

Logistic Distribution

Logistic Distribution is used to describe growth using extensively in machine learning in logistic regression neural networks etc.

It has three parameters:

loc — ~~mean~~ mean, where the peak is. Default 0

Scale — Standard deviation, the flatness of distribution
Default 1

Size — The shape of the returned array.

eg: Draw 2x3 samples from a logistic distribution mean at 1 and stdev 2.0.

```
from numpy import random
```

```
x = random.logistic(loc=1, scale=2, size=(2, 3))
```

```
print(x)
```

Output

```
[[ 10.93492709 -0.7545  1.970300]
 [ 3.8267      6.9883  3.2587]]
```

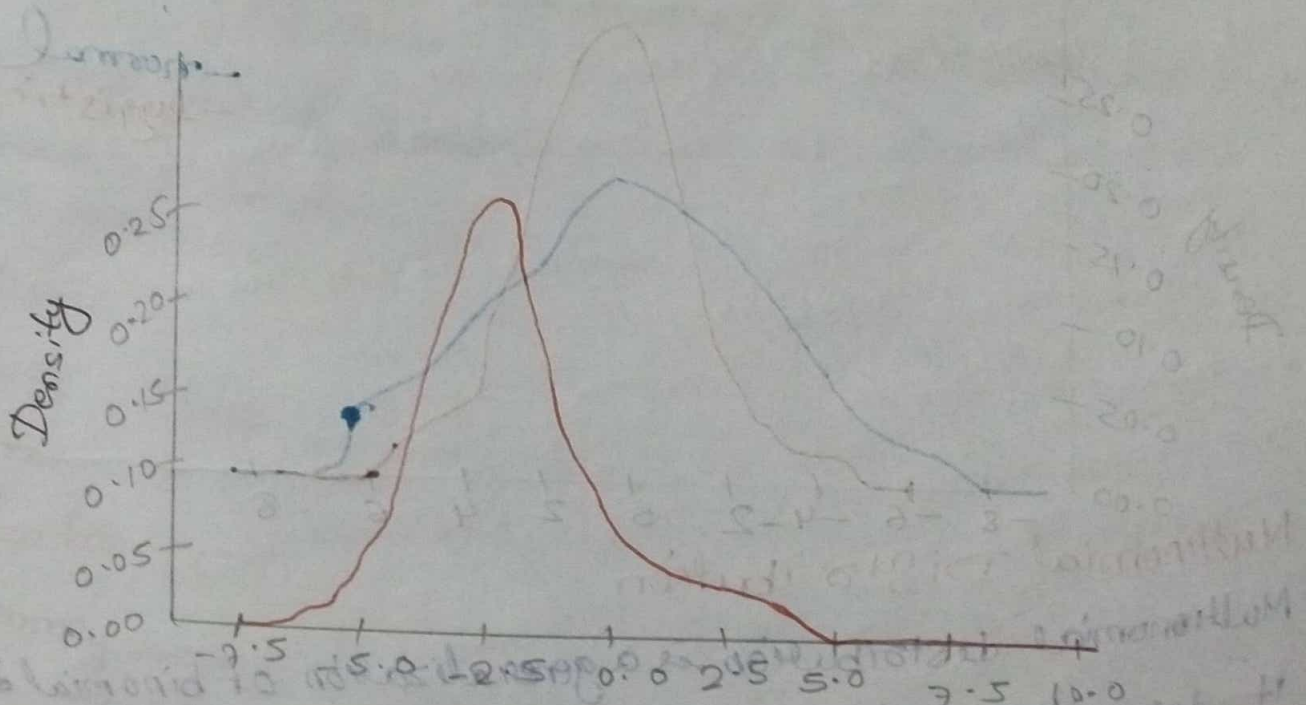
Visualization of Logistic Distribution

```
from numpy import random
```

```
import matplotlib.pyplot as plt
```

```
import seaborn as sns
```

```
sns.set(fontsize=16)
plt = sns.plt
plt.show()
```



Difference between Logistic and Normal Distribution

Both distributions are near identical but logistic, but logistic distribution has more area under the tails i.e. it represents more possibility of occurrence of an event further away from mean

For higher value of scale (standard deviation) the normal and logistic distribution are near identical apart from the peak

