

Minor in AI

Hypothesis Testing with Z-Test

1 The Chocolate Factory Dilemma

Real-World Motivation

A renowned chocolate factory markets its bars as "precisely 50g." During routine quality checks, you randomly select 10 bars and find an average weight of 52g with a standard deviation of 2g. **Is this 2g difference meaningful**, or could it occur by random chance in a properly calibrated production line?

Why This Matters:

- **Cost Implications:** Halting production for adjustments costs \$20,000/hour
- **Regulatory Compliance:** Products must stay within $\pm 3\text{g}$ of claimed weight
- **Brand Trust:** Consistent weight maintains customer loyalty

Hypothesis Testing Approach:

1. **Define Thresholds:** Establish a 95% confidence level (5% error tolerance)
2. **Quantify Uncertainty:** Calculate how much variation is expected from random sampling
3. **Statistical Proof:** Determine if 52g is statistically different from 50g using the Z-test

Key Insight: A 2g difference in a small sample ($n=10$) carries more uncertainty than in larger samples. The Z-test helps distinguish *meaningful discrepancies* from *random fluctuations* using probability theory.

2 ABC of Z-Testing

2.1 Statistical Hypotheses

Every test begins with two mutually exclusive claims:

- **Null Hypothesis (H_0):** Assumes no effect/difference
(Factory claim: $\mu = 50\text{g}$)
- **Alternative Hypothesis (H_1):** Challenges the status quo
(Actual mean $\neq 50\text{g}$)

The Z-test mathematically compares these using sample data. A key requirement is either:

- Large sample size ($n \geq 30$), or
- Known population standard deviation

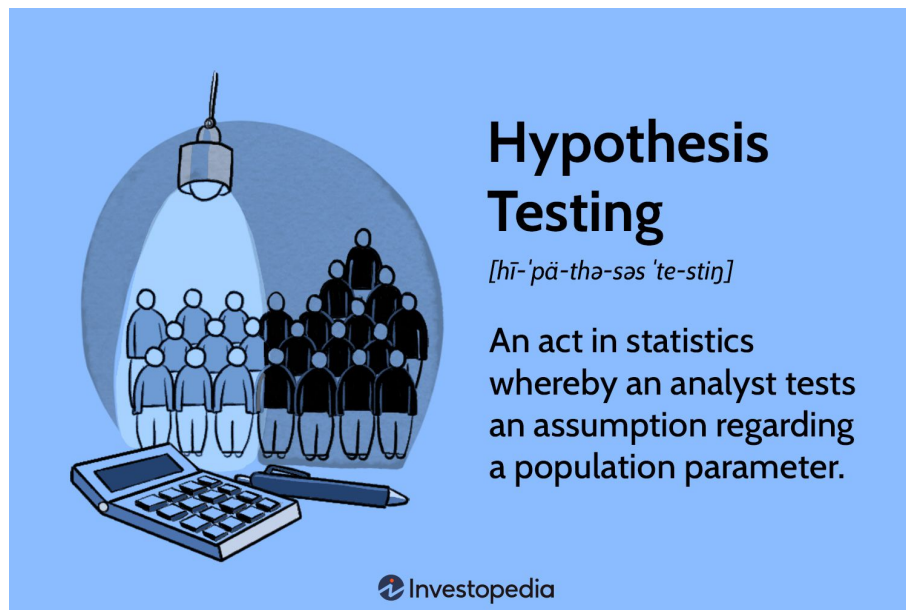


Figure 1: Source: Investopedia, *Hypothesis testing*.

2.2 The Z-Score Formula

Central Equation

$$Z = \frac{\bar{X} - \mu}{\sigma / \sqrt{n}}$$

Where:

- \bar{X} : Observed sample mean (52g)
- μ : Hypothesized population mean (50g)
- σ : Standard deviation (2g)
- n : Number of observations (10)

This Z-score represents how many standard errors the sample mean deviates from the claimed mean. Larger absolute values indicate stronger evidence against H_0 .

2.3 Decision Framework

Hypothesis testing follows a structured workflow:

1. **Define Significance Level (α):** Typically 5% (0.05)
2. **Calculate Critical Value:** $Z = \pm 1.96$ for 95% confidence
3. **Compute Test Statistic:** Z-score from sample data
4. **Compare and Conclude:**
 - Reject H_0 if $|Z| > \text{Critical Value}$
 - Fail to reject H_0 otherwise

3 Getting Hands-In

3.1 Visualizing Critical Regions

The following Python code visualizes critical regions in a normal distribution using the SciPy and Matplotlib libraries. It plots the sampling distribution and highlights the rejection zones based on a 95% confidence level.

