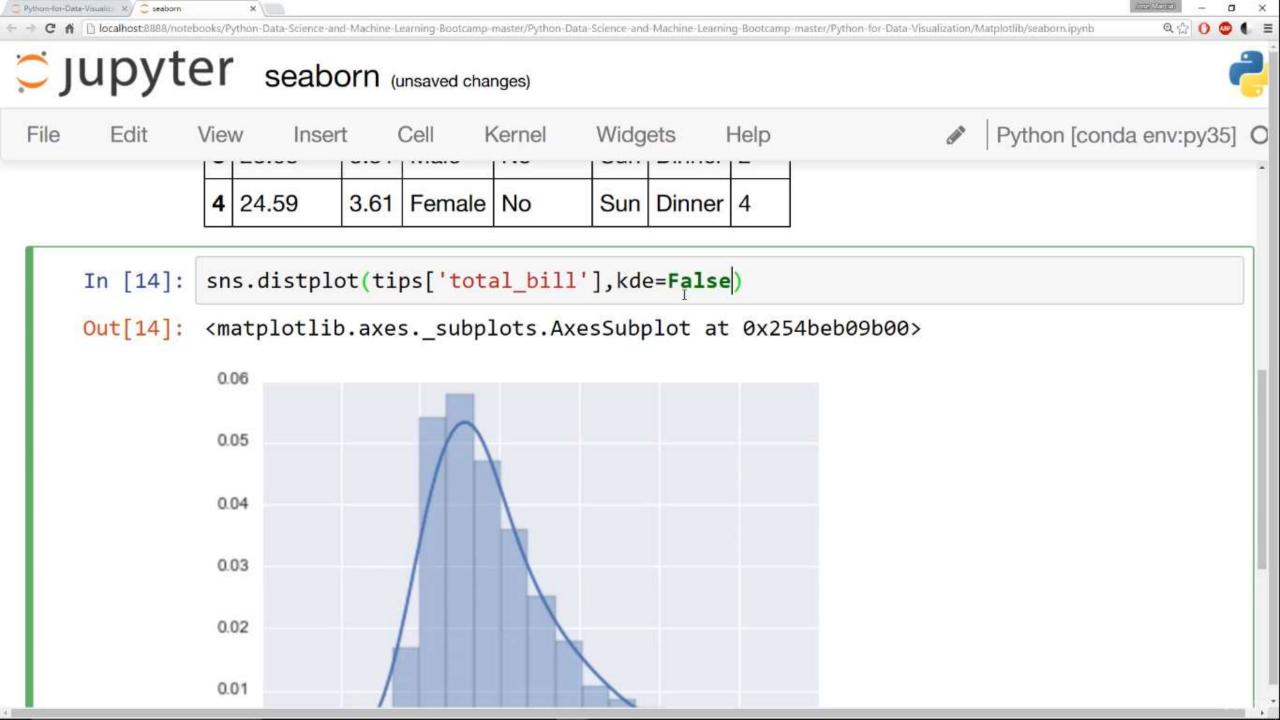
In []:

