Introduction to Programming and Data Structures

Python – Randomization

Malay Bhattacharyya

Associate Professor

MIU, CAIML, TIH
Indian Statistical Institute, Kolkata

August, 2023

Shuffling of data

```
import random
ls = [10, 20, 30, 40, 50]
random.shuffle(ls)
print(ls)
```

Output: [40, 20, 10, 50, 30]

Randomization of data

```
import random
random.randint(1, 100) # The interval is [1, 100]
```

Output: 15

```
import random
random.random() # The interval is [0.0, 1.0)
```

Output: 0.4289859005273219

Random sampling with numpy

```
import numpy as np
np.random.randint(1, 100) # From uniform distribution
```

Output: 97

The interval is [1, 100)

Random sampling with numpy

```
import numpy as np
np.random.randint(1, 100) # From uniform distribution
```

Output: 97 The interval is [1, 100)

```
import numpy as np
np.random.random(5) # From uniform distribution
```

Output: array([0.37076725, 0.10547203, 0.21298417, 0.96296838, 0.15390583]) The interval is [0.0, 1.0)

Random sampling with numpy

```
import numpy as np
np.random.randint(1, 100) # From uniform distribution
```

Output: 97 The interval is [1, 100)

```
import numpy as np
np.random.random(5) # From uniform distribution
```

Output: array([0.37076725, 0.10547203, 0.21298417, 0.96296838, 0.15390583]) The interval is [0.0, 1.0)

Note: Unlike the random() function in random module, the one in the random submodule of numpy module optionally takes size of the array.

Random sampling with numpy

```
import numpy as np
np.random.randn(5) # From normal distribution
```

Output: array([1.62029576, 0.29112406, 1.21198839, 0.26851418, -0.46712281])

```
import numpy as np
np.random.randn(3, 3) # From normal distribution
```

Output: array([[1.13217437, 0.56093212, -2.36792091], [1.42652606, 0.68953983, 0.521175], [1.36766496, 0.9488446 , -1.10042531]])

Effect of the seed value on random sampling

Code 1:

```
import numpy as np
print(np.random.randint(1, 100))
print(np.random.randint(1, 100))
print(np.random.randint(1, 100))
```

Effect of the seed value on random sampling

Code 1:

```
import numpy as np
print(np.random.randint(1, 100))
print(np.random.randint(1, 100))
print(np.random.randint(1, 100))
```

Code 2:

```
import numpy as np
np.random.seed(20)
print(np.random.randint(1, 100))
print(np.random.randint(1, 100))
print(np.random.randint(1, 100))
```

Effect of the seed value on random sampling

Code 1:

```
import numpy as np
print(np.random.randint(1, 100))
print(np.random.randint(1, 100))
print(np.random.randint(1, 100))
```

Code 2:

```
import numpy as np
np.random.seed(20)
print(np.random.randint(1, 100))
print(np.random.randint(1, 100))
print(np.random.randint(1, 100))
```

Note: Unlike Code 1, Code 2 will generate the same set of random values whenever executed.

Drawing samples from different distributions using `numpy`

beta(a, b[, size])	– Samples from Beta distribution
binomial(n, p[, size])	– Samples from binomial distribution
chisquare(df[, size])	– Samples from chi-square distribution
dirichlet(alpha[, size])	– Samples from Dirichlet distribution
exponential([scale, size])	– Samples from exponential distribution
f(dfnum, dfden[, size])	– Samples from F distribution
gamma(shape[, scale, size])	– Samples from Gamma distribution
geometric(p[, size])	– Samples from geometric distribution
gumbel([loc, scale, size])	– Samples from Gumbel distribution

Table: Functions in `random` submodule of `numpy`

Drawing samples from different distributions using `numpy`

hypergeometric(ngood, nbad, nsample[, size])	– Samples from hypergeometric distribution
laplace([loc, scale, size])	– Samples from Laplace distribution
logistic([loc, scale, size])	– Samples from logistic distribution
lognormal([mean, sigma, size])	– Samples from lognormal distribution
logseries(p[, size])	– Samples from logarithmic series distribution

Table: Functions in `random` submodule of `numpy`

Drawing samples from different distributions using `numpy`

multinomial(n, pvals[, size])	– Samples from multinomial distribution
multivariate_normal(mean, cov[, size, ...)	– Samples from multivariate normal distribution
negative_binomial(n, p[, size])	– Samples from negative binomial distribution
noncentral_chisquare(df, nonc[, size])	– Samples from noncentral chi-square distribution
noncentral_f(dfnum, dfden, nonc[, size])	– Samples from noncentral F distribution
normal([loc, scale, size])	– Samples from normal distribution

