*You are currently looking at **version 1.0** of this notebook. To download notebooks and datafiles, as well as get help on Jupyter notebooks in the Coursera platform, visit the [Jupyter Notebook FAQ (https://www.coursera.org/learn/python-data-analysis/resources/0dhYG)](https://www.coursera.org/learn/python-data-analysis/resources/0dhYG) course resource.*

Distributions in Pandas

In [1]:
```
import pandas as pd
import numpy as np
```

Binomial Distribution ¶

第一个参数是我们想 run 的次数，第二个参数是得到 0 的概率
np.random.binomial 输出为多少次是 1
如果有第三个参数意味着以前两个参数为一组，一共重复 n 次。
如下：一共实行 15 组，每组实行 10 次 0/1 结果，每次得到 0 的概率为 0.5

In [2]:
```
np.random.binomial(10, 0.5, 15)
```

Out[2]:
```
array([3, 4, 4, 6, 5, 6, 6, 7, 3, 4, 2, 4, 4, 4, 6])
```

In [3]:
```
np.random.binomial(1000, 0.5)/1000
```

Out[3]:
```
0.535
```

某地发生龙卷风的概率为 0.01%, 100000 次龙卷风，有多少次会发生在当地。

In [4]:
```
chance_of_tornado = 0.01/100
np.random.binomial(100000, chance_of_tornado)
```

Out[4]:
```
10
```

模拟 1M 次龙卷风发生。Sampling Distribution

In [5]:
```
# 在一百万天理连续两天发生龙卷风的次数
chance_of_tornado = 0.01

tornado_events = np.random.binomial(1, chance_of_tornado, 1000000)

two_days_in_a_row = 0
for j in range(1,len(tornado_events)-1):
    if tornado_events[j]==1 and tornado_events[j-1]==1:
        two_days_in_a_row+=1

print('{} tornadoes back to back in {} years'.format(two_days_in_a_row, 100
0000/365))
```

```
95 tornadoes back to back in 2739.72602739726 years
```

Uniform Distribution

numpy.random.uniform(low=0.0, high=1.0, size=None)

Output 为：在 uniform distribution 里随机取的数

In [6]:
```
np.random.uniform(0, 1, 10)
```

Out[6]:
```
array([0.76987103, 0.96363774, 0.3939777 , 0.98191273, 0.98217591,
       0.77716212, 0.00564514, 0.10536054, 0.92097738, 0.06180463])
```

Normal Distribution

numpy.random.normal(loc=0.0, scale=1.0, size=None)

- loc : Mean (“centre”) of the distribution.
- scale : Standard deviation (spread or “width”) of the distribution.
- size : Output shape. If the given shape is, e.g., (m, n, k), then m *n* k samples are drawn. If size is None (default), a single value is returned if loc and scale are both scalars. Otherwise, np.broadcast(loc, scale).size samples are drawn.

Output 为：在 normal distribution 里随机取的数

In [7]:
```
np.random.normal(0.75, size=10)
```

Out[7]:
```
array([ 1.16848679, -0.35725201, -0.15355074,  0.15951085, -0.10320638,
       -0.71475168,  0.62631011,  1.01245122,  0.6886017 , -0.18199536])
```

Formula for standard deviation

$$\sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \overline{x})^2}$$

In [8]:
```
distribution = np.random.normal(0.75,size=1000)

np.sqrt(np.sum((np.mean(distribution)-distribution)**2)/len(distribution))
```

Out[8]: 1.0019974421108742

In [9]:
```
np.std(distribution)
```

Out[9]: 1.0019974421108742

可以使用 Scipy 中的 kurtosis 来计算分布尾巴的形状。

负值表示 normal distribtuion 的曲线更平坦，正值表示曲线更陡。

In [10]:
```
import scipy.stats as stats
stats.kurtosis(distribution)
```

Out[10]: 0.4495442578904312

也可以移动 normal distribution 的曲线，推动曲线的峰值向左或向右。This is called `skew`

In [11]:
```
stats.skew(distribution)
```

Out[11]: 0.15614556289756998

Chi Squared Distribution

Chi Squared 分布只有一个参数：degree of freedom。
degree of freedom 和从 normal population (标准样本)中，获取的样本数量密切相关。
随着自由度增加，Chi Squared 分布形状发生变化：左偏斜开始向中心移动。

In [12]:
```
# 从 Chi Squared 分布中挑选 1000 个值且自由度为 2.
chi_squared_df2 = np.random.chisquare(2, size=10000)
stats.skew(chi_squared_df2)
```

Out[12]: 2.1390895634299176

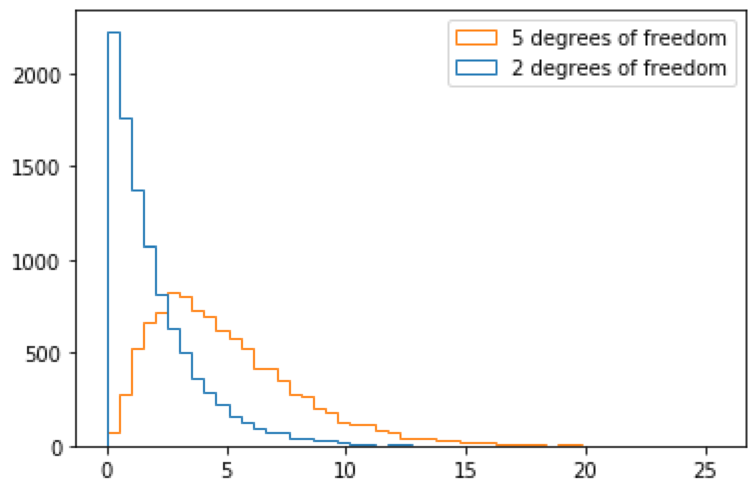
In [13]:
```
# 当自由度提升，skew 下降
chi_squared_df5 = np.random.chisquare(5, size=10000)
stats.skew(chi_squared_df5)
```

