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Lecture - 10 Hierarchical and Non hierarchical clustering algorithms

In this lecture we continue the discussion on hierarchical clustering. Particularly the problem of forming part families, we then moved to a Non hierarchical clustering algorithm. In the previous lecture we saw the hierarchical clustering algorithm where given a machine component incidence matrix; we could get groups ranging from all points or all machines in one group as one extreme versus each machine forming a separate group by itself. For example, if we look at the machine component incidence matrix given in the picture, there are 6 rows representing 6 machines and 8 columns representing 8 parts or components.

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So, we could starting with a solution which has each of these machine as a group we then merge the groups to get to a final solution which has all the machines in one group, we used the Jaccards Similiarty coefficient matrix which is shown here.

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Now, we said at the end of the exercise that if the user defines a certain number of groups then we can identify the groups and give it to the user. So, let us assume that we have identified that we want 2 groups in this solution and therefore, the 2 group solution from the hierarchical clustering algorithm is given here with 1, 3, 4 and 2, 5, 6.

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So, I am going to write 1, 3, 4 here and 2, 5, 6 as machines.

So, there are 2 groups the first group has machines 1, 3 and 4 the second group has machines 2, 5 and 6. So, we have formed the machine groups using the algorithm now

we have to form the part families. Now the part families can be formed in more than 1. way one of the way is to look at the same matrix and instead of creating a Jaccard similarity coefficient for the rows or the machines, we can create the similarity coefficient matrix for the columns or for the parts. In that case we would have an 8 by 8 matrix and the similarities would be found column wise for example, similarity between part 1 and part 2 would be similarity between this column and this column which would be.

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For part 1 the values are 1 0 1 1 0 1 and for part 2 it is 0 1 0 0 1 0 0 1 1. So, the Jaccard similarity coefficient for 1 and 2 would be the number of common ones which happens here this is the numerator 1 by 1 2 3 4 5 6 1 by 6, only 1 machine is common to both these parts. So, that comes as a numerator. Put together these 2 parts visit all the 6 machines. So, 6 comes as a denominator. So, the Jaccard similarity coefficient could be 1 by 6.

Like this we can complete an 8 into 8 matrix and use the same hierarchical clustering idea to make part groups starting from each part as a separate group and finally, finishing with all parts as a single group. So, there will be a solution for 2 groups. So, we could take that solution part wise and then we can easily find out whether that will go to this group which 1 will go to this group and which 1 will go to the other group that is 1 way

of looking at it, but we are going to propose another way which is somewhat simpler and more or less as effective as the previous way.

So, what we are going to do is we are not going to construct a Jaccard similarity coefficient for the parts instead we are going to take each part by part and we are going to try and assign it to a known machine group. For example, if we take the first part now the first part visits machines 1 3 4 and 6 from that figure. So, look at this 1 3 4 and 6 the first part should go to this machine group because 3 out of the 4 required machines are here. So, I will right part here and I will put 1. So, part 1 will go to this machine group because it has maximum number of machines required and right away we can say that if we are assigning part 1 to this part 1 requires machines 1 3 4 and 6 1 3 and 4 are here 6 is here. So, we create 1 intercell move 1 intercell move which is 1 to 6.

If we had put part 1 here then we would have created 3 intercell moves which is not desirable therefore, we will put this part here such that it either has 0 or it has all the requirements or it creates minimum number of intercell moves. We look at part number 2 which requires machines 2 5 and 6, 2 5 and 6 are here. So, part number 2 part will go to this part no intercell moves are created part number 3 requires 5 and 6. So, 5 and 6 are here. So, part number 3 will go to this.

We also observe that part number 3 goes to this does not visit all the machines it actually does not visit machine number 2, but then part number 3 will still go here because part number 3 does not require any of these. So, part number 4 has 1 3 and 6, 1 3 and 6, 2 machines out of the 3 are here 1 is here. So, part 4 will go here. So, part 4 will go here and it will have 1 intercell move with 4 and 6. So, let us write this second intercell move which is part 4 to machine 6.

Part 5 requires 1 4 and 5 so 1 4 and 5. So, part 5 will go here because it has 2 machines here only 1 machine here, so part 1 4 and 5. So, it creates 1 more intercell move with 4 and 5 part 4 goes to machine 5, part 6 has 1 2 3 4. So, 1 3 4 are here 2 is here no part 6 will go here and 1 intercell move is created part 6 with machine number 2, part 7 requires 2 5 6, 2 5 6 are all here. So, part 7 will go here part 8 requires 2 5 6 part 8 also will go here. So, instead of creating another Jaccard similarity coefficient matrix for parts and carrying out a non-hierarchical carrying out a hierarchical clustering analysis and identify the solution with 2 groups. We now have groups that are created using this

particular rule this rule is fairly intuitive because once the machine groups are known each part will visit the machine group or will be attached to the machine group where it has maximum machines that it is visiting.

