

1. In the following, I will present a decision matrix designed for comparing universities, tailored to the context of Multi-Attribute Decision Making (MADM). This decision matrix will aid in evaluating the relative merits of several universities by using various attributes that are crucial for decision-making.

**Note.**

Let  $a_1$  represent the **Tuition Fees (USD)**,  
Let  $a_2$  represent the **World Ranking**,  
Let  $a_3$  represent the **Average Graduate Salary (USD)**,  
Let  $a_4$  represent the **Campus Crime Rate (per 100,000)**.

**Note.**

Let  $o_1$  represent **Harvard**,  
Let  $o_2$  represent **Stanford**,  
Let  $o_3$  represent **MIT**,  
Let  $o_4$  represent **UC Berkeley**.

The **Decision Matrix** is as follows:

$$D_{4 \times 4} = \begin{array}{c|ccccc} & \text{Uni} & a_1^- & a_2^- & a_3^+ & a_4^- \\ \hline o_1 & & 56,000 & 3 & 120,000 & 290 \\ o_2 & & 57,000 & 2 & 130,000 & 250 \\ o_3 & & 55,000 & 1 & 125,000 & 310 \\ o_4 & & 43,000 & 15 & 110,000 & 350 \end{array}$$

In this document, the original decision matrix is denoted by  $D_{4 \times 4}$ . After applying the normalization methods, the resulting normalized matrix is denoted by  $N_{4 \times 4}$ , which will allow for easier comparison across the attributes.

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## 1. NORMALIZATION METHODS

In this section, we perform normalization on the original decision matrix  $D_{4 \times 4}$  to create a normalized matrix  $N_{4 \times 4}$ . Each normalization method is detailed below, and the final normalized matrix for each method is presented.

1.1. **Linear Normalization.** The formula for Linear Normalization is:

$$n_{ij} = \frac{r_{ij}}{\sum_{i=1}^m r_{ij}}, \quad j = 1, \dots, n, \quad i = 1, \dots, m$$

After applying the formula, we obtain the following normalized matrix  $N$ :

Uni	$a_1^-$	$a_2^-$	$a_3^+$	$a_4^-$
$o_1$	0.265	0.143	0.247	0.242
$o_2$	0.270	0.095	0.268	0.208
$o_3$	0.261	0.048	0.258	0.258
$o_4$	0.204	0.714	0.227	0.292

Here is corresponding python code for the discussed:

LISTING 1. Code for Linear Normalization

```
# Python code for Linear Normalization Method
def linear_normalization(dm: pd.DataFrame):
    n = dm.copy().astype(float)
    for col_name in n.columns:
        n[col_name] /= n[col_name].sum()
    return n.round(3)
```

1.2. **Euclidean Normalization.** The formula for Euclidean Normalization is:

$$n_{ij} = \frac{r_{ij}}{\sqrt{\sum_{i=1}^m r_{ij}^2}}$$

After applying the formula, we obtain the following normalized matrix  $N$ :

Uni	$a_1^-$	$a_2^-$	$a_3^+$	$a_4^-$
$o_1$	0.528	0.194	0.494	0.480
$o_2$	0.537	0.129	0.535	0.414
$o_3$	0.518	0.065	0.515	0.513
$o_4$	0.405	0.970	0.453	0.579

Here is corresponding python code for the discussed:

LISTING 2. Code for Euclidean Normalization

```
# Python code for Euclidean Normalization Method
def euclidean_normalization(dm: pd.DataFrame):
```

```

n = dm.copy().astype(float)
for col_name in n.columns:
    col_sum = (n[col_name] ** 2).sum()
    n[col_name] /= math.sqrt(col_sum)
return n.round(3)

```

**1.3. Max-Min Normalization.** This method depends on whether the attribute is beneficial ( $a_j^+$ ) or non-beneficial ( $a_j^-$ ):

$$\text{If } a_j^+ : n_{ij} = \frac{r_{ij}}{r_j^{\max}}, \quad \text{and if } a_j^- : n_{ij} = \frac{r_j^{\min}}{r_{ij}}$$

After applying the formula, we obtain the following normalized matrix  $N$ :

Uni	$a_1^+$	$a_2^+$	$a_3^+$	$a_4^+$
$o_1$	0.982	0.333	0.923	0.862
$o_2$	1.000	0.500	1.000	1.000
$o_3$	0.965	1.000	0.962	0.806
$o_4$	0.754	0.067	0.846	0.714

As you see, after applying this normalization method (which is the only one of the three), both  $a_j^+$  and  $a_j^-$  are transformed into  $a_j^+$ .

Here is corresponding python code for the discussed:

LISTING 3. Code for Max Min Normalization

```

# Python code for Max Min Normalization Method
def max_min_normalization(dm: pd.DataFrame):
    n = dm.copy().astype(float)
    for col_name in n.columns:
        # criteria_types is defined before
        # accessing the criteria types df in order to find the type
        criteria_type = criteria_types.iloc[0, n.columns.get_loc(col_name)]
        if criteria_type == "-":
            n[col_name] = n[col_name].min() / n[col_name]
        # +
        else:
            n[col_name] /= n[col_name].max()
    return n.round(3)

```

***Note.***

Each method produces a unique normalized matrix  $N$ , providing a standardized basis for decision-making.