

# **Multiple Criteria Decision Making (MCDM) using TOPSIS**

**By**

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# Case Study I

**M3 model is best**

Model	Corr	R <sup>2</sup>	RMSE	Accuracy
M1	0.79	0.62	1.57	60.89
M2	0.66	0.44	2.89	63.07
M3	<b>0.82</b>	<b>0.67</b>	<b>1.25</b>	<b>80.39</b>
M4	0.56	0.31	2.68	70.19
M5	0.75	0.56	1.3	62.87

# Case Study II

Which model is best?

Model	Corr	Rseq	RMSE	Accuracy
M1	0.79	0.62	1.25	60.89
M2	0.66	0.44	2.89	63.07
M3	0.56	0.31	1.57	62.87
M4	0.82	0.67	2.68	70.19
M5	0.75	0.56	1.3	80.39

# Poor Approach

**We cannot add or average  
all the parameters.**

## **Example:**

**Selection of a cricket player.**

- **Batsman**
- **Bowler**
- **All rounder (Hardik Pandya)**

This is known as **multiple-criteria decision making** problem.

**Solution is TOPSIS**

(Technique for Order of Preference by Similarity to Ideal Solution)



# Case Study II

## Output

Model	Corr	Rseq	RMSE	Accuracy
M1	0.79	0.62	1.25	60.89
M2	0.66	0.44	2.89	63.07
M3	0.56	0.31	1.57	62.87
M4	0.82	0.67	2.68	70.19
M5	0.75	0.56	1.3	80.39

Topsis Score	Rank
0.55	5
0.87	1
0.6	4
0.79	2
0.66	3

# Implementation in R

```
#install.packages("topsis")
```

```
library(topsis)
```

```
mydata=read.csv('data.csv')
```

```
d <- as.matrix(mydata[,-1])    // Drop 1st column
```

```
w <- c(1, 1, 1, 1)           // Weights
```

```
i <- c("+", "+", "-", "+")    // Impacts
```

```
topsis(d, w, i)
```



# Applications

## Selection of Mobile Phone

Attribute Or Criteria →	Price or Cost	Storage Space	Camera	Looks
Mobile 1	250 \$	16 GB	12 MP	Excellent
Mobile 2	200 \$	16 GB	8 MP	Average
Mobile 3	300 \$	32 GB	16MP	Good
Mobile 4	275 \$	32 GB	8MP	Good
Mobile 5	225 \$	16 GB	16 MP	Below Average

# Other Applications

- **Selection of Car**
- **Selection of Home**
- **Selection of Life Partner**
- **..... and many more**

# Project Idea 1

**Develop an APP for selection of singers for Indian Idol.**

Singer ID	Sur	Taal	Laye	Pitch	Pace	Topsis Score	Rank
S1	0.79	0.62	1.25	60.89	11	0.55	5
S2	0.66	0.44	2.89	63.07	20	0.87	1
S3	0.56	0.31	1.57	62.87	16	0.6	4
S4	0.82	0.67	2.68	70.19	16	0.79	2
S5	0.75	0.56	1.3	80.39	20	0.66	3

**Algorithmic approach give same result always**

# Some Points

- 1. Advantage: Algorithmic approach give same result always rather than human judge.**
- 2. Organize a Hackthon with leaderboard.**
- 3. Helpful in data collection**
- 4. Validate the approach with multiple human  
Don't depend 100% on algorithm selection.**
- 5. Reduction in labor intensive job; select top 10% or 20% or 30%.**



# Project Idea 2

- **Selection of models for an Ad**
- **Selection of Photogenic face**

ID	Eyes	Nose	Forehead	Lips	Chin	Topsis Score	Rank
S1	0.79	0.62	1.25	60.89	11	0.55	5
S2	0.66	0.44	2.89	63.07	20	0.87	1
S3	0.56	0.31	1.57	62.87	16	0.6	4
S4	0.82	0.67	2.68	70.19	16	0.79	2
S5	0.75	0.56	1.3	80.39	20	0.66	3

# Self Study

## Mathematics for Topsis

**Learn the Mathematics for Topsis from Youtube.**

**<https://www.youtube.com/watch?v=aRBdrCB1K4k>**



# Mathematics of TOPSIS

**Input:** Given Dataset of mobile phones

Attribute Or Criteria 	Price or Cost	Storage Space	Camera	Looks
Mobile 1	250 \$	16 GB	12 MP	Excellent
Mobile 2	200 \$	16 GB	8 MP	Average
Mobile 3	300 \$	32 GB	16MP	Good
Mobile 4	275 \$	32 GB	8MP	Good
Mobile 5	225 \$	16 GB	16 MP	Below Average

**Output:** Select the best Mobile

**Given\*:** (1) Weights (2) Impacts

\* Assume yourself if not given

# Step 1: Convert categorical to numeric

## Convert Looks to Numerical

Using 5 point Scale	
Low	1
Below Average	2
Average	3
Good	4
Excellent	5

Attribute Or Criteria	Price or Cost	Storage Space	Camera	Looks
Mobile 1	250 \$	16 GB	12 MP	Excellent
Mobile 2	200 \$	16 GB	8 MP	Average
Mobile 3	300 \$	32 GB	16MP	Good
Mobile 4	275 \$	32 GB	8MP	Good
Mobile 5	225 \$	16 GB	16 MP	Below Average