Out[13]: 1.2555478337050152

In [14]:
```
%matplotlib inline
import matplotlib
import matplotlib.pyplot as plt

output = plt.hist([chi_squared_df2,chi_squared_df5], bins=50, histtype='ste
p',
                  label=['2 degrees of freedom','5 degrees of freedom'])
plt.legend(loc='upper right')
```

Out[14]: <matplotlib.legend.Legend at 0xa0c1748>



Modality Distribution

Modality Distribution has Multiple Peaks:

- Bimodal Distribution: 有 2 个 peaks (data mining 有很多)。可以用两个带有不同参数的 normal distribution 来合成产生(Gaussian Mixture Models)。在 clustering data 时很有用。

Hypothesis Testing

Hypothesis: A statement we can test (两组假设互相对立)

- Alternative(对立) hypothesis: Our idea, e.g. there is a difference between groups
- Null hypothesis: The alternative of our idea, e.g. there is no difference between groups

检验 Null hypothesis 是否正确。如果能举出反例，则认定 Alternative hypothesis 是正确的。

在进行 Hypothesis Test 时，我们需选择一个 significance level 作为门槛，来表示多少概率的偶然性，我们愿意接受，超过这个偶然性，则考虑是否是常态，从而不接受假设结果。

Critical Value alpha(α)：

- The threshold as to how much chance you are willing to accept
- Typical values in social sciences are 0.1, 0.05, or 0.01

In [15]:
```
df = pd.read_csv('grades.csv')
```

In [16]:
```
df.head(2)
```

Out[16]:

	student_id	assignment1_grade	assignment1_submission	assignment2_grade	assignment2
0	B73F2C11-70F0-E37D-8B10-1D20AFED50B1	92.733946	2015-11-02 06:55:34.282000000	83.030552	02:22:5
1	98A0FAE0-A19A-13D2-4BB5-CFBFD94031D1	86.790821	2015-11-29 14:57:44.429000000	86.290821	17:41:1

In [17]:
```
len(df)
```

Out[17]: 2315

In [18]:
```
early = df[df['assignment1_submission'] <= '2015-12-31']
late = df[df['assignment1_submission'] > '2015-12-31']
```

In [19]:
```
early.head(2)
```

Out[19]:

	student_id	assignment1_grade	assignment1_submission	assignment2_grade	assignment2
0	B73F2C11-70F0-E37D-8B10-1D20AFED50B1	92.733946	2015-11-02 06:55:34.282000000	83.030552	02:22:5
1	98A0FAE0-A19A-13D2-4BB5-CFBFD94031D1	86.790821	2015-11-29 14:57:44.429000000	86.290821	17:41:1

```
In [20]: early.mean()
```

```
Out[20]: assignment1_grade    74.972741
         assignment2_grade    67.252190
         assignment3_grade    61.129050
         assignment4_grade    54.157620
         assignment5_grade    48.634643
         assignment6_grade    43.838980
         dtype: float64
```

```
In [21]: late.mean()
```

```
Out[21]: assignment1_grade    74.017429
         assignment2_grade    66.370822
         assignment3_grade    60.023244
         assignment4_grade    54.058138
         assignment5_grade    48.599402
         assignment6_grade    43.844384
         dtype: float64
```

SciPy 库里包含了不同的统计测试，构成了 Python 中假设检定的基础。

- ttest 是比较两种不同种群的平均值的一种方法。ttest 返回结果是 t-statistic (测试统计量) 和 p 值 (p-value) 的 tuple。

```
In [22]: from scipy import stats
         stats.ttest_ind?
```

```
In [23]: stats.ttest_ind(early['assignment1_grade'], late['assignment1_grade'])
```

```
Out[23]: Ttest_indResult(statistic=1.400549944897566, pvalue=0.16148283016060577)
```

```
In [24]: stats.ttest_ind(early['assignment2_grade'], late['assignment2_grade'])
```

```
Out[24]: Ttest_indResult(statistic=1.3239868220912567, pvalue=0.18563824610067967)
```

```
In [25]: stats.ttest_ind(early['assignment3_grade'], late['assignment3_grade'])
```

```
Out[25]: Ttest_indResult(statistic=1.7116160037010733, pvalue=0.08710151634155668)
```

上述 p-value 都大于 5 %,所以不能抛弃 Null hypothesis 假设。

P-hacking:

导致虚假的相关性，而非普遍性的结果。

- Doing many tests until you find one which is of statistical significance
- At a confidence level of 0.05, we expect to find one positive result 1 time out of 20 tests
- Remedies:
  - Bonferroni correction: 按照测试次数，紧缩 α 值。如第一次测试 α = 5%, 想运行 3 次测试，第二次 α = 5% * 1/3...
  - Hold-out sets: 多用于 Machine Learning - cross fold validation
  - Investigation pre-registration: 概述期望找到的内容及为什么，并描述测试，它将提供一个积极的证明。如将过程结果发给第三方。