

Crop analysis and pesticides Recommendation system

Mr. Devdas - Guide





MINI PROJECT GROUP 7

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1) Crop Prediction: Crop Prediction Data, CSV file format

	Α	В	С	D	Е	F	G	Н	1	J	K	L	М	N	0	Р	Q	R	S	Т	U	V	W
Dist	t Code Ye	ar	State Code	State Nam E	ist Nam	e RICE AREA	RICE PROE	RICE YIELE V	VHEAT AF V	VHEAT PE	WHEAT YII	KHARIF SO	KHARIF SO	KHARIF SO	RABI SORG	RABI SORE	RABI SORG	SORGHUN	SORGHUN	SORGHUN	PEARL MIL	PEARL MIL	PEARL MIL M.
2	1	1966	14	Chhattisga [Ourg	548	185	337.59	44	20	454.55	0.6	0.4	666.67	0	0	0	0.6	0.4	666.67	0	0	0
3	1	1967	14	Chhattisga [Ourg	547	409	747.71	50	26	520	1.1	0.9	818.18	0	0	0	1.1	0.9	818.18	0	0	0
ļ.	1	1968	14	Chhattisga [Ourg	556.3	468	841.27	53.7	30	558.66	0.5	0.4	800	0	0	0	0.5	0.4	800	0	0	0
,	1	1969	14	Chhattisga E	Ourg	563.4	400.8	711.4	49.4	26.5	536.44	0.8	0.6	750	0	0	0	0.8	0.6	750	0	0	0
5	1	1970	14	Chhattisga [Ourg	571.6	473.6	828.55	44.2	29	656.11	0.9	0.6	666.67	0	0	0	0.9	0.6	666.67	0	0	0
,	1	1971	14	Chhattisga [Ourg	581.8	412.9	709.69	44.4	25.8	581.08	0.3	0.2	666.67	0	0	0	0.3	0.2	666.67	0	0	0
3	1	1972	14	Chhattisga [Ourg	582.2	381	654.41	39.6	20.6	520.2	0.3	0.3	1000	0	0	0	0.3	0.3	1000	0	0	0
9	1	1973	14	Chhattisga E	Ourg	600	471.9	786.5	37.3	18.6	498.66	0.2	0.2	1000	0	0	0	0.2	0.2	1000	0	0	0
0	1	1974	14	Chhattisga [Ourg	587.4	219	372.83	36.5	22.4	613.7	0.5	0.4	800	0	0	0	0.5	0.4	800	0	0	0
1	1	1975	14	Chhattisga [Ourg	598.3	454	758.82	49.2	27.8	565.04	0.2	0.2	1000	0	0	0	0.2	0.2	1000	0	0	0
2	1	1976	14	Chhattisga E	Ourg	593.6	327.1	551.04	46.9	10	213.22	0.1	0.1	1000	0	0	0	0.1	0.1	1000	0	0	0
3	1	1977	14	Chhattisga [Ourg	600.7	572.4	952.89	53.1	27.1	510.36	0.1	0.1	1000	0	0	0	0.1	0.1	1000	0	0	0
4	1	1978	14	Chhattisga E	Ourg	612.5	362.2	591.35	48.7	25.6	525.67	0.1	0.1	1000	0	0	0	0.1	0.1	1000	0	0	0
5	1	1979	14	Chhattisga [Ourg	616.8	330.6	535.99	44.6	17.8	399.1	0.5	0.5	1000	0	0	0	0.5	0.5	1000	0	0	0
6	1	1980	14	Chhattisga E	Ourg	634.9	515.6	812.1	44.1	33.6	761.9	0.2	0.2	1000	0	0	0	0.2	0.2	1000	0	0	0
7	1	1981	14	Chhattisga E	Ourg	630	506.9	804.6	41.5	23.6	568.67	0.2	0.2	1000	0	0	0	0.2	0.2	1000	0	0	0
8	1	1982	14	Chhattisga [Ourg	627.9	513.3	817.49	41.1	23.9	581.51	0.1	0.1	1000	0	0	0	0.1	0.1	1000	0	0	0
9	1	1983	14	Chhattisga E	Ourg	626.7	711	1134.51	39.9	20.6	516.29	0.1	0.1	1000	0	0	0	0.1	0.1	1000	0	0	0
0	1	1984	14	Chhattisga E	Ourg	632.2	563.8	891.81	40.5	19.9	491.36	0.3	0.3	1000	0	0	0	0.3	0.3	1000	0	0	0
1	1	1985	14	Chhattisga [Ourg	630.8	699.8	1109.38	39.4	21	532.99	0.3	0.2	666.67	0	0	0	0.3	0.2	666.67	0	0	0
2	1	1986	14	Chhattisga [Ourg	643	525	816.49	37	24	648.65	0.2	0.1	500	0	0	0	0.2	0.1	500	0	0	0
3	1	1987	14	Chhattisga E	Ourg	648	523	807.1	43	23	534.88	0.3	0.2	666.67	0	0	0	0.3	0.2	666.67	0	0	0
4	1	1988	14	Chhattisga D	Ourg	652.7	549.7	842.19	43.7	20.2	462.24	0.1	0.1	1000	0	0	0	0.1	0.1	1000	0	0	0
5	1	1989	14	Chhattisga [Ourg	660.2	457.3	692.67	43.8	22.7	518.26	0.1	0.1	1000	0	0	0	0.1	0.1	1000	0	0	0
6	1	1990		Chhattisga [682.9	806.8	1181.43	36.2	24.8	685.08	0.5	0.4	800	0	0	0	0.5	0.4	800	0	0	0
7	1	1991	14	Chhattisga E	Ourg	680.8	773.6	1136.31	34.8	21.6	620.69	2.3	1.8	782.61	0	0	0	2.3	1.8	782.61	0	0	0
0		1003	1.4	Chimina		C00	777 1	1120.0	FC 4	20.5	205.42			000 00	^	^	^		- 1	000 00	^	^	0
<	>	Crop	Prediction	Data	+									:	4								•