Listing 1: Distribution Plotting in Python

```
1 import numpy as np
2 import matplotlib.pyplot as plt
3 from scipy.stats import norm
4
5 # Parameters
6 population_mean = 50
7 sample_std = 2
8 sample_size = 10
9
10 # Calculations
11 standard_error = sample_std / np.sqrt(sample_size)
12 critical_z = 1.96 # 95% confidence level
13 lower_bound = population_mean - critical_z * standard_error
14 upper_bound = population_mean + critical_z * standard_error
15
16 # Visualization
17 x = np.linspace(46, 54, 500)
18 y = norm.pdf(x, population_mean, standard_error)
19 plt.figure(figsize=(10,4))
20 plt.plot(x, y, label='Sampling Distribution')
21 plt.axvline(lower_bound, color='red', linestyle='--',
22             label='Rejection Boundary')
23 plt.axvline(upper_bound, color='red', linestyle='--')
24 plt.fill_between(x, y, where=(x < lower_bound)|(x > upper_bound),
25                 color='orange', alpha=0.3, label='Rejection Zone')
26 plt.legend()
27 plt.title('Normal Distribution with 95% Confidence Interval')
28 plt.xlabel('Sample Mean (grams)')
29 plt.ylabel('Probability Density')
30 plt.show()
```

3.1.1 Code Explanation

This code snippet visualizes a normal distribution along with critical regions by computing confidence intervals and plotting them. Below is a breakdown of each section:

- **Importing Libraries:** The necessary libraries such as NumPy, Matplotlib, and SciPy are imported for numerical computation and visualization.
- **Defining Parameters:**
 - $\mu = 50$ (Population Mean)
 - $\sigma = 2$ (Sample Standard Deviation)
 - $n = 10$ (Sample Size)

- **Computing Standard Error:**

$$SE = \frac{\sigma}{\sqrt{n}}$$

This gives an estimate of the variability of the sample mean.

- **Determining Critical Values:** Using the standard normal table, the critical z-score for a 95% confidence level is 1.96. The lower and upper rejection boundaries are calculated as:

$$\text{Lower Bound} = \mu - Z_{critical} \times SE$$

$$\text{Upper Bound} = \mu + Z_{critical} \times SE$$

- **Plotting the Distribution:**

- The probability density function (PDF) of the normal distribution is plotted.
- Vertical dashed red lines indicate the rejection boundaries.
- The rejection regions (where the sample mean is unlikely to fall) are shaded in orange.

- **Displaying the Plot:** The final plot provides a visual representation of the sampling distribution and critical regions, helping in hypothesis testing.

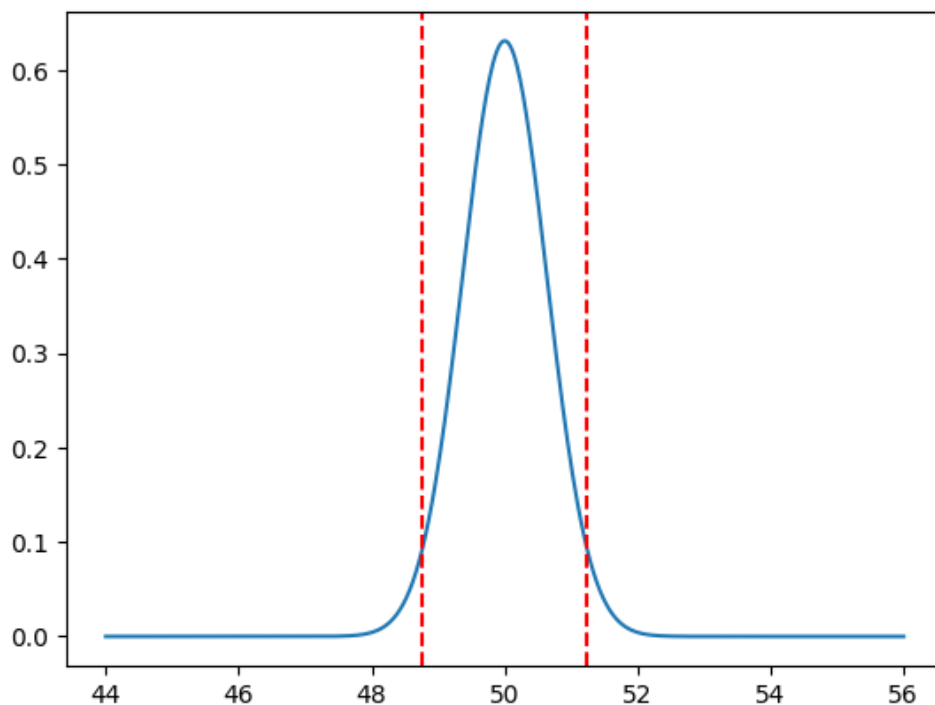


Figure 2: Source: Investopedia, Visual guide to decision boundaries: Sample means beyond red lines (51.24g/48.76g) would reject H_0

3.2 Automated Hypothesis Testing

The following Python code performs a Z-test for hypothesis testing. It calculates the Z-score and compares it with a critical value to determine whether to reject the null hypothesis (H_0).