Attribute Or Criteria	Price or Cost	Storage Space	Camera	Looks
Mobile 1	250 \$	16 GB	12 MP	5
Mobile 2	200 \$	16 GB	8 MP	3
Mobile 3	300 \$	32 GB	16MP	4
Mobile 4	275 \$	32 GB	8MP	4
Mobile 5	225 \$	16 GB	16 MP	2

# Step 2.1: Vector Normalization

## Calculate Root of Sum of Squares

$$\bar{X}_{ij} = \frac{X_{ij}}{\sqrt{\sum_{j=1}^n X_{ij}^2}}$$

Attribute Or Criteria →	Price or Cost	Storage Space	Camera	Looks
Mobile 1	250 \$	16 GB	12 MP	5
Mobile 2	200 \$	16 GB	8 MP	3
Mobile 3	300 \$	32 GB	16MP	4
Mobile 4	275 \$	32 GB	8MP	4
Mobile 5	225 \$	16 GB	16 MP	2
	564.579	53.0659	28	8.3666

For Price  $250^2 + 200^2 + 300^2 + 275^2 + 225^2 = 318750$   
 $\sqrt{318750} = 564.579$

# Step 2.2: Vector Normalization

**Find Normalized Decision Metrix -**

**Divide every column value its Root of Sum of Squares**

Attribute Or Criteria	Price or Cost	Storage Space	Camera	Looks
Mobile 1	$\frac{250}{564.579}$	$\frac{16}{53.0659}$	$\frac{12}{28}$	$\frac{5}{8.3666}$
Mobile 2	$\frac{200}{564.579}$	$\frac{16}{53.0659}$	$\frac{8}{28}$	$\frac{3}{8.3666}$
Mobile 3	$\frac{300}{564.579}$	$\frac{32}{53.0659}$	$\frac{16}{28}$	$\frac{4}{8.3666}$
Mobile 4	$\frac{275}{564.579}$	$\frac{32}{53.0659}$	$\frac{8}{28}$	$\frac{4}{8.3666}$
Mobile 5	$\frac{225}{564.579}$	$\frac{16}{53.0659}$	$\frac{16}{28}$	$\frac{2}{8.3666}$

Attribute Or Criteria	Price or Cost	Storage Space	Camera	Looks
Mobile 1	0.4428	0.3015	0.4286	0.5976
Mobile 2	0.3542	0.3015	0.2857	0.3586
Mobile 3	0.5314	0.6030	0.5714	0.4781
Mobile 4	0.4871	0.6030	0.2857	0.4781
Mobile 5	0.3985	0.3015	0.5714	0.2390

**Value in every cell is known as Normalized performance value.**

# Step 3.1: Weight Assignment

**Assign weight** to every columns (0.25)

Weightage 	0.25	0.25	0.25	0.25
Attribute Or Criteria 	Price or Cost	Storage Space	Camera	Looks
Mobile 1	0.4428	0.3015	0.4286	0.5976
Mobile 2	0.3542	0.3015	0.2857	0.3586
Mobile 3	0.5314	0.6030	0.5714	0.4781
Mobile 4	0.4871	0.6030	0.2857	0.4781
Mobile 5	0.3985	0.3015	0.5714	0.2390

**\*Weights** can be (1,1,1,1) or (1,1,0.5,0.5) or (1,1,2,2)



# Step 3.2: Weight Assignment

**Calculate** Weight  $\times$  Normalized performance value

Weightage →	0.25	0.25	0.25	0.25
Attribute Or Criteria →	Price or Cost	Storage Space	Camera	Looks
Mobile 1	$0.4428 \times 0.25$	$0.3015 \times 0.25$	$0.4286 \times 0.25$	$0.5976 \times 0.25$
Mobile 2	$0.3542 \times 0.25$	$0.3015 \times 0.25$	$0.2857 \times 0.25$	$0.3586 \times 0.25$
Mobile 3	$0.5314 \times 0.25$	$0.6030 \times 0.25$	$0.5714 \times 0.25$	$0.4781 \times 0.25$
Mobile 4	$0.4871 \times 0.25$	$0.6030 \times 0.25$	$0.2857 \times 0.25$	$0.4781 \times 0.25$
Mobile 5	$0.3985 \times 0.25$	$0.3015 \times 0.25$	$0.5714 \times 0.25$	$0.2390 \times 0.25$

Weightage →	0.25	0.25	0.25	0.25
Attribute Or Criteria →	Price or Cost	Storage Space	Camera	Looks
Mobile 1	0.1107	0.0754	0.1071	0.1494
Mobile 2	0.0886	0.0754	0.0714	0.0896
Mobile 3	0.1328	0.1508	0.1429	0.1195
Mobile 4	0.1218	0.1508	0.0714	0.1195
Mobile 5	0.0996	0.0754	0.1429	0.0598