2) Crop Analysis:

Crop Analysis Data, CSV file format

4	Α	В	С	D	E	F	G	Н	1	J	K	L	М	N	0	Р	Q	R
1	N	P	K	temperature	humidity	ph	rainfall	label										
2	90	42	43	20.87974371	82.00274423	6.502985292	202.9355362	rice										
3	85	58	41	21.77046169	80.31964408	7.038096361	226.6555374	rice										
4	60	55	44	23.00445915	82.3207629	7.840207144	263.9642476	rice										
5	74	35	40	26.49109635	80.15836264	6.980400905	242.8640342	rice										
6	78	42	42	20.13017482	81.60487287	7.628472891	262.7173405	rice										
7	69	37	42	23.05804872	83.37011772	7.073453503	251.0549998	rice										
8	69	55	38	22.70883798	82.63941394	5.70080568	271.3248604	rice										
9	94	53	40	20.27774362	82.89408619	5.718627178	241.9741949	rice										
10	89	54	38	24.51588066	83.5352163	6.685346424	230.4462359	rice										
11	68	58	38	23.22397386	83.03322691	6.336253525	221.2091958	rice										
12	91	53	40	26.52723513	81.41753846	5.386167788	264.6148697	rice										
13	90	46	42	23.97898217	81.45061596	7.50283396	250.0832336	rice										
14	78	58	44	26.80079604	80.88684822	5.108681786	284.4364567	rice										
15	93	56	36	24.01497622	82.05687182	6.98435366	185.2773389	rice										
16	94	50	37	25.66585205	80.66385045	6.94801983	209.5869708	rice										
17	60	48	39	24.28209415	80.30025587	7.042299069	231.0863347	rice										
18	85	38	41	21.58711777	82.7883708	6.249050656	276.6552459	rice										
19	91	35	39	23.79391957	80.41817957	6.970859754	206.2611855	rice										
20	77	38	36	21.8652524	80.1923008	5.953933276	224.5550169	rice										
21	88	35	40	23.57943626	83.58760316	5.85393208	291.2986618	rice										
22	89	45	36	21.32504158	80.47476396	6.442475375	185.4974732	rice										
23	76	40	43	25.15745531	83.11713476	5.070175667	231.3843163	rice										
24	67	59	41	21.94766735	80.97384195	6.012632591	213.3560921	rice										
25	83	41	43	21.0525355	82.67839517	6.254028451	233.1075816	rice										
26	98	47	37	23.48381344	81.33265073	7.375482851	224.0581164	rice										
27	66	53	41	25.0756354	80.52389148	7.778915154	257.0038865	rice										



