

Lesson 14 Summary: Distributions

Data Science with Python – Key Concepts

Data Science Program

Probability Distributions



Key Concepts:

PDF | CDF | Quantiles | Q-Q plots | Goodness of fit

Financial returns have fat tails - not normal!

Understanding distributions is key to statistical analysis

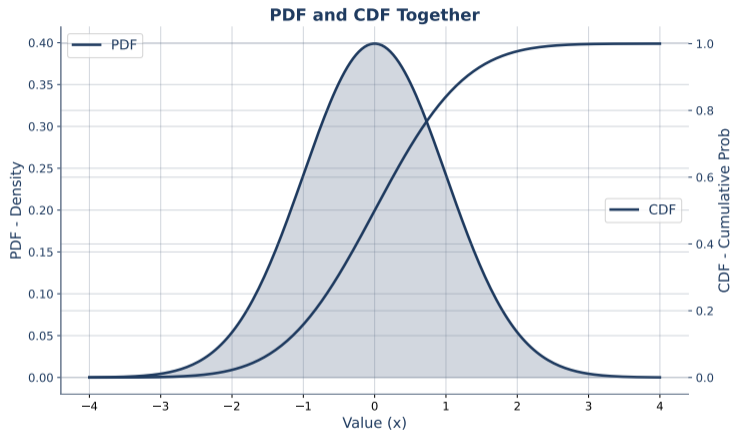
The bell curve – most important distribution:

- Symmetric around mean
- Defined by μ (mean) and σ (std)
- 68-95-99.7 rule for standard deviations

Python:

```
from scipy import stats
stats.norm.pdf(x, loc=mu, scale=sigma)
```

Many natural phenomena follow normal distribution



PDF: probability density; CDF: cumulative probability

Discrete outcomes with fixed probability:

- n trials, each with probability p of success
- Number of successes in n trials
- Example: Coin flips, trading win rates

Python:

```
stats.binom.pmf(k, n=10, p=0.5) # P(X=k)
```

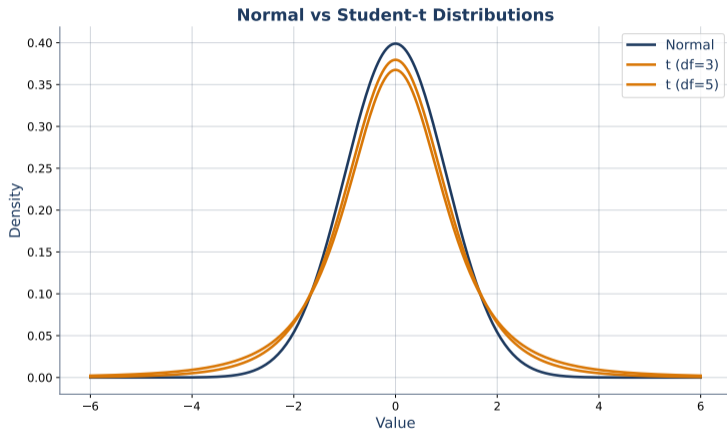
Converges to normal as n increases

Like normal but with heavier tails:

- Used when sample size is small
- Degrees of freedom (df) parameter
- Converges to normal as df increases

Finance: Better model for stock returns than normal

t-distribution captures fat tails in financial data



Financial returns have fatter tails than normal predicts

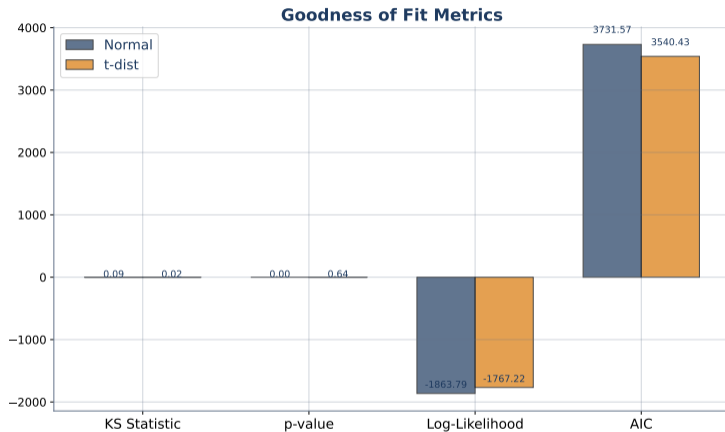
Compare empirical vs theoretical distribution:

- Points on diagonal = good fit
- Deviations at tails = fat tails
- S-curve = skewness

Python:

```
from scipy import stats
stats.probplot(data, dist="norm", plot=plt)
```

Q-Q plots reveal departures from normality



Statistical tests verify distribution assumptions

Essential Distribution Operations:

Distribution	scipy.stats
Normal	<code>stats.norm(loc, scale)</code>
t-distribution	<code>stats.t(df, loc, scale)</code>
Binomial	<code>stats.binom(n, p)</code>
Lognormal	<code>stats.lognorm(s, loc, scale)</code>
Method	
PDF	<code>.pdf(x)</code>
CDF	<code>.cdf(x)</code>
Quantile	<code>.ppf(q)</code>
Random	<code>.rvs(size=n)</code>

scipy.stats provides comprehensive distribution support