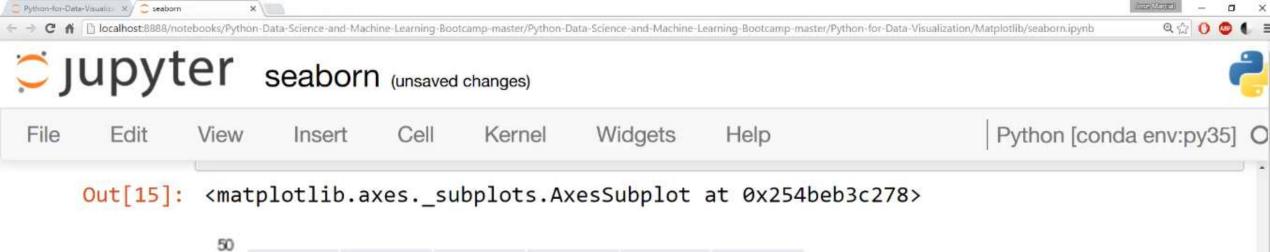


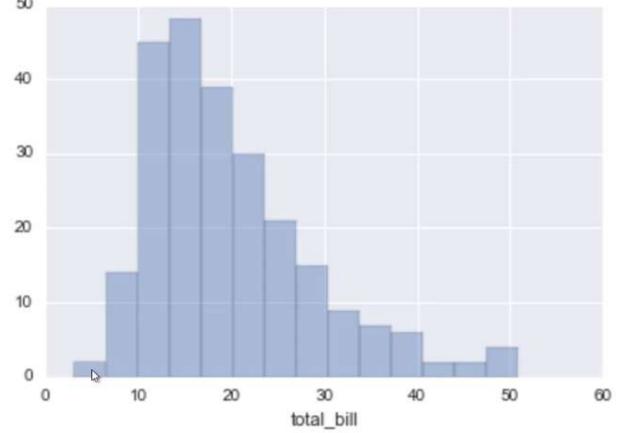


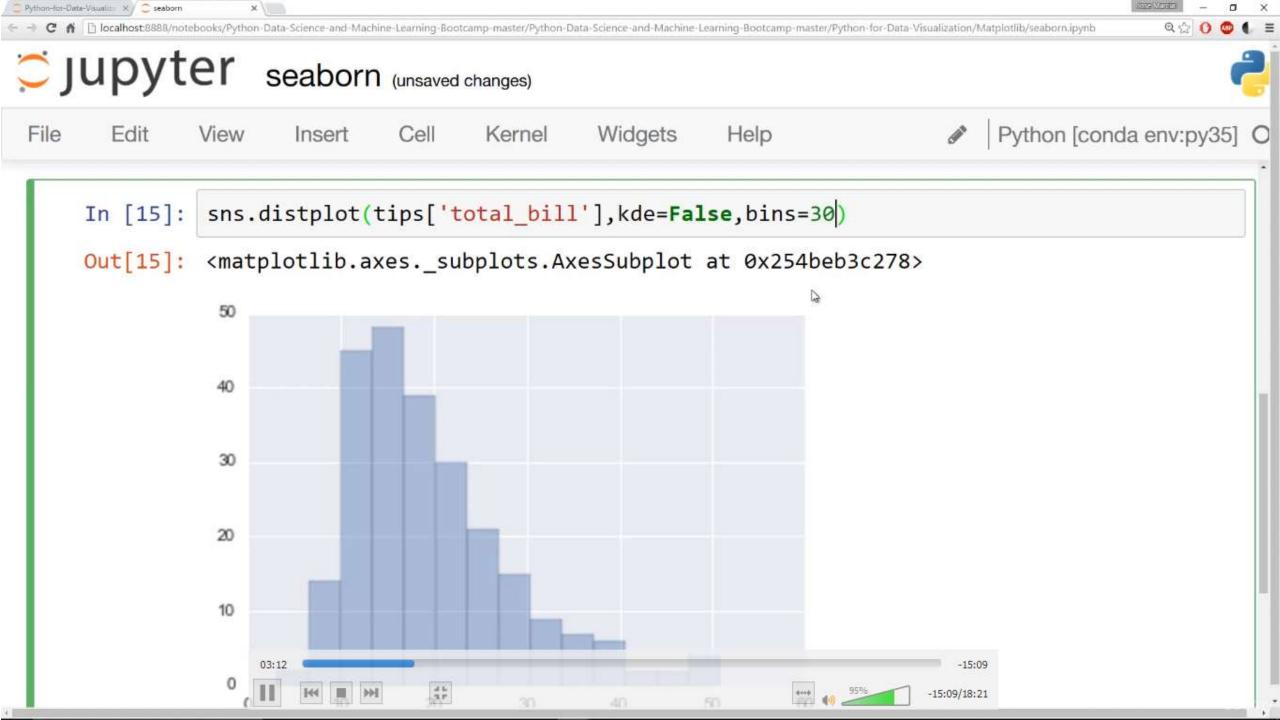


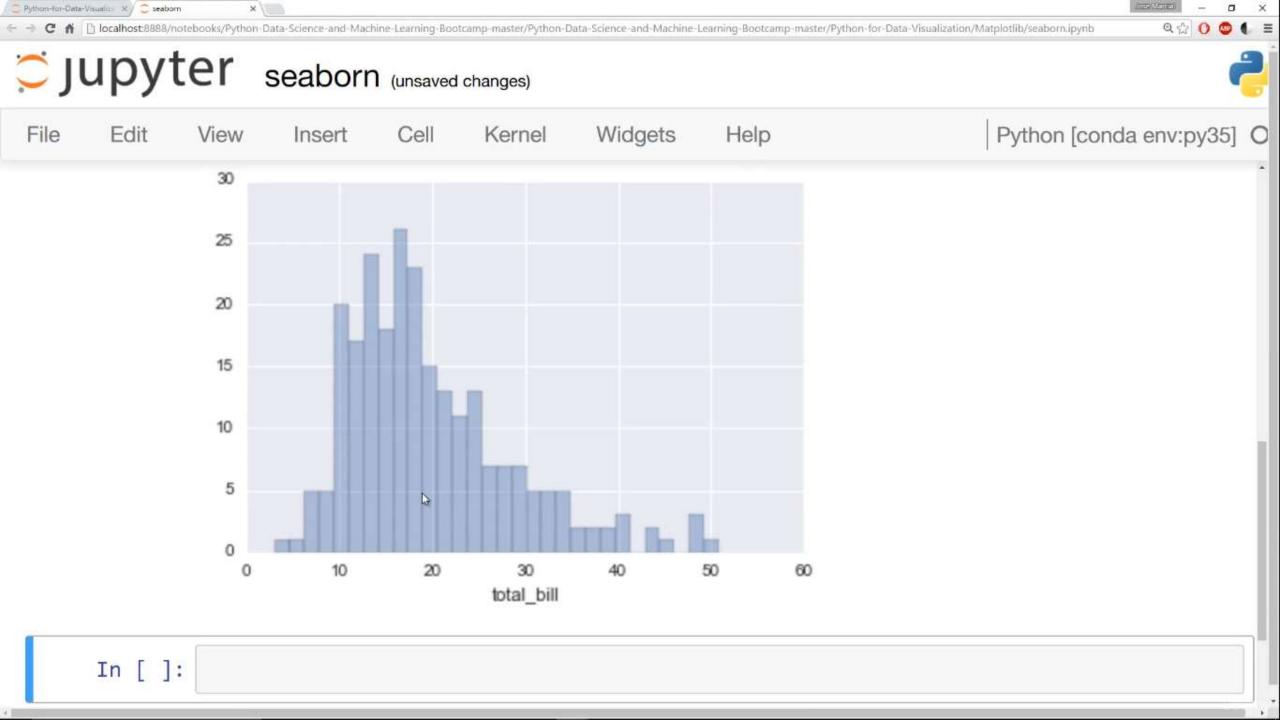


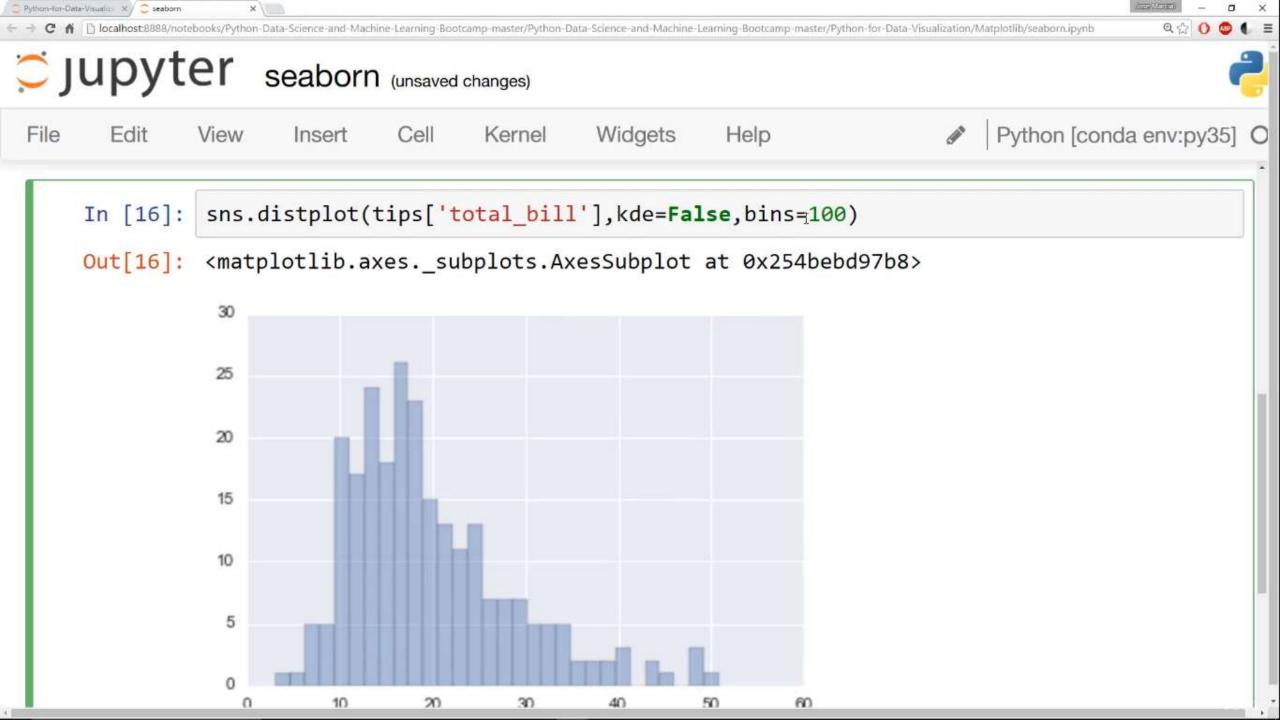


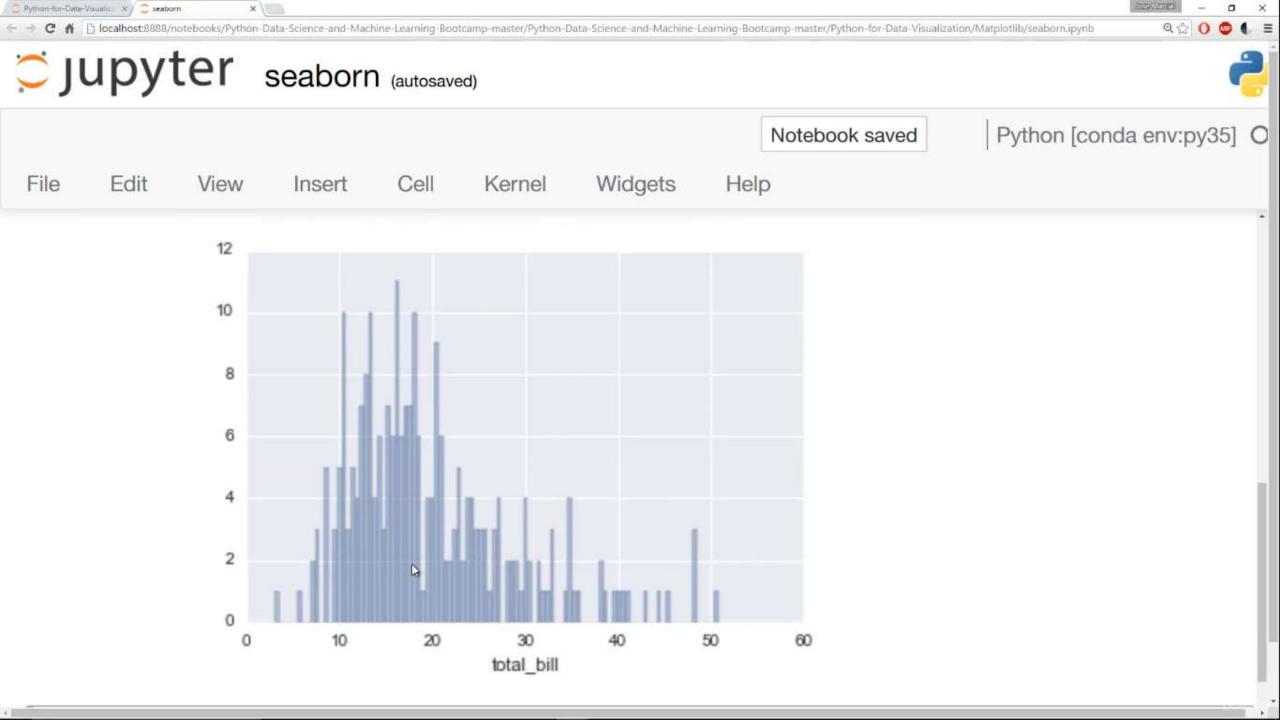


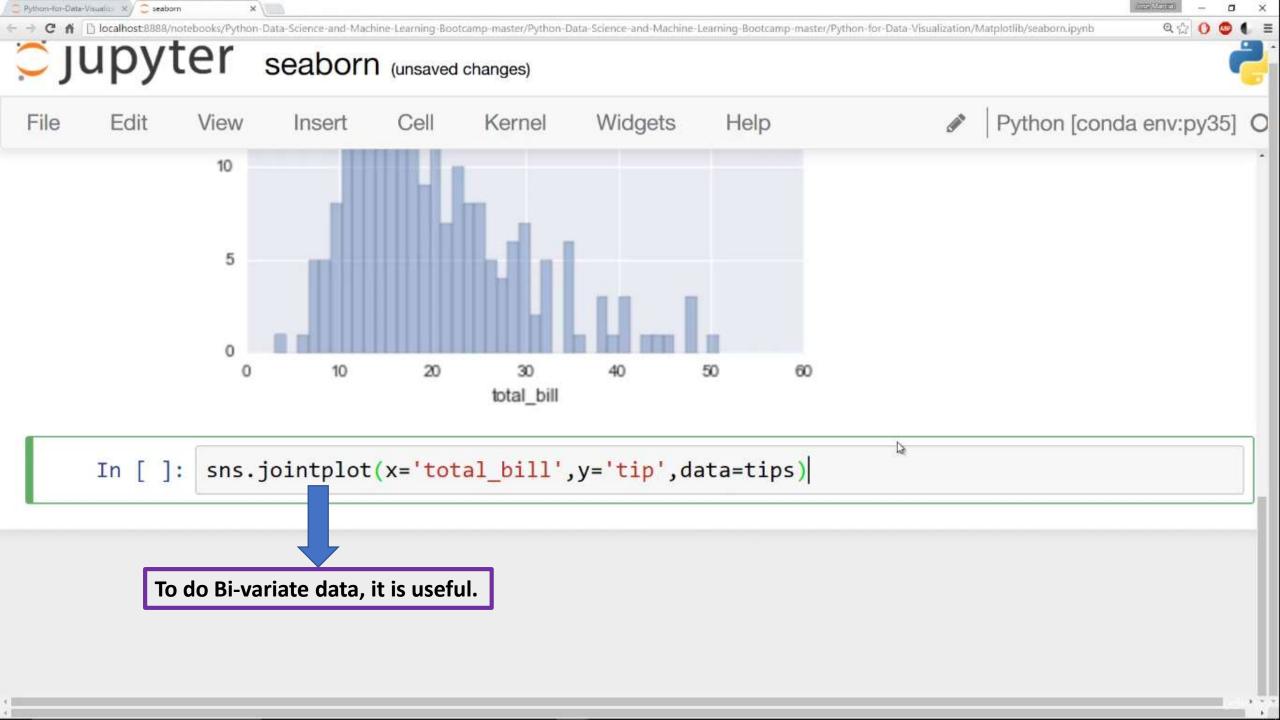


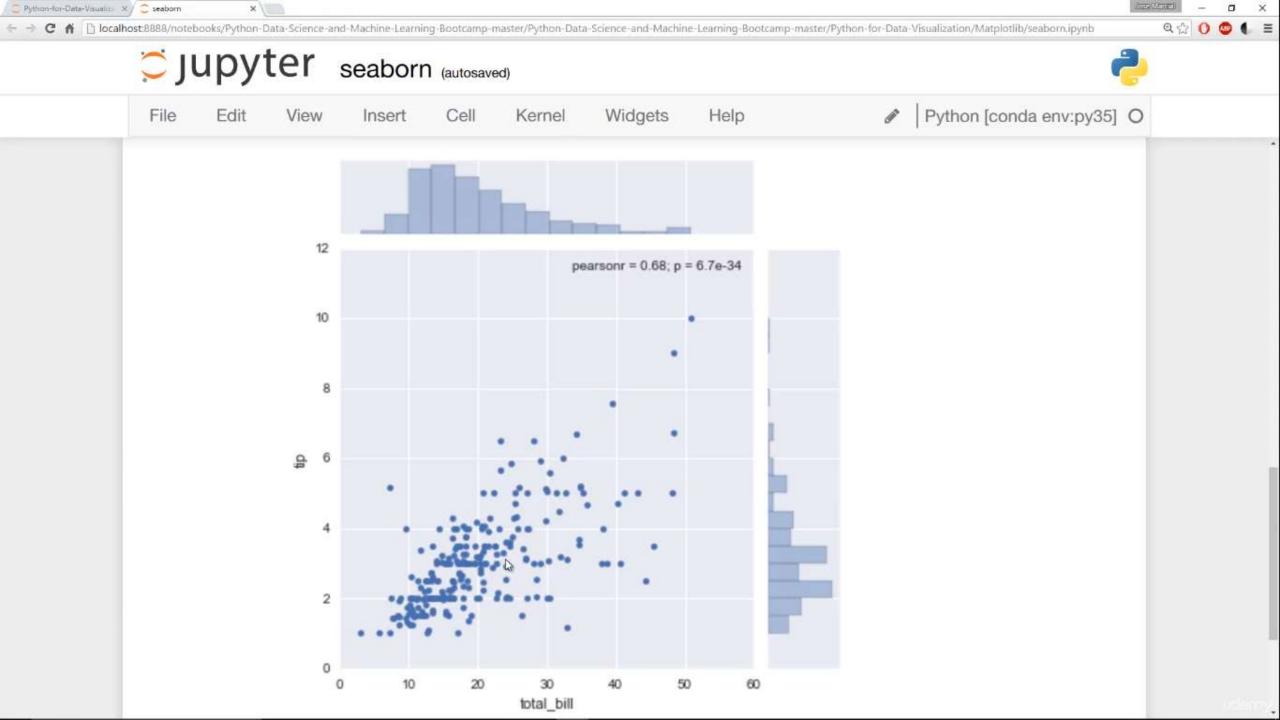


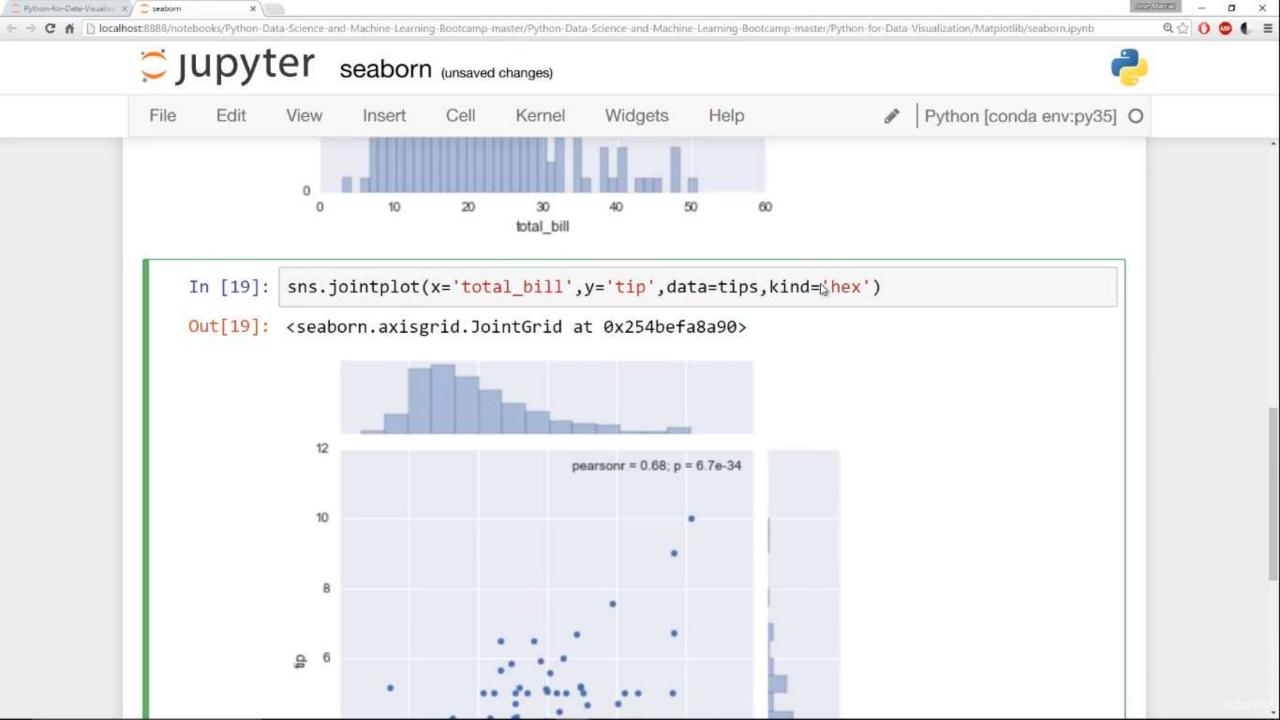




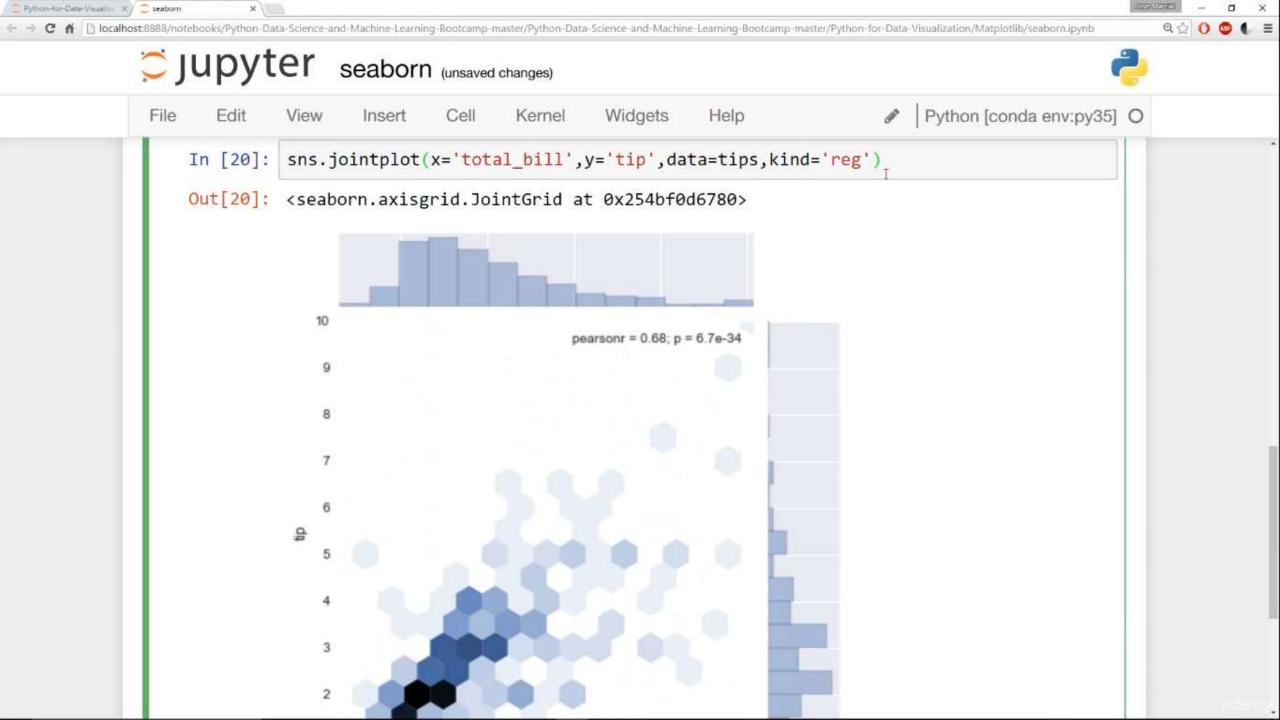


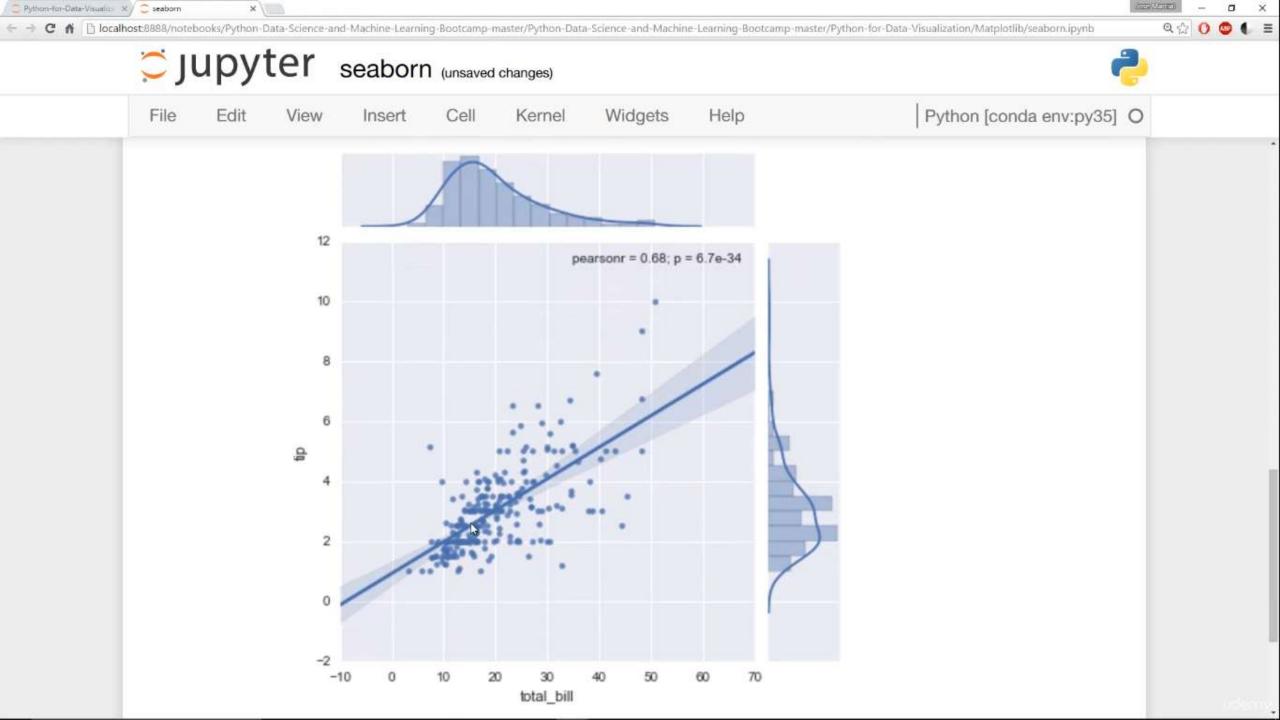


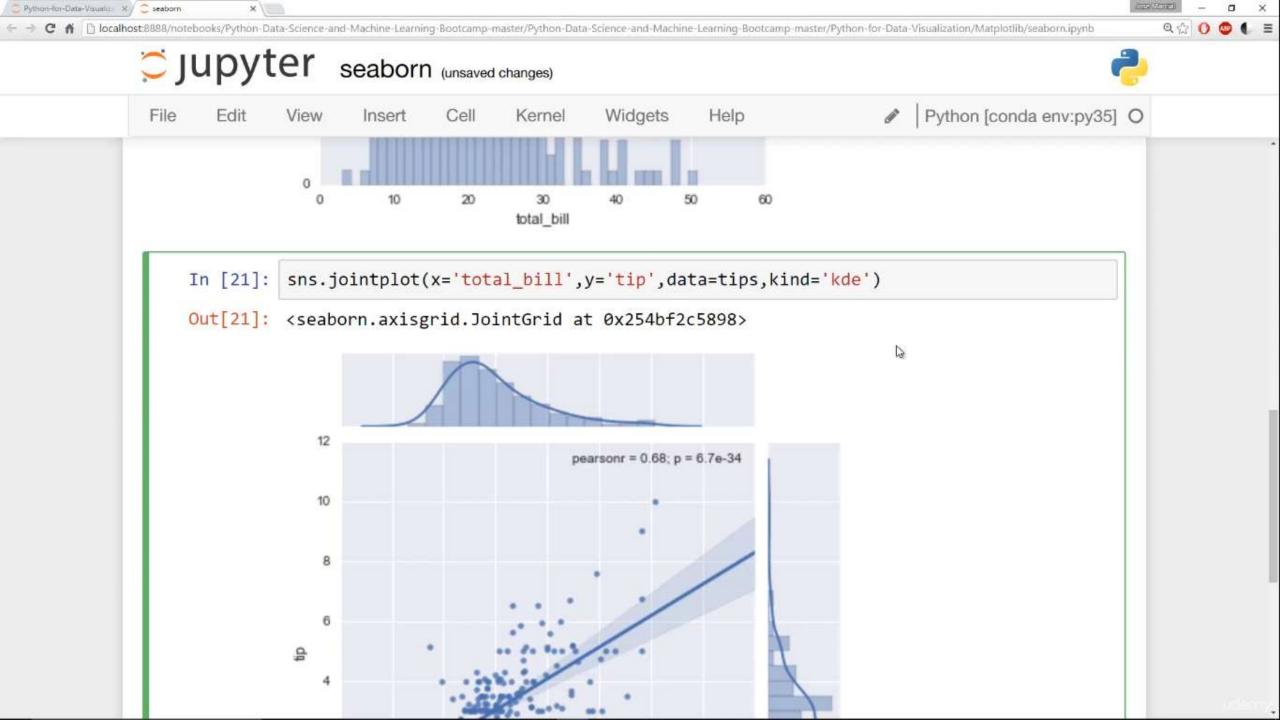