Table: Functions in `random` submodule of `numpy`

Drawing samples from different distributions using `numpy`

pareto(a[, size])	– Samples from pareto distribution
poisson([lam, size])	– Samples from Poisson distribution
power(a[, size])	– Samples from power distribution
rayleigh([scale, size])	– Samples from Rayleigh distribution
standard_cauchy([size])	– Samples from standard Cauchy distribution
standard_exponential([size])	– Samples from standard exponetial distribution
standard_gamma(shape[, size])	– Samples from standard Gamma distribution
standard_normal([size])	– Samples from standard normal distribution

Table: Functions in `random` submodule of `numpy`

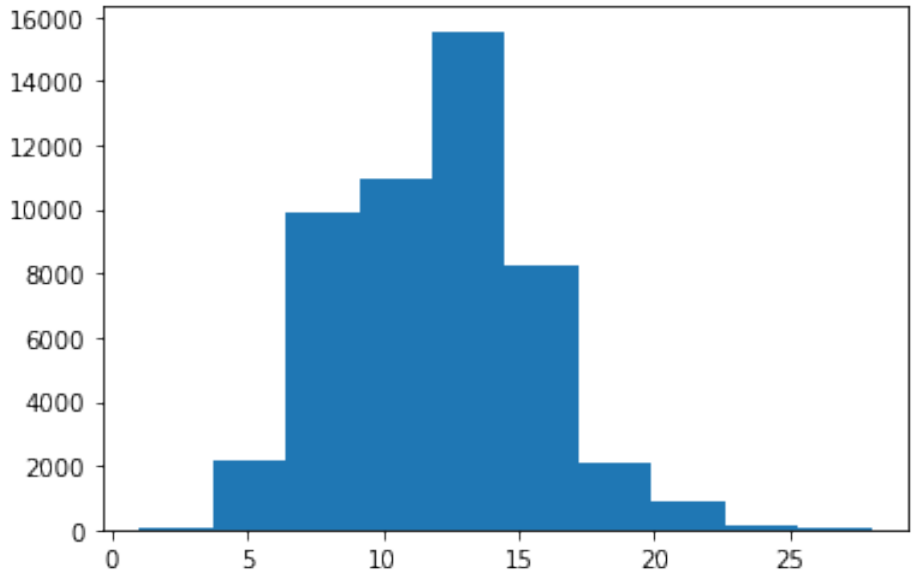
Drawing samples from different distributions using `numpy`

standard_t(df[, size])	– Samples from standard Student's t distribution
triangular(left, mode, right[, size])	– Samples from triangular distribution
uniform([low, high, size])	– Samples from uniform distribution
vonmises(mu, kappa[, size])	– Samples from von Mises distribution
wald(mean, scale[, size])	– Samples from Wald distribution
weibull(a[, size])	– Samples from Weibull distribution
zipf(a[, size])	– Samples from Zipf distribution

Table: Functions in `random` submodule of `numpy`

Visualizing a distribution

```
import numpy as np
sample = np.random.poisson(10, 50000)
import matplotlib.pyplot as plt
plt.hist(sample, 10)
plt.show()
```



Problems

1. Write a program to generate a set of random samples drawn from the following distributions:
   - Symmetric Gaussian distribution with the value of skewness as 0 (zero).
   - Right-skewed Gaussian distribution with the value of skewness as positive and given as user input.
   - Left-skewed Gaussian distribution with the value of skewness as negative and given as user input.

Problems

2. Evaluate the quality of the random number generation function `randint()` on a random binary stream generated with it by applying the following popular randomness tests.
   - **Frequency test:** This is based on Kolmogorov-Smirnov or the chi-square test to verify whether the distribution of the set of numbers generated matches with uniform distribution.
   - **Runs test:** It is basically a chi-square test that examines the runs up and down or the runs above and below the mean by comparing the generated values to the expected values.
   - **Autocorrelation test:** This tests the correlation between numbers and compares the sample correlation to the expected correlation, which is zero.
   - **Gap test:** It counts the number of digits appearing between repetitions of a particular digit and uses Kolmogorov-Smirnov test to compare with the expected size of gaps.
   - **Poker test:** This treats the generated numbers to be grouped together as a poker hand. Then these hands are compared to what is expected using chi-square test.