We may encounter a situation where there right now we do not have that in this example, but if there was a if there was we could have a situation where a part could visit it may require 4 machines 2 of them maybe here 2 of them maybe here.



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For example, if we have a machine, If we have 7 machines and let us say 1, 4 and 5 are here 2, 3, 6 and 7 are here and if there is a part that requires 1, 2, 3 and 4 if it requires machines 1, 2, 3 and 4. So, here it has 2 machines here it has 2 machines. So, based on our rule it could go here or it could go here either way it will create 2 intercell moves, but in such a case we will assign it if there is a tie based on this then we will assign it to a smaller size to go. So, it will go here instead of going here. So, there are 2 rules rule number 1 is a part will be assigned to a group if it has all the machines in that group. So, intercell move created will be 0 the same rule extended the part will visit or will be assigned to a machine group where it visits maximum number of machines. So, that the number of intercell moves created is minimum.

If there is a tie then the part will be assigned to the group which has the smallest size. So, here the size is 3 here the size is 4 if there is a tie then it will go to the group. So, there are 2 important rules part will be assigned to a machine group where it visits maximum

number of machines and in the event of a tie it will be allocated to the smallest sized cell further ties can be resolved arbitrarily. So, we could use this rule to create this solution with part families 1, 4, 5, 6 and 2, 3, 7 8 with 4 intercell moves from this solution.



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We also observe that this actually is the final solution with part families the group 1 3 4 has 1 4 5 6 you can see that in the picture it has 1 4 5 6 and the machine group 2 5 6 has parts 2 3 7 8 which we can see there the 4 intercell moves, part 1 to machine 6, part 4 to machine 6, part 5 to machine 5. So, let us check that in the previous picture.

So, part 5 requires machines 1 4 and 5. So, part 5 will go to this group with 1 and 4 and there will be an intercell move for part 5 to machine 5 and the fourth one part 6 to machine 2 they are all shown in red color. So, this way using this rule we can now assign parts to available machine groups the rule has 2 important aspects each part will go to the machine group where it visits maximum number of machines and in the event of a tie it will be assigned to a group which has smallest number of machines.

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So, we can call this rule as a part assignment rule as part assignment rule and use this rule to assign parts to given machine groups, we will revisit this part assignment rule in the context of clustering later. So, this way we can use the non-hierarchical cluster analysis method initially to form machine groups and then use the part assignment rule to assign parts to existing groups to minimize intercell moves. Now we have not answered 1 question which is what is the best number of groups that we should choose, this solution from the hierarchical clustering started with Started with all of the machines as 1 group and from there we had 1 3 then 1 3 4.

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	1,3	2	4	5	6	
,3		1/6	3/4	1/8	3/4	
2			1/6	1/2	3/7	
4				1/7	1/8	
5		-			4/7	
6		-	-	-		-
), [2 en	2}, [5} 5 and	, {6}. Ti 6 and the sol	he next we hav	highes ve a so 1.3.4}a	t simila lution { ind {2,5	rity coefficien 1,3,4}, {2}, [5, 6} with 2 grou

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These were the 6 solutions we got for number of groups varying from 6 to 1. So, from here we got when we assigned part families we did for this solution and then we got 4 intercell moves. It is also very obvious that if we have all of these into a single cell if you have all of these into a single cell then all the parts will go to only one group and there will be 0 inter cell moves and; obviously, this will have maximum intercell moves for a given number of groups the part assignment rule is able to give us a solution with minimum intercell moves, but then we can apply this part assignment rule to all these 6 and we will observe that this will have 0 this will have maximum.

So, if you are going to let this help us choose the correct number of groups then we will make the mistake of choosing this because this will have 0 intercell moves. So, we need other criteria to fix the number of groups if we do not if we have not decided this a priory otherwise it is good to solve the problem with known number of groups. So, that we can get the corresponding machine groups and the part families from here and we minimize the intercell moves.

Now, there are other measures which we can use to actually try and find out the best number of groups. So, when the problem is looked at from a theoretical perspective as to what is the optimum number of groups, then we should adopt different criteria to choose the best one, but if we look at this problem in the context of cell formation now we should look at it in 2 ways; one is it is a practical problem therefore, we would assume that the user or the person from the factory or who is going to apply this technique will have a good idea as to what is the number of groups that is required. Ones that is conveyed by the user to the decision maker then we could go back and choose that this looks like the best number of groups that is true for 2 groups this is the machine cell configuration this is the part family configuration and we can do that.