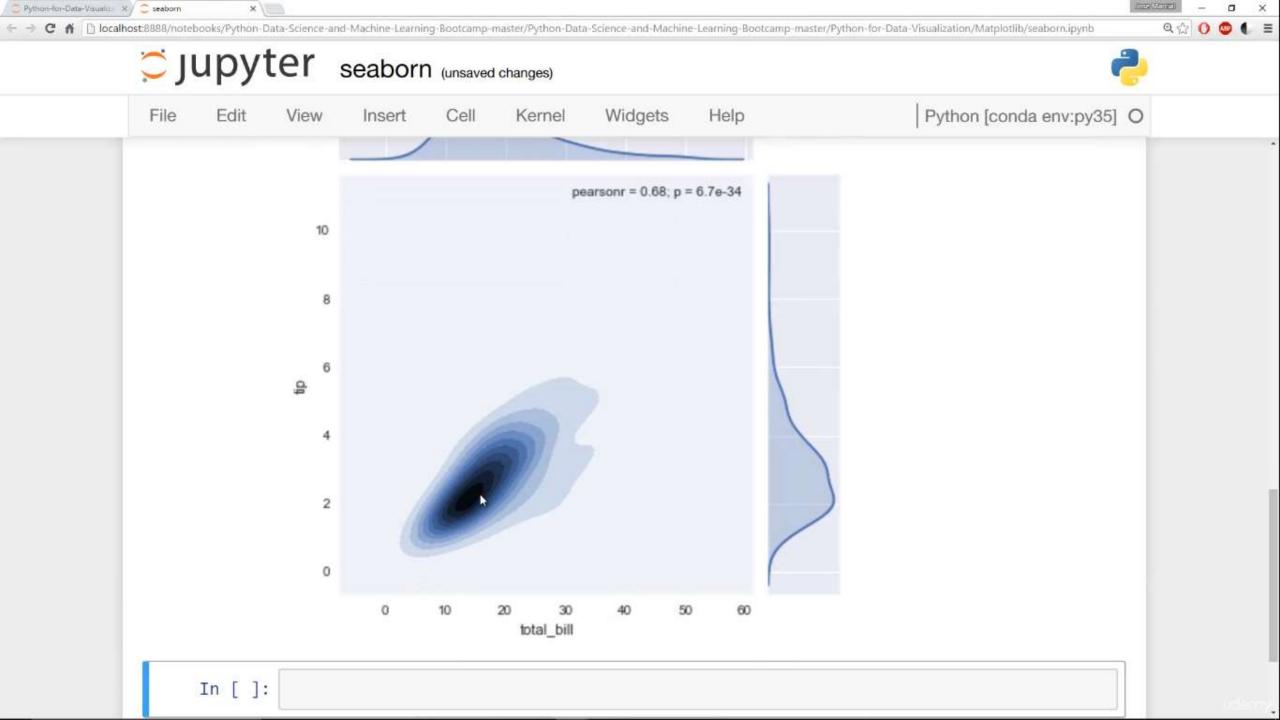


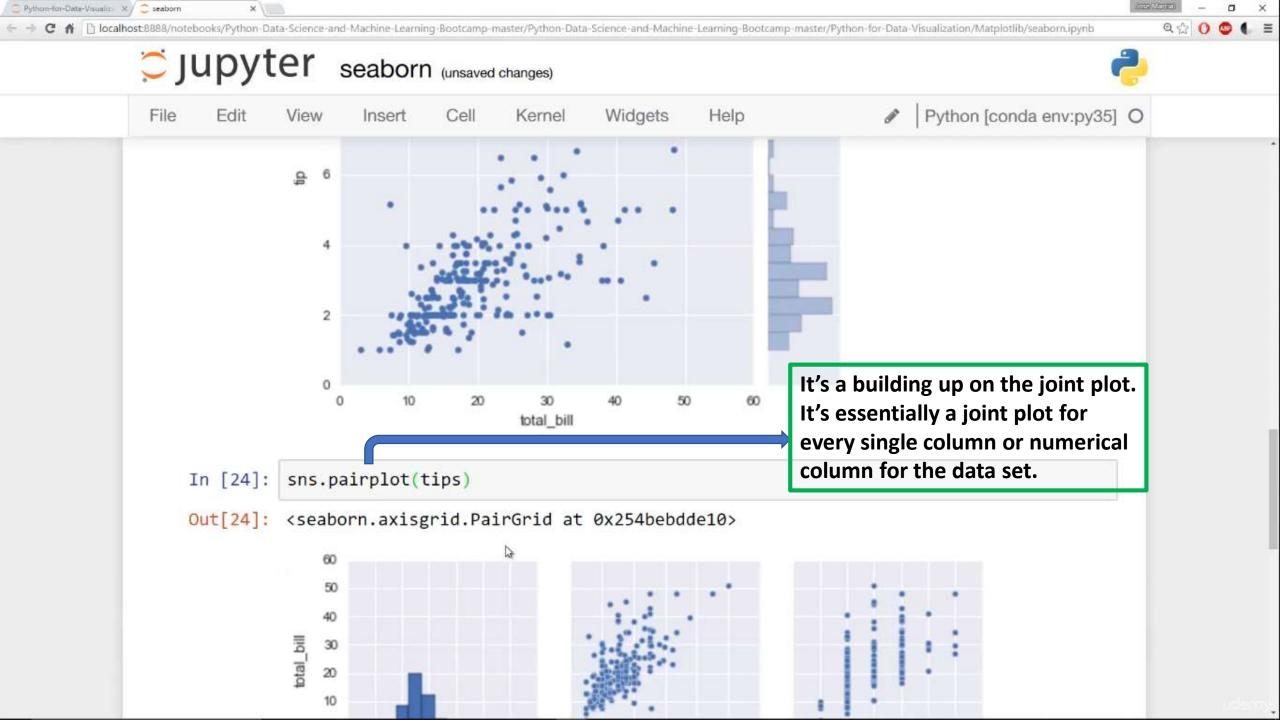


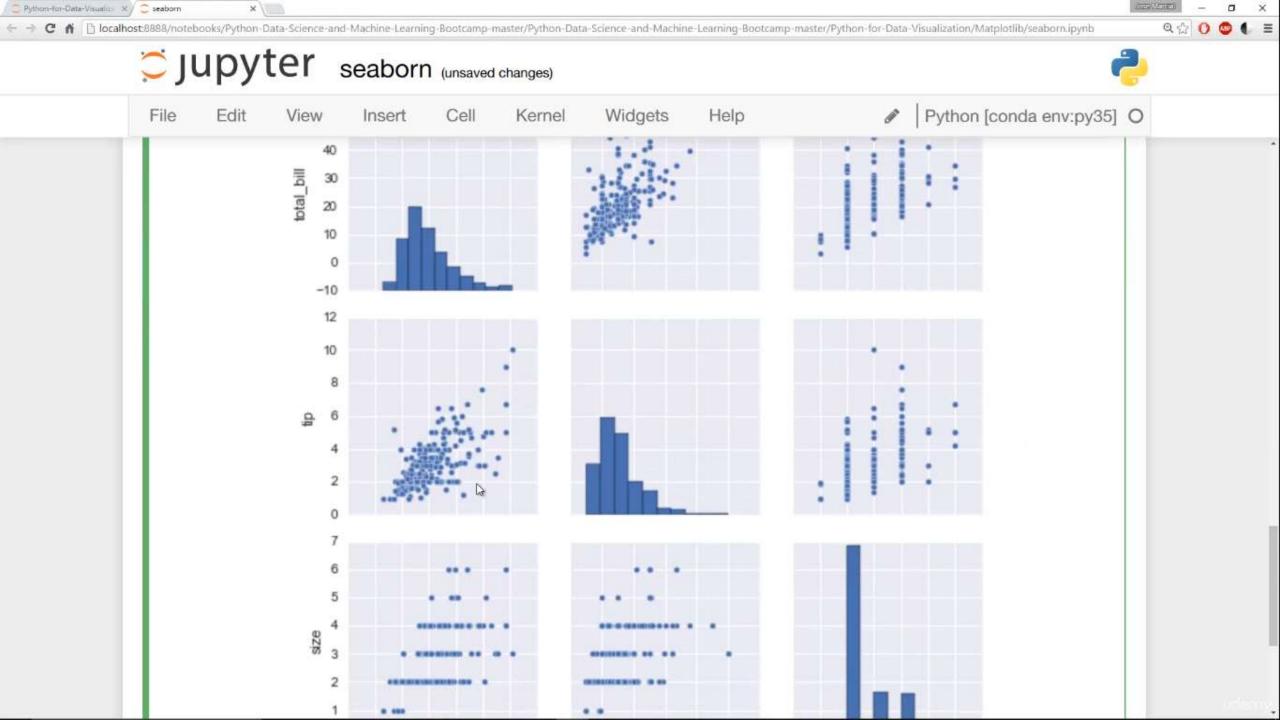




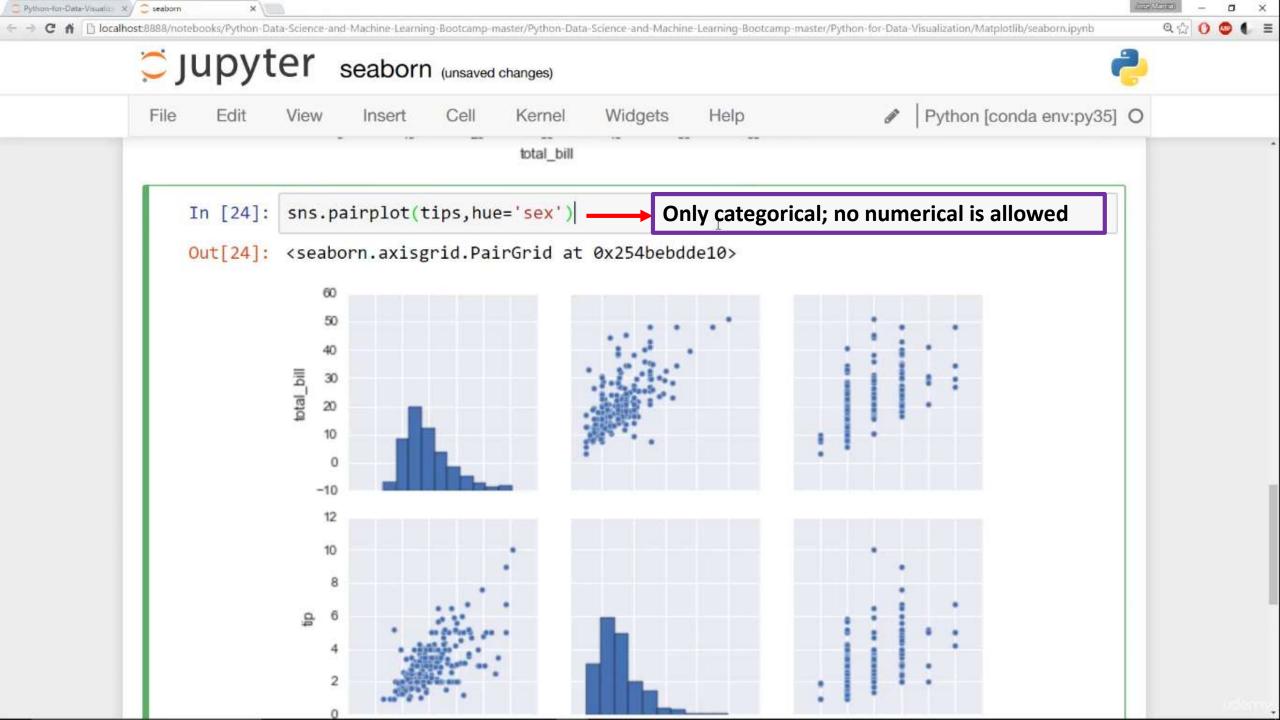


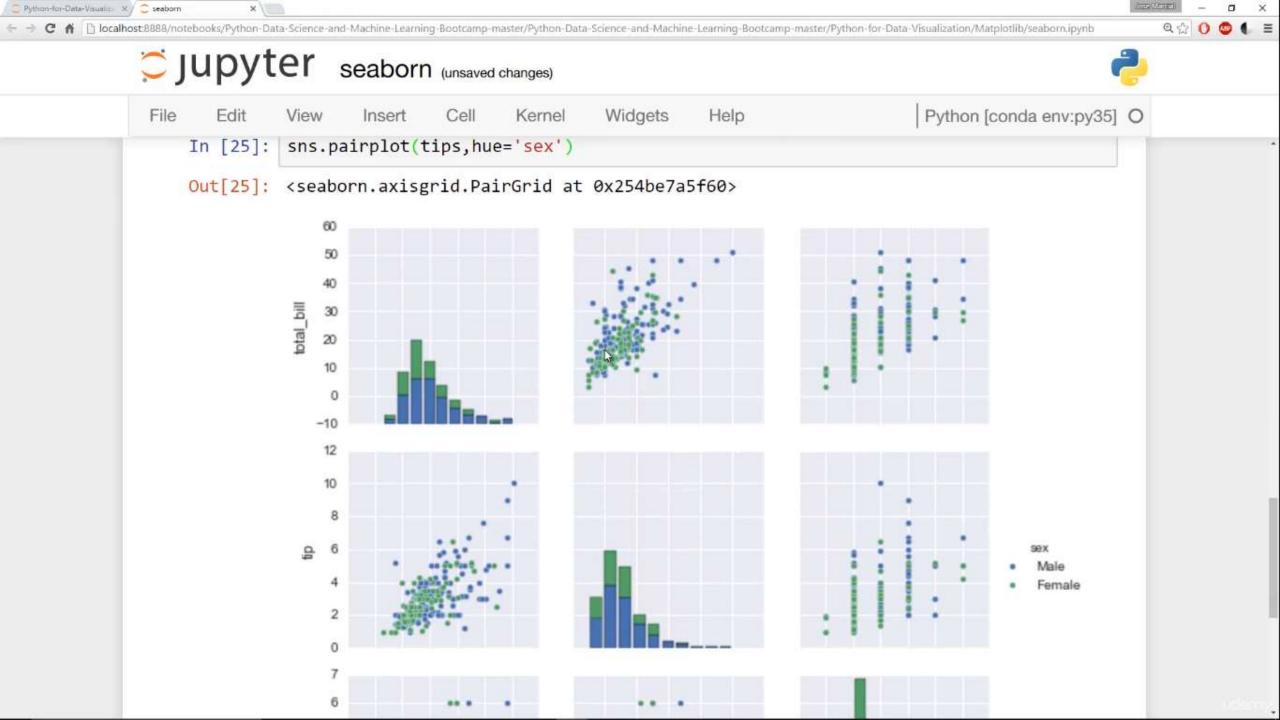


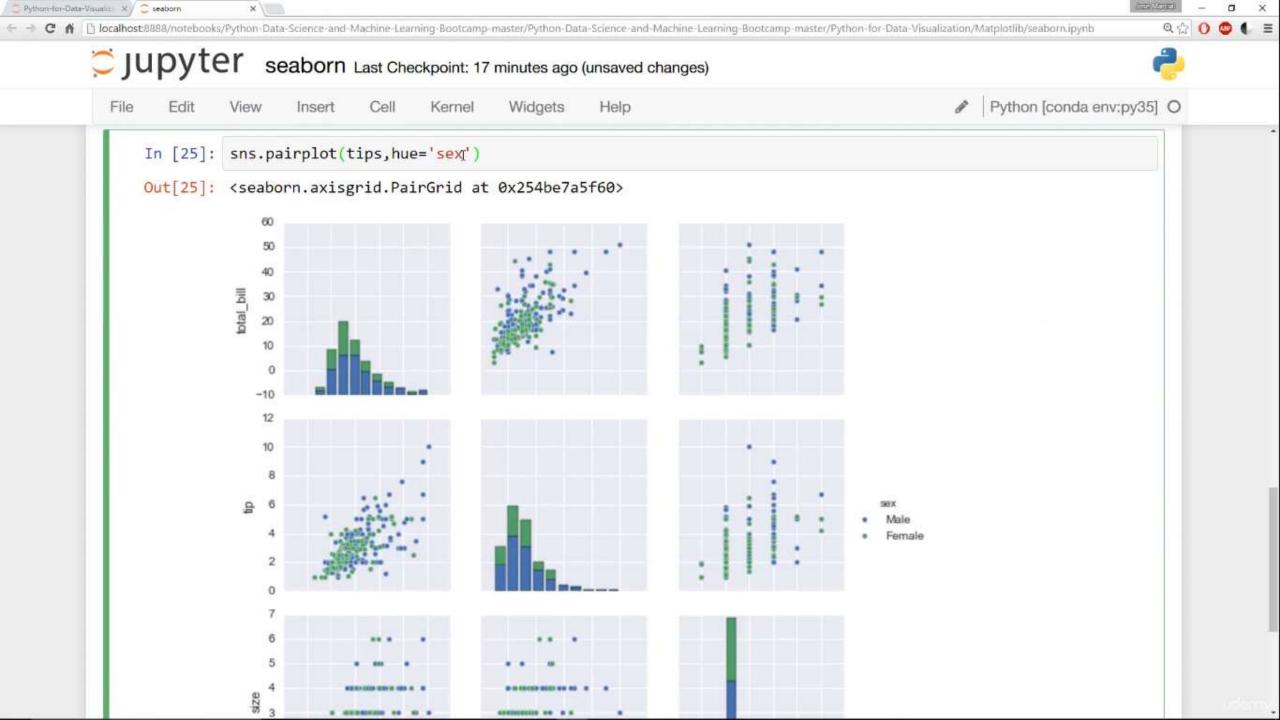


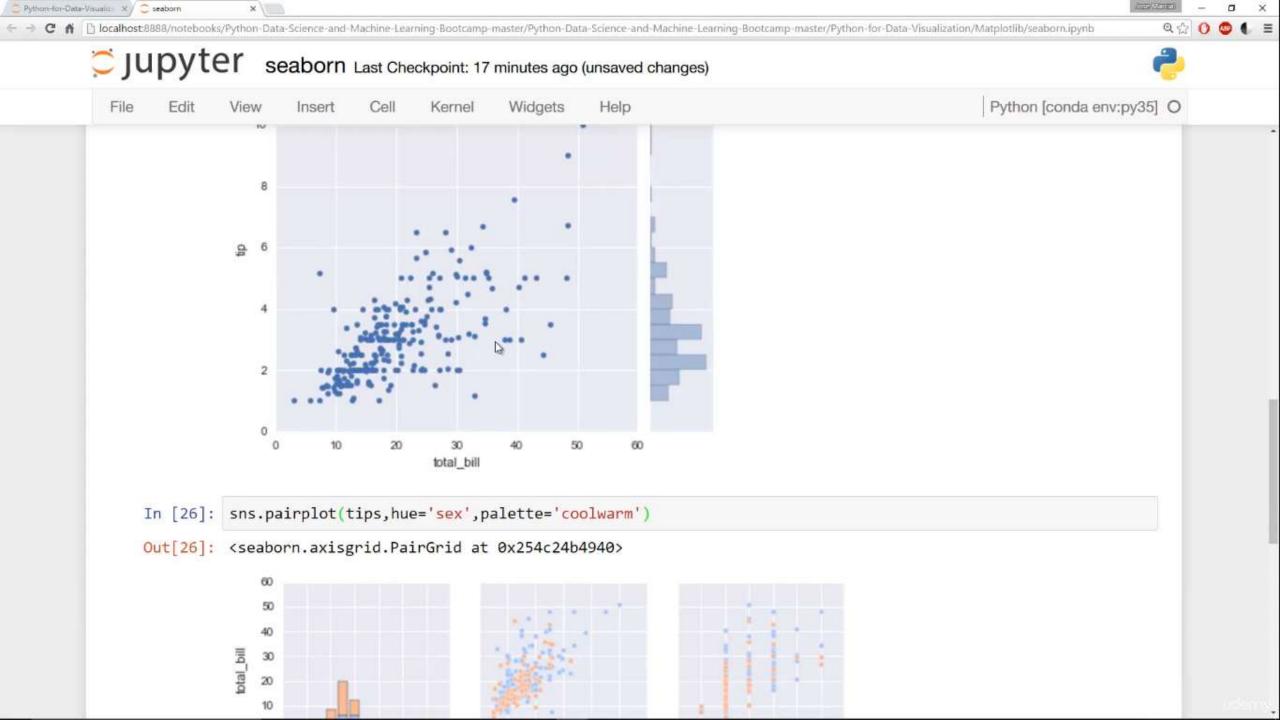


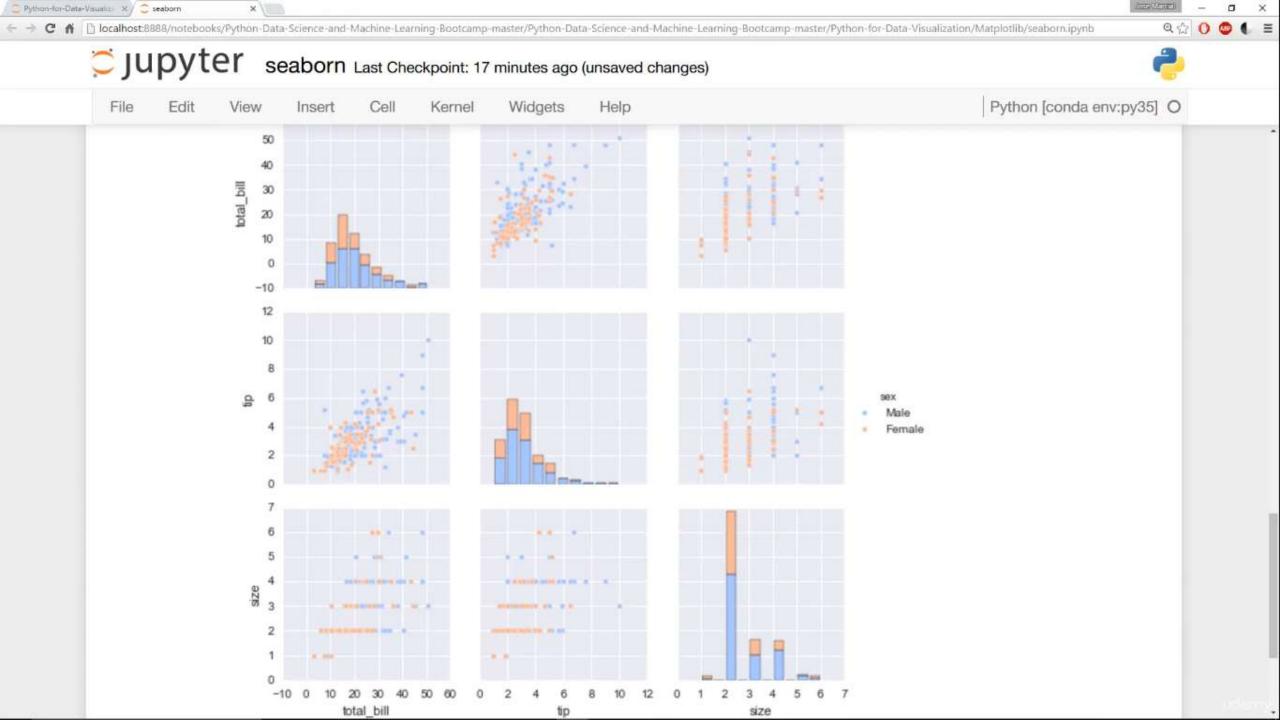














Not logged in Talk Contributions Create account Log in

Search

Edit View history

Read

Q



The Free Encyclopedia

Main page

Contents

Featured content

Current events

Random article