eg:

```
from numpy import random
```

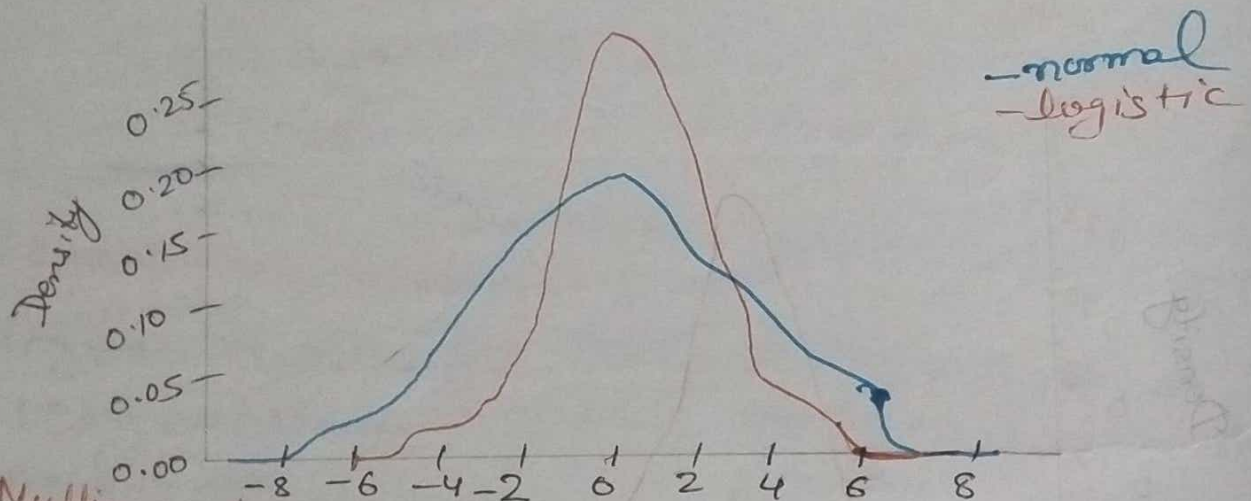
```
import matplotlib.pyplot as plt
```

```
import seaborn as sns
```

```
sns.distplot (random.normal (scale=2, size=1000) hist=False,  
label='normal')
```

```
sns.distplot (random.logistic (size=1000), hist=False,  
label='logistic')
```

```
plt.show()
```



Multinomial Distribution

Multinomial distribution is a generalization of binomial distribution. It describes outcomes of multi-nomial scenarios unlike binomial where scenarios must be only one of two e.g. Blood type of a population dice roll outcome. It has three parameters.

n = number of possible outcomes (e.g. 6 for dice roll).

pvals = list of probabilities of outcomes (e.g. $(1/6, 1/6, 1/6, 1/6, 1/6)$ for dice roll)

Size - The shape of the returned array.

- Multinomial samples will NOT produce a single value! They will produce one value for each pval.

Ans - As they are generalization of binomial distribution their visual representation similarity of normal distribution is same as that of multiple binomial distributions.

Exponential Distribution

Exponential distribution is used for describing time till next event eg. failure/success etc.

It has two parameters;

Scale - inverse of rate (seen lam in poisson distribution)
defaults to 1.0

Size - The shape of the returned array.

eg: Draw out a sample for exponential distribution with 2.0
Scale with 2x3 Size:

from numpy import random

x = random.exponential(scale=2, size=(2, 3))
print print(x)

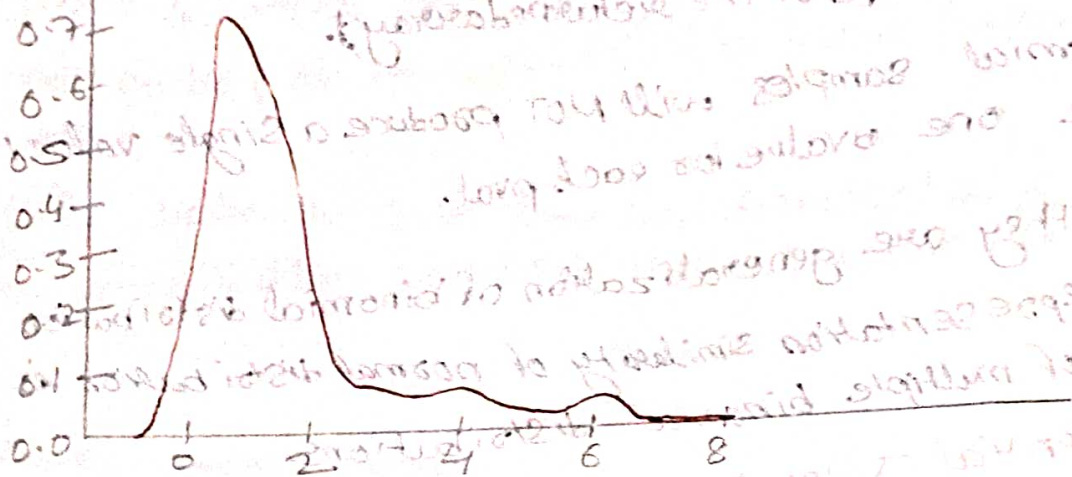
Output

```
[ [ 3.2193 0.3662 1.057714 ]  
  [ 0.11261 0.20269 0.69513 ] ]
```

Visualization of Exponential Distribution

from numpy import random
import matplotlib.pyplot as plt
import seaborn as sns

sns.distplot(random.exponential(size=1000), hist=False)
plt.show()



Relation B/W Poisson and Exponential Distribution

Poisson distribution deals with number of occurrences of an event in a time whereas exponential distribution deals with the time between these events.

Chi Square Distribution

Chi Square distribution is used as a basis to verify the hypothesis.

It has two parameters:

df - (degree of freedom)

Size - The shape of the returned array.

Draw out a sample for chi square distribution with degree of freedom 2 with size 2x3 from numpy import random

$x = \text{random.chisquare}(df=2, \text{Size}=(2,3))$

print(x)

Visualization of Chi Square Distribution

from numpy import random

import matplotlib.pyplot as plt

import seaborn as sns

sns.distplot

hist = false

plt.show()

(random.chisquare(df=1, Size=1000).