3) Crop Clustering:

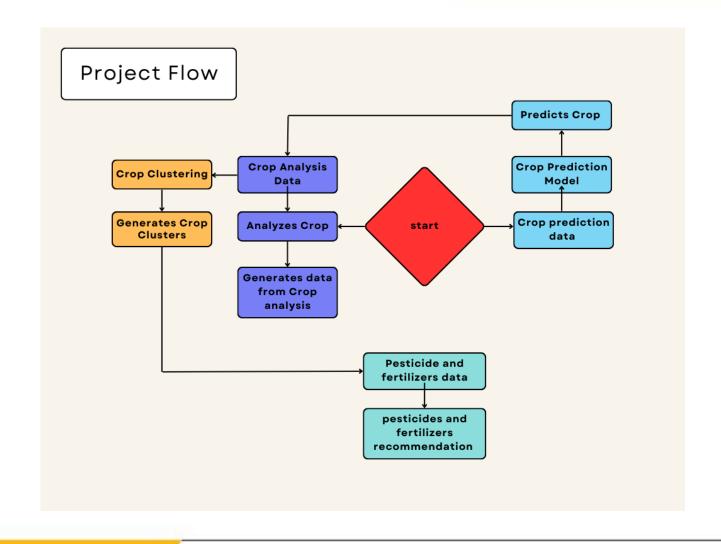
In crop clustering, we use data that we have extracted from the crop analysis.



4) Pesticides and Fertilizers Recommendation: P&F Data, CSV file format

					4	/ \	U		
1	Entity	Code	Year	Nutrient	1	Entity	Code	Year	Pesticides (to
2	Afghanistan	AFG	1961	0.13	2	Africa (FA	AO)	1990	65944.26
3	Afghanistan	AFG	1962	0.13	3	Africa (FA	AO)	1991	62723.2
4	Afghanistan	AFG	1963	0.13	4	Africa (FA	AO)	1992	54428.07
5	Afghanistan	AFG	1964	0.13	5	Africa (FA	AO)	1993	49620.53
6	Afghanistan	AFG	1965	0.13	6	Africa (FA	AO)	1994	51095.37
7	Afghanistan	AFG	1966	0.13	7	Africa (FA	4O)	1995	56939.78
8	Afghanistan	AFG	1967	1.13	8	Africa (FA	4O)	1996	58563.56
9	Afghanistan	AFG	1968	1.75	9	Africa (FA	AO)	1997	59473.66
10	Afghanistan	AFG	1969	1.88	10	Africa (FA	AO)	1998	60770.25
11	Afghanistan	AFG	1970	2	11	Africa (FA	AO)	1999	63027.14
12	Afghanistan	AFG	1971	1.84	12	Africa (FA	AO)	2000	63894.15
13	Afghanistan	AFG	1972	1.99	13	Africa (FA	AO)	2001	64523.1
14	Afghanistan	AFG	1973	2.2	14	Africa (FA	AO)	2002	67516.16
15	Afghanistan	AFG	1974	3.01	15	Africa (FA	AO)	2003	69697.31
16	Afghanistan	AFG	1975	3.44	16	Africa (FA	AO)	2004	73268.59
17	Afghanistan	AFG	1976	3.81	17	Africa (FA	AO)	2005	71312.94
18	Afghanistan	AFG	1977	4.6	18	Africa (FA	AO)	2006	77401.08
19	Afghanistan	AFG	1978	4.41	19	Africa (FA	(O)	2007	75657.45
20	Afghanistan	AFG	1979	4.13	20	Africa (FA	AO)	2008	79274.89