Donate to Wikipedia

Wikipedia store

Interaction

Help

About Wikipedia Community portal

Recent changes

Contact page

Tools

What links here

Related changes

Upload file

Special pages

Permanent link

Page information

Article Talk



Wiki Loves Monuments: The world's largest photography competition is now open! Photograph a historic site, learn more about our history, and win prizes.



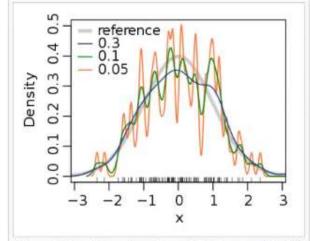
Kernel density estimation

From Wikipedia, the free encyclopedia

In statistics, kernel density estimation (KDE) is a non-parametric way to estimate the probability density function of a random variable. Kernel density estimation is a fundamental data smoothing problem where inferences about the population are made, based on a finite data sample. In some fields such as signal processing and econometrics it is also termed the Parzen-Rosenblatt window method, after Emanuel Parzen and Murray Rosenblatt, who are usually credited with independently creating it in its current form. [1][2]

Contents [hide]

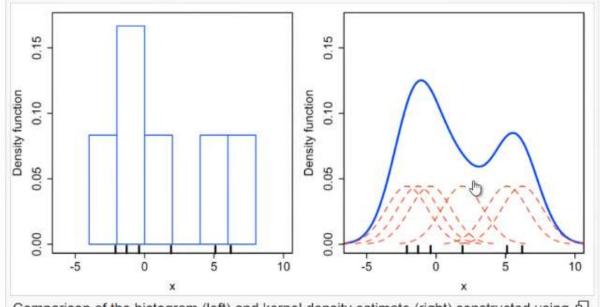
