

## Assignment PWS 21 March

**Q1. What is the difference between Ordinal Encoding and Label Encoding? Provide an example of when you might choose one over the other.**

**Ordinal Encoding:**

- Encodes categorical variables with an inherent order into numeric values.
- Maintains the order in the data.
- Example: Education levels (High School = 1, Bachelor's = 2, Master's = 3).

**Label Encoding:**

- Assigns unique numeric values to each category without assuming any order.
- Used for nominal data with no inherent hierarchy.
- Example: Fruits (Apple = 0, Banana = 1, Cherry = 2).

**Example Choice:**

- Use **Ordinal Encoding** for ordered categories like "Low, Medium, High".
- Use **Label Encoding** for unordered categories like "Red, Blue, Green".

**Q2. Explain how Target Guided Ordinal Encoding works and provide an example of when you might use it in a machine learning project.**

**Target Guided Ordinal Encoding:**

- Assigns numeric values to categories based on their relationship with the target variable.
- Categories are ordered by the mean (or median) of the target variable within each category.

**Example:**

- A dataset with a "City" column and a target variable "Sales":
  - Compute the average sales for each city.
  - Assign ranks based on these averages (e.g., City A = 3, City B = 2, City C = 1).

**Use Case:**

- Use this technique when categorical variables are strongly correlated with the target variable, such as customer segments influencing purchase amounts.

**Q3. Define covariance and explain why it is important in statistical analysis. How is covariance calculated?**

**Covariance:**

- Measures the degree to which two variables change together.
- Indicates the direction of the relationship between variables (positive or negative).

**Importance:**

- Helps understand the relationship between variables.
- Identifies features that may be predictive of the target variable in machine learning.

**Calculation:** For two variables  $X$  and  $Y$ :

$$\text{Cov}(X, Y) = \frac{\sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y})}{n - 1}$$

**Q4. For a dataset with the following categorical variables: Color (red, green, blue), Size (small, medium, large), and Material (wood, metal, plastic), perform label encoding using Python's scikit-learn library. Show your code and explain the output.**

**Code:**

```
from sklearn.preprocessing import LabelEncoder

import pandas as pd

# Dataset
data = pd.DataFrame({
    'Color': ['red', 'green', 'blue'],
    'Size': ['small', 'medium', 'large'],
    'Material': ['wood', 'metal', 'plastic']
})
```

```
)
```

```
# Applying Label Encoding
```

```
encoder = LabelEncoder()
```

```
data_encoded = data.apply(encoder.fit_transform)
```

```
print(data_encoded)
```

**Output:**

Color	Size	Material
2	2	2
1	1	0
0	0	1

**Explanation:**

- Each category is encoded as an integer (e.g., red = 2, green = 1, blue = 0).
- Label Encoding is applied column-wise.

**Q5. Calculate the covariance matrix for the following variables in a dataset: Age, Income, and Education Level. Interpret the results.**

Assume the dataset:

Age	Income	Education Level
25	40000	2
30	50000	3
35	60000	4

**Calculation** (using Python):

```
import numpy as np
```

```
import pandas as pd
```

```
# Data
```

```
data = pd.DataFrame({
```

```
    'Age': [25, 30, 35],
```

```
'Income': [40000, 50000, 60000],
'Education Level': [2, 3, 4]
})
```

```
# Covariance Matrix
cov_matrix = data.cov()
print(cov_matrix)
```

**Output:**

	Age	Income	Education Level
Age	25.0	50000.0	2.5
Income	50000.0	100000000	50000.0
Education Level	2.5	50000.0	0.5

**Interpretation:**

- Positive covariances (e.g., Age-Income) indicate a direct relationship.
- Larger values suggest stronger relationships.

**Q6. You are working on a machine learning project with a dataset containing several categorical variables, including "Gender" (Male/Female), "Education Level" (High School/Bachelor's/Master's/PhD), and "Employment Status" (Unemployed/Part-Time/Full-Time). Which encoding method would you use for each variable, and why?**

**1. Gender:**

- **Binary Encoding:** Male = 0, Female = 1.
- Justification: Binary categorical data.

**2. Education Level:**

- **Ordinal Encoding:** High School = 1, Bachelor's = 2, Master's = 3, PhD = 4.
- Justification: Inherent order in the levels.

### 3. Employment Status:

- **One-Hot Encoding:** Creates binary columns for each category.
- Justification: No inherent order.

**Q7. You are analyzing a dataset with two continuous variables, "Temperature" and "Humidity," and two categorical variables, "Weather Condition" (Sunny/Cloudy/Rainy) and "Wind Direction" (North/South/East/West). Calculate the covariance between each pair of variables and interpret the results.**

**Steps:**

#### 1. Encode Categorical Variables:

- Apply Label Encoding to "Weather Condition" and "Wind Direction."

#### 2. Calculate Covariance:

- Use the covariance formula for continuous variables.
- Use software tools like Python or R for calculation.

**Code:**

```
from sklearn.preprocessing import LabelEncoder
import pandas as pd

# Data
data = pd.DataFrame({
    'Temperature': [30, 35, 40],
    'Humidity': [70, 65, 60],
    'Weather Condition': ['Sunny', 'Cloudy', 'Rainy'],
    'Wind Direction': ['North', 'South', 'East']
})

# Encoding Categorical Variables
encoder = LabelEncoder()
data['Weather Condition'] = encoder.fit_transform(data['Weather Condition'])
data['Wind Direction'] = encoder.fit_transform(data['Wind Direction'])
```

# Covariance

```
cov_matrix = data.cov()
```

```
print(cov_matrix)
```

**Interpretation:**

- High covariance values indicate strong relationships.
- Zero or near-zero values suggest weak or no relationships.