1) Crop Prediction:

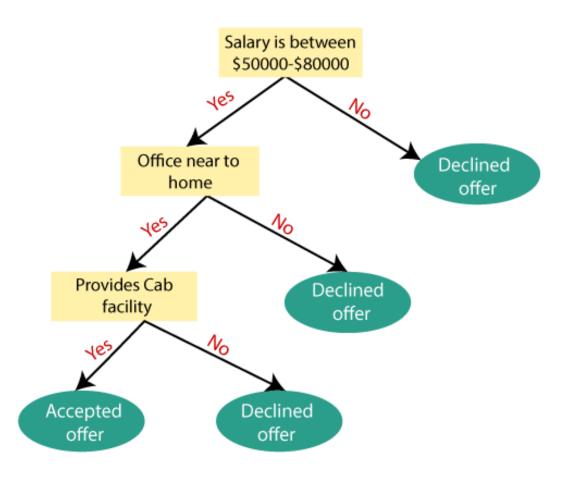
1) Decision Tree

- **Step-1**: Begin the tree with the root node, says S, which contains the complete dataset.
- •Step-2: Find the best attribute in the dataset using Attribute Selection Measure (ASM).
- •Step-3: Divide the S into subsets that contains possible values for the best attributes.
- •Step-4: Generate the decision tree node, which contains the best attribute.
- •Step-5: Recursively make new decision trees using the subsets of the dataset created in step -3. Continue this process until a stage is reached where you cannot further classify the nodes and called the final node as a leaf node.

Example

- 1) Suppose there is a candidate who has a job offer and wants to decide whether he should accept the offer or Not.
- **2)** So, to solve this problem, the decision tree starts with the root node (Salary attribute by ASM).
- **3)** The root node splits further into the next decision node (distance from the office) and one leaf node based on the corresponding labels.
- **4)** The next decision node further gets split into one decision node (Cab facility) and one leaf node.
- **5)** Finally, the decision node splits into two leaf nodes (Accepted offers and Declined offer).







1) Crop Prediction:

2) Random Forest:

Step-1: Select random K data points from the training set.

Step-2: Build the decision trees associated with the selected data points (Subsets).

Step-3: Choose the number N for decision trees that you want to build.

Step-4: Repeat Step 1 & 2.

Step-5: For new data points, find the predictions of each decision tree, and assign the new data points to the category that wins the majority votes.

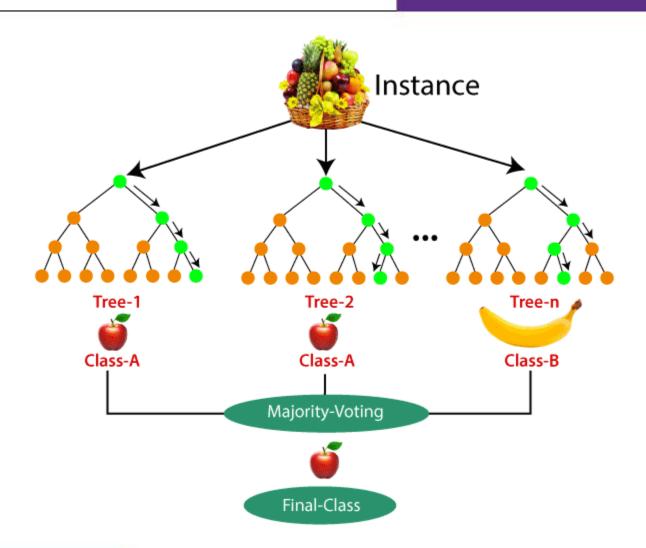
Example:

Suppose there is a dataset that contains multiple fruit images.

So, this dataset is given to the Random forest classifier. The dataset is divided into subsets and given to each decision tree.

