CS425A: Computer Networks
Assignment 1

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1 Path Loss Exponent

In this experiment, I utilized a WiFi Analyzer app to analyze path loss in an unknown environment. The app identified my WiFi AP and recorded RSSI values. Measurements were taken at different distances, with the smartphone in four orientations: vertical, horizontal, slanted, and diagonal. This approach was aimed at capturing realistic usage scenarios. For each position, I collected 5 RSSI samples, documenting signal strength variation across orientations. All the readings are written in dBm.

Distance (m)	Observation 1	Observation 2	Observation 3	Observation 4	Average RSSI
1	-43	-38	-40	-41	-40.5
3	-49	-46	-45	-47	-46.75
6	-56	-57	-55	-56	-56
11	-61	-61	-62	-60	-61
17	-65	-63	-64	-65	-64.25

Table 1: WiFi Analyzer App Readings

To find the best fit line for this data, I used the following python code to plot the best line along with my observations.

```python
import numpy as np
import matplotlib.pyplot as plt

# Define data
distances = np.array([1, 3, 6, 11, 17])

#x as log of the distance
x = np.log10(distances)
# y is negative of RSSI
y = np.array([-40.5, -46.75, -56, -61, -64.25])

# Find line of best fit
m, c = np.polyfit(x, y, 1)

fig, ax = plt.subplots()

ax.scatter(x, y, color='green', marker = 'x', label='Obsrvations')
ax.plot(x, m*x+c, color='red', label='Line of Best Fit')

ax.set_xlabel('log (d)')
ax.set_ylabel('$P_{r}(d)$')

ax.legend()
ax.grid(False)
plt.show()
```

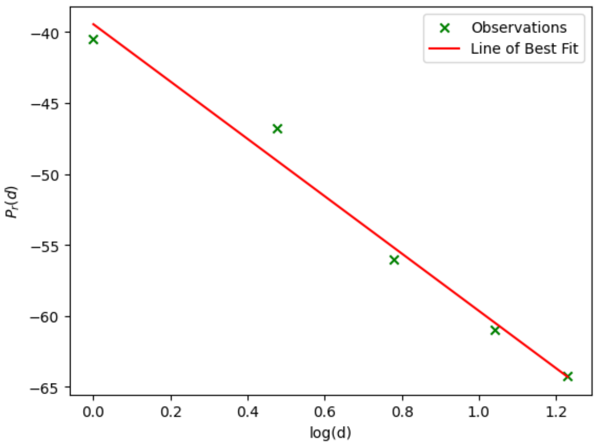

Figure 1: Plotting RSSI Observations and line of best fit

The variable `m` in the code represents the slope of the line of best fit. Once the slope is found, we calculate the path loss exponent (PLE) using the formula:

$$\text{PLE} = \left|\frac{\text{slope}}{10}\right|$$

Given that the slope is **-20.197** in this context, the path loss exponent is thus calculated as $y = \left|\frac{-20.197}{10}\right|$, where **y** represents the PLE. The absolute value is taken to ensure a positive exponent, consistent with the convention that path loss increases with distance. Thus, the path loss exponent for the given data is **2.02**.

For finding the variance, σ^2, with respect to the line of best fit firstly, the mean, μ, is calculated using the formula:

$$\mu = \frac{1}{k}\sum_{i=1}^{k}(y_i - mx_i - c)$$

where y_i is the observed value, $mx_i + c$ is the predicted value from the line of best fit (with m being the slope and c the intercept), and k is the number of observations.

After computing the mean, the variance is found using the formula:

$$\sigma^2 = \frac{1}{k}\sum_{i=1}^{k}(y_i - mx_i - c - \mu)^2$$

In this analysis, the variance calculated using this method was approximately **1.51**.

2 Range Estimation

Further readings were taken at different distances:

Actual Distance (m)	Average Reading (dBm)	Calculated Distance (m)	Error
2	-45.5	1.99	0.01
12	-62	13.07	1.07
14	-63.25	15.08	1.08
34	-71.75	39.74	5.74
62	-76	64.51	2.51

Table 2: Distance error estimation

Distances were estimated using the path loss exponent with the formula:

$$P_r(d)[\text{dBm}] = P_r(d_0)[\text{dBm}] - 10n\log_{10}\left(\frac{d}{d_0}\right)$$

where $P_r(d_0)$ is the received power at 1 m, n is the path loss exponent, and d is the estimated distance. And then the distance error was calculated by comparing the calculated and actual distances for five different distances to assess the estimation accuracy.

The initial reference power, $P_r(d_0)$, is **-39.45** dBm which we found from the best fit line. Using the new readings, the average error from these measurements is 2.08 m.