**Known as weighted  
normalized decision  
matrix**

# Step 4: Find Ideal Best and Ideal Worst

- Calculate ideal best value and ideal worst value
- **Impacts:** Price (-) Storage (+) Camera(+) Looks (+)  
**-ve means** → min is best | **+ve means** → max is best

- For price min value is best
- For storage, camera, Looks max value is best

Weightage →	0.25	0.25	0.25	0.25
Attribute Or Criteria →	Price or Cost	Storage Space	Camera	Looks
Mobile 1	0.1107	0.0754	0.1071	0.1494
Mobile 2	0.0886	0.0754	0.0714	0.0896
Mobile 3	0.1328	0.1508	0.1429	0.1195
Mobile 4	0.1218	0.1508	0.0714	0.1195
Mobile 5	0.0996	0.0754	0.1429	0.0598
$V_j^+$	0.0886	0.1508	0.1429	0.1494
$V_j^-$	0.1328	0.0754	0.0714	0.0598

$V_j^+$  = ideal best

$V_j^-$  = ideal worst

# Step 5: Calculate Euclidean distance

Calculate Euclidean distance from ideal best value and ideal worst value

$$S_i^+ = \left[ \sum_{j=1}^m (V_{ij} - V_j^+)^2 \right]^{0.5}$$
$$S_i^- = \left[ \sum_{j=1}^m (V_{ij} - V_j^-)^2 \right]^{0.5}$$

# Step 5: Calculate Euclidean distance

Calculate Euclidean distance from ideal best value and ideal worst value

$$((0.1107 - 0.0886)^2 + (0.0754 - 0.1508)^2 + (0.1071 - 0.1429)^2 + (0.1494 - 0.1494)^2)^{0.5} = 0.0863$$

Attribute Or Criteria	Price or Cost	Storage Space	Camera	Looks	$S_i^+$	$S_i^-$
Mobile 1	0.1107	0.0754	0.1071	0.1494	0.0863	0.0990
Mobile 2	0.0886	0.0754	0.0714	0.0896	0.1198	0.0534
Mobile 3	0.1328	0.1508	0.1429	0.1195	0.0534	0.1198
Mobile 4	0.1218	0.1508	0.0714	0.1195	0.0842	0.0968
Mobile 5	0.0996	0.0754	0.1429	0.0598	0.1176	0.0788
$V_j^+$	0.0886	0.1508	0.1429	0.1494		
$V_j^-$	0.1328	0.0754	0.0714	0.0598		

$$S_i^+ = \left[ \sum_{j=1}^m (V_{ij} - V_j^+)^2 \right]^{0.5} \quad S_i^- = \left[ \sum_{j=1}^m (V_{ij} - V_j^-)^2 \right]^{0.5}$$

# Step 6: Calculate Performance Score

## Calculate Performance Score

### TOPSIS

performance score

Attribute Or Criteria	$S_i^+$	$S_i^-$	$S_i^+ + S_i^-$	$P_i$
Mobile 1	0.0863	0.0990	0.1853	0.534269
Mobile 2	0.1198	0.0534	0.1732	0.308314
Mobile 3	0.0534	0.1198	0.1732	0.691686
Mobile 4	0.0842	0.0968	0.181	0.534807
Mobile 5	0.1176	0.0788	0.1964	0.401222

$$P_i = \frac{S_i^-}{S_i^+ + S_i^-}$$

# Step 7: TOPSIS Score and Rank

## Final Result

Attribute Or Criteria	$P_i$	Rank
Mobile 1	0.534269	3
Mobile 2	0.308314	5
Mobile 3	0.691686	1
Mobile 4	0.534807	2
Mobile 5	0.401222	4



# Assignment

## Given Input Data

**Impacts:** Corr(+) Rseq (+) RMSE (-) Accuracy (+)

Model	Corr	Rseq	RMSE	Accuracy
M1	0.79	0.62	1.25	60.89
M2	0.66	0.44	2.89	63.07
M3	0.56	0.31	1.57	62.87
M4	0.82	0.67	2.68	70.19
M5	0.75	0.56	1.3	80.39

**Find the TOPSIS score and model rank for:**

1. Weights (1, 1, 1, 1)
2. Weights (1, 1, 2, 1)
3. Weights (1, 1, 0.5, 1)
4. Weights (2, 2, 1, 1)
5. Weights (2, 2, 0.5, 1)

# Project Work 1

**1. Learn the mathematics for TOPSIS from given below link.**

**<https://www.youtube.com/watch?v=aRBdrCB1K4k>**

**2. Implement the technique in python and develop a cmd line solution (i.e. run through cmd line), handle all the exceptions like file format, number of parameters, etc :**

**Usages: python topsis.py <InputDataFile> <Weights>  
<Impacts> <ResultFileName>**

**Example: python topsis.py myData.csv "1,2,1,1" "+,+, -+"  
result.csv**

**3. Develop a python package.**

**4. Test and validate it on different datasets**

**5. Upload the package on pypi.org**

**Thanks**

**Learning by Doing**

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