During the training phase, each decision tree produces a prediction result when a new data point occurs, then based on the majority of results, the Random Forest classifier predicts the final decision







2) Crop Analysis:

1) Multiple Linear Regression:

Step 1: Encoding the Categorical Data.

Step 2: Splitting the Data set into Training Set

and Test Set.

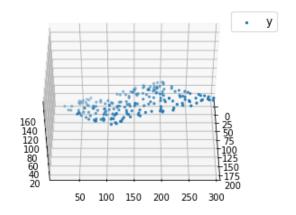
Step 3: Fitting Multiple Linear Regression to the

Training set

Step 4: Predict the Test set results.

Example:

GENDER	MALE	FEMALE
Male	1	0
Male	1	0
Female	0	1
Female	0	1
Male	1	0
Female	0	1
Male	1	0





Example:

	mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness	mean concavity	mean concave points	mean symmetry	mean fractal dimension	 worst radius	worst texture	worst perimeter	worst area	worst smoothness
0	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.3001	0.14710	0.2419	0.07871	 25.38	17.33	184.60	2019.0	0.1622
1	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.0869	0.07017	0.1812	0.05667	 24.99	23.41	158.80	1956.0	0.1238
2	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.1974	0.12790	0.2069	0.05999	 23.57	25.53	152.50	1709.0	0.1444
3	11.42	20.38	77.58	386.1	0.14250	0.28390	0.2414	0.10520	0.2597	0.09744	 14.91	26.50	98.87	567.7	0.2098
4	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.1980	0.10430	0.1809	0.05883	 22.54	16.67	152.20	1575.0	0.1374

5 rows × 30 columns

MODULES:

2) Crop Analysis:

2)Principal Component Analysis:

Step 1: Getting the dataset

Step 2: Representing data into a structure

Step 3: Standardizing the data

Step 4: Calculating the Covariance of Z

Step 5: Calculating the Eigen Values and Eigen

Vectors

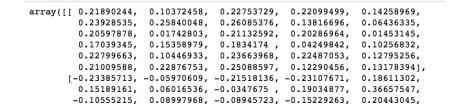
Step 6: Sorting the Eigen Vectors

Step 7: Calculating the new features Or Principal

Components

Step 8: Remove less or unimportant features

from the new dataset.

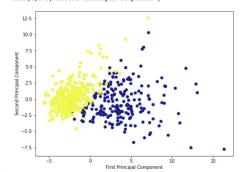


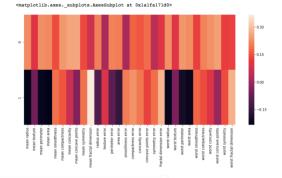
-0.21986638, -0.0454673 , -0.19987843, -0.21935186, 0.17230435, 0.14359317, 0.09796411, -0.00825724, 0.14188335, 0.27533947]])

0.2327159 , 0.19720728, 0.13032156, 0.183848 , 0.28009203,

Text(0,0.5, 'Second Principal Component')

pca.components







Example:

3) Crop Clustering:

1)K-Means Clustering:

Step-1: Select the number K to decide the number of clusters.

Step-2: Select random K points or centroids. (It can be other from the input dataset).

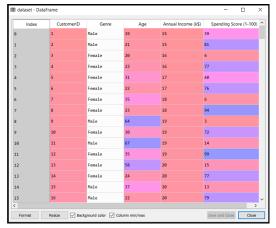
Step-3: Assign each data point to their closest centroid, which will form the predefined K clusters.

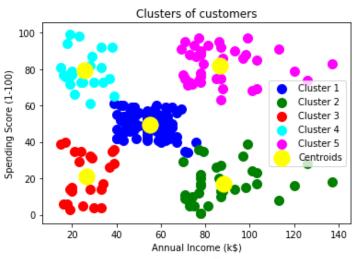
Step-4: Calculate the variance and place a new centroid of each cluster.

Step-5: Repeat the third steps, which means reassign each datapoint to the new closest centroid of each cluster.

Step-6: If any reassignment occurs, then go to step-4 else go to FINISH.