Listing 2: Python Z-Test Code

```
1 from scipy.stats import norm
2
3 def z_test(pop_mean, sample_mean, sample_std, n, alpha=0.05):
4     # Standard error calculation
5     se = sample_std / (n ** 0.5)
6
7     # Z-score computation
8     z = (sample_mean - pop_mean) / se
9
10    # Critical value (two-tailed)
11    critical_z = norm.ppf(1 - alpha/2)
12
13    # Decision logic
14    if abs(z) > critical_z:
15        print(f"Reject H0 (Z = {z:.2f}, Critical Z = +/-{critical_z:.2f}
16              )")
17    else:
18        print(f"Fail to reject H0 (Z = {z:.2f})")
19
20    return z
21
22 # Chocolate factory test
23 z_test(pop_mean=50, sample_mean=52, sample_std=2, n=10)
```

3.2.1 Code Explanation

This function automates hypothesis testing using the Z-test, a statistical test to determine if a sample mean significantly differs from a population mean.

- **Importing SciPy's Norm:** The function uses `norm.ppf()` from SciPy to compute the critical Z-value.
- **Function Parameters:**
 - `pop_mean`: Population mean (μ)
 - `sample_mean`: Sample mean (\bar{x})
 - `sample_std`: Sample standard deviation (s)
 - `n`: Sample size
 - `alpha`: Significance level (default = 0.05 for a 95% confidence level)
- **Standard Error Calculation:**

$$SE = \frac{s}{\sqrt{n}}$$

The standard error measures the variability of the sample mean.

- **Z-Score Calculation:**

$$Z = \frac{\bar{x} - \mu}{SE}$$

The Z-score measures how many standard errors the sample mean is away from the population mean.

- **Critical Value Calculation:** The critical value for a two-tailed test at 95% confidence is obtained using:

$$Z_{\alpha/2} = \text{norm.ppf}(1 - \alpha/2)$$

This represents the threshold beyond which the null hypothesis is rejected.

- **Decision Rule:**

- If $|Z| > Z_{\alpha/2}$, reject H_0 (significant difference).
- Otherwise, fail to reject H_0 (no significant difference).

- **Example Application:** The function is tested with a chocolate factory scenario where:

- $\mu = 50$ (Expected weight of a chocolate bar)
- $\bar{x} = 52$ (Observed sample mean)
- $s = 2$ (Sample standard deviation)
- $n = 10$ (Sample size)

The function determines if the observed sample mean significantly differs from the expected weight.

4 Real-World Applications

Case Studies

1. Pharmaceutical Quality Control

A drug manufacturer claims tablets contain 100mg active ingredient. 50 tablets average 98mg (SD=5mg).

Z-test reveals $Z = -2.83$ ($p=0.0047$) - reject H_0 , indicating underdosing.

2. E-Commerce A/B Testing

Website A: 12% conversion rate (10,000 visitors)

Website B: 13% conversion rate (10,000 visitors)

$Z = 5.0$ ($p < 0.0001$) - statistically significant improvement.

3. Clinical Research

New treatment reduces recovery time from 14 to 13 days (SD=2 days, $n=100$).

$Z = -5.0$ shows strong evidence for treatment efficacy.

5 Key Insights

Essential Takeaways

- **Confidence vs Significance:** 95% confidence level corresponds to 5% significance ($\alpha = 0.05$).
- **Sample Size Sensitivity:** Larger samples increase test power but require smaller differences to reject H_0 .
- **Error Types:**
 - Type I: False positive (rejecting true H_0)
 - Type II: False negative (failing to reject false H_0)
- **Assumptions:** Normally distributed data or large sample (Central Limit Theorem).

References

- **Figure 1 Source:** Investopedia¹
- **Figure 2 Source:** Investopedia²
- **Z-Test Implementation:** Colab Notebook Link

¹Retrieved from <https://www.investopedia.com/terms/h/hypothesistesting.asp>.

²Retrieved from <https://www.investopedia.com/terms/h/hypothesistesting.asp>.