The other thing is we could compute this and not make a decision based on this we could see for example, these 2 are extreme points therefore, we will not be considering these 2 we will be considering in this range. Now we can show each solution to the decision maker with certain number of intercell moves; obviously, increasing from here to here and let the decision maker choose the number of groups required. And for the chosen are given number of groups we can provide a good solution that minimizes the number of intercell moves.

Now with this we move to a non-hierarchical clustering algorithm and try to understand some aspects of non-hierarchical clustering. Now as we did in the hierarchical clustering we again go to an example where we consider points on the board or on a plane and then explain the non-hierarchical clustering algorithm and then related to cellular manufacturing like what we did.

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So, let us assume that we have 5 points here. So, we call them 1 2 3 4 and 5 now let us assume that we need to create 2 groups in this this is a difference between the non-hierarchical approach and the non-hierarchical approach.

Here we are initially deciding what is the number of groups that we want to create, now in order to create these groups let us try and identify 2 points which we call as seed points S 1 and S 2, we call them as 2 seed points S 1 and S 2. Now the moment we fix these 2 seed points now we have to group the remaining 5 points into the 2 seed points. So, we take point number 1 which is to be grouped and find out to which seed point it is near or we find out the nearest seed point to point number 1. So, that happens to be S 1. So, point number 1 will go to S 1, which means we will find out the distance between 1 and S 1 1 and S 2 and allocate it to S 1 based on minimum distance. Similarly 0.2 again we find the distance between S 1 and S 2 and allocate 0.2 to S 1. So, 0.3 will automatically go to S 2.4 will go to S 2 and 0.5 will also go to S 2.

So, a 2 group solution for this will be 1 and 2 belonging to 1 group 3 4 and 5 belonging to the second group. Now the only important consideration here is in the choice of these seed points and incorrect choice of these seed points can actually give us some times poor solutions. For example, in for example, instead of choosing the seed points the way we did 1 of them here and the other 1 here if we had chosen the first seed point here.



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And if we had chosen the second seed point here, then what happens to the groups now 1 will again be attached to this 1 because this is nearer 2 again will go to this 3 again will go to this 4 will go to this and 5 will go to this. So, one seed point would attract all the 5 the other will not be able to attract anything. So, the groups will not be 1 2 3 4 5, but it will be 1 2 3 4 5 and blank.

So, we have to make sure that the seed points are well chosen. So, that the solution is good now 1 of the ways of doing that is by not keeping is by.

1 5 ×2 5 ×3 S VPTEL S 4 3

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Now, in the 2 previous examples we have chosen seed points which are actually different from the points themselves. So, now, if I choose if I want 2 groups if I choose 2 out of the 5 points themselves as seed points then let us see what happens. Now this 1 also becomes let us say S 1 and say 4 also becomes S 2.

So, now, we look at 1 between 1 and S 1 and between 1 and S 2 and then put point number 1 to the seed which has minimum distance. So, distance between 1 and S 1 is 0 because 1 is S 1 this is a positive. So, 1 will sit on S 1 2 again I will see the distance between 2 and this and 2 and this. So, 2 will go here 3 will go here 4 will sit on itself and 5 will go here. So, now, I have correct number of now we have the correct solution because of a good and correct choice of seed points, now we understand that choosing the seed points from among the given points helps us in 1 thing that that point will get attached to itself and therefore, we will not have what is called a null cluster.

In the previous case when we picked 1 here and 1 here we had a null cluster the second seed was not able to attract any point. So, 1 of the ways of overcoming the null cluster is by having points themselves as seed points. So, now, instead of choosing S 1 here and S 2 here if we had chosen S 1 here and S 2 here.

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Now, what happens? Now 1 will get attached to itself, 2 will get attached to itself, 3 will go to 2 4 will go to 2 and 5 let us say will go to 1 let us assume this is shorter or say 5 will go to 1. Now again we do not have the correct solution because we know that based on distances 1 2 and 3 4 5 is the correct solution. So, not only should the seed points be given points themselves the seed points should also be sufficiently far away from each other. So, that they are able to attract points that are closer to them and therefore, get good groups therefore, if we want to choose 2 seed points here.

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If I want to choose 2 seed points here I would prefer to choose twos points which are farthest from each other as to seed points.

So, my seed point choice will become 1 and 4 which would give me a group 1 2 3 4 5. So, the rule is keep the seed point as large or as far away as possible keep the distances as large as possible. So, what are the ways of doing this is by when we know the number of groups identify as many seed points as the number of groups keep or make the given points themselves as seed points and choose seed points such that they are sufficiently far away from each other. So, these are the basic rules now let us apply this basic rule to the cell formation problem the same example and try to see what happens when we create groups.