Step-7: The model is ready.







3) Crop Clustering:

2) Fuzzy Clustering:

Step 1: Initialize the data points into the desired number of clusters randomly.

Step 2: Find out the centroid.

Step 3: Find out the distance of each point from the centroid.

Step 4: Updating membership values.

Step 5: Repeat the steps(2-4) until the constant values are obtained for the membership values or the difference is less than the tolerance value

Step 6: Defuzzify the obtained membership values.

Example:

Cluster (1, 3) (2, 5) (4, 8) (7, 9)

1) 0.8 0.7 0.2 0.1

2) 0.2 0.3 0.8 0.9

Cluster Centers:

[[0.42363557 0.68304616]

[0.52768166 0.38180987]

[0.39967863 0.31042639]]

Cluster Membership:

 $\begin{bmatrix} 1 & 0 & 1 & 2 & 1 & 0 & 0 & 2 & 0 & 2 & 1 & 0 & 0 & 0 & 1 & 2 & 1 & 1 & 0 & 2 & 2 & 1 & 1 & 2 & 0 & 1 & 0 \\ 0 & 2 & 0 & 2 & 1 & 1 & 0 & 0 & 1 & 1 & 1 & 1 & 2 & 2 & 0 & 1 & 1 & 2 & 0 & 0 & 1 & 1 & 2 & 2 & 0 & 1 & 1 & 2 & 0 & 0 \\ 1 & 0 & 2 & 0 & 0 & 2 & 1 & 0 & 1 & 1 & 1 & 1 & 2 & 2 & 0 & 1 & 1 & 0 & 0 & 2 & 2 & 2 & 0 & 1 & 1 & 2 & 0 & 0 \\ \end{bmatrix}$

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4) Pesticide and Fertilizer recommendation

1) Collabarative Based filtering:

Step 1: Finding the similarity of users to the target user U.

Step 2: Prediction of missing rating of an item

Example: Consider a matrix that shows four users Alice, U1, U2 and U3 rating on different news apps. The rating range is from 1 to 5 on the basis of users' likability of the news app.

Step 1: Calculating the similarity between Alice and all the other users At first we calculate the averages of the ratings of all the user excluding I5 as it is not rated by Alice.

Step 2:Predicting the rating of the app not rated by Alice Now, we predict Alice's rating for BBC News App.



Example:

Name	Inshor BBC(I5	` '	HT(I2)	NYT(I3)	TOI(I4)		
Alice	5	4	1	4	?		
U1	3	1	2	3	3		
U2	4	3	4	3	5		
U3	3	3	1	5	4		

Step 1:

Name	Inshorts(l1)	HT(I2)	NYT(I3)	TOI(I4)
Alice	1.5	0.5	-2.5	0.5	
U1	0.75	-1.25	-0.25	0.75	
U2	0.5	-0.5	0.5	-0.5	
U3	0	0	-2	2	

Step 2:

$$[Tex]r_{(Alice,I5)}=3.5 + \frac{(0.301*0.75)+(-0.33*1.5)+(0.707*1)}{|0.301|+|-0.33|+|0.707|}=3.83\\ newline$$



4) Pesticide and Fertilizer recommendation

2) Content Based filtering:

Content-based filtering makes recommendations by using keywords and attributes assigned to objects in a database (e.g., items in an online marketplace) and matching them to a user profile. The user profile is created based on data derived from a user's actions, such as purchases, ratings (likes and dislikes), downloads, items searched for on a website and/or placed in a cart, and clicks on product links.

Example: suppose you're recommending accessories to a user that just purchased a smartphone from your website and has previously bought smartphone accessories. Aside from keywords such as the smartphone manufacturer, make, and model, the user profile indicates prior purchases include phone holders with sleeves for credit cards. Based on this information, the recommender system may suggest similar phone holders for the new phone with attributes such as an RFID blocking fabric layer to help prevent unauthorized credit card scanning. In this example, the user would expect recommendations for similar phone holders, but the RFID blocking feature may be something they didn't expect yet appreciate.



Mank