- Definition
- 2 Bandwidth selection
 - 2.1 A rule-of-thumb bandwidth estimator
- 3 Relation to the characteristic function density estimator
- 4 Statistical implementation
- 5 See also
- 6 References



Kernel density estimation of 100 normally □ distributed random numbers using different smoothing bandwidths.

the range of the data. In this case, we have 6 bins each of width 2. Whenever a data point falls inside this interval, we place a box of height 1/12. If more than one data point falls inside the same bin, we stack the boxes on top of each other.

For the kernel density estimate, we place a normal kernel with variance 2.25 (indicated by the red dashed lines) on each of the data points x_i . The kernels are summed to make the kernel density estimate (solid blue curve). The smoothness of the kernel density estimate is evident compared to the discreteness of the histogram, as kernel density estimates converge faster to the true underlying density for continuous random variables.[6]



Comparison of the histogram (left) and kernel density estimate (right) constructed using 6 the same data. The 6 individual kernels are the red dashed curves, the kernel density estimate the blue curves. The data points are the rug plot on the horizontal axis.

Bandwidth selection [edit]

The bandwidth of the kernel is a free parameter which exhibits a strong influence on the resulting estimate. To illustrate its effect, we take a simulated random sample from the standard normal distribution (plotted at the blue spikes in the rug plot on the horizontal axis). The grey curve is the