So, let us go back to the same machine components incidence matrix which is this and now we need a distance matrix now the Jaccard similarity coefficient matrix is given here in the previous lecture we defined at dissimilarity or a distance. (Refer Slide Time: 29:55)



So, dissimilarity was defined as distance or dissimilarity between rows i and j is given as summation over k absolute value. So, if we take rows 1 and 2 row 1 has 1 0 0 1 1 0 0, row number 2 will have 0 1 0 0 0 0 1 0 0 row 1 has 1 0 0 1 1 1 0 0 row 2 has 0 1 0 0 0 1 1 1.

Now, here ik minus ijk. So, if you have a 1 0 pair or a 0 1 pair the absolute value is 1, if you have a 1 1 pair and a 0 0 pair the absolute value is 0. So, we should look at all the 1 0 or 0 1 pairs and add them so 1 2 3 4 5 and 6. So, d 1 2 will be equal to 6. So, this way we can create a distance matrix assuming that each of these rows or machines is points in an 8 dimensional binary space. So, if we construct such a distance matrix we will get this matrix the 6 that be computed between 1 and 2 is here.



Now, we have to now let us assumed that we need 2 groups for which we need 2 seed points and we said the seed points have to be the points themselves. So, the maximum distance is between 3 and 5 maximum distance is between 3 and 5. So, row 3 and row 5 or machine 3 and machine 5 acts as 2 seed points. So, they act as 2 seed points with this is the seed points 3 and 5 act as 2 seed points.

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Now, look at machine 1 machine 1 has minimum distance with 3, now we have to find out the distance between machine number 1 or row number 1 with the seed points 3 and

5 and assign it to the seed where it has minimum distance. So, $1 \ 2 \ 3$ is 1 from the picture and 1 to 5 is 7 from this picture. So, 1 has minimum distance with 3 and therefore, machine 1 will go here, machine number 2 is not assigned. So, 2 to 3 distance is 5 2 to 5 distance is 2 it goes to minimum distance 2 to 5 distance is 2 2 is here, machine number 3 is already a seed. So, it will go to itself. So, I can write again 3 here because 3 will go to itself, machine number 4 4 to 3 the distance is the same as 3 to 4 which is 2 4 to 5 is 6. So, 4 to 3 is 2 4 to 5 is 6 it will go to 3. So, 1 3 4 5 is a seed. So, 5 will go to itself. So, 5 will go to itself 6 3 to 6 is 5 5 to 6 is 3. So, 5 to 6 is smaller. So, 6 will go to 5. So, now, we have a solution which has 2 machine groups with 1 3 and 4 as 1 and 2 5 and 6 as another.

Now, we have to do the question of part assignment now we could go back to this matrix and quickly do the part assignment we actually observed that the solution is the same that we got for the hierarchical clustering therefore, the parts assigned will be the same if we apply the assignment rule nevertheless we repeat it. So, part 1 visits 1 3 4 and 6. So, part 1 will come here with 1 intercell move, part 2 has 2 5 and 6 so part 2 will come here, part 3 requires only 5 and 6 so part 3 will come here, part 4 requires 1 3 and 6. So, part 4 will come here another intercell move here, part 5 requires 1 4 and 5. So, part 5 will come here third intercell move, part 6 requires 1 2 3 4. So, part 6 will come here with a fourth intercell move 6 to 2, part 7 requires 2 5 6. So, 7 will come here, part 8 requires 2 5 6 8 will come here.

So, we have the solution with 4 inter cell moves and we have seen a non-hierarchical clustering algorithm the only thing that we need to do is we were able to pictorially show the seeds in the earlier case because these points were points on a 2 dimension. So, we could show the seeds, but then we cannot show the seeds in this case we will now say that 3 and 5 are the seeds and the rest of them with minimum distance with 3 and 5 will automatically.

Another way of doing it is by saying that row 3 which has 1 4 and 6 component.

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 $\frac{Seed}{3} \begin{array}{|c|c|c|} \underline{Machines} & \underline{Parts} & S_{1} = \begin{bmatrix} 1 & 0 & 0 & 1 & 0 & 0 \\ \hline 1 & 3 & 1 & 3 & 4 \\ \hline 5 & 2 & 5 & 6 \\ \hline 2 & 3 & 5 & 6 \\ \hline 2 & 3 & 7 & 8 \\ \hline non huratchical \\ Part assignment \\ rule \\ \end{array}$

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So, this algorithm that we have seen is a non-hierarchical clustering algorithm non hierarchical clustering algorithm now we have used our part assignment rule part assignment rule to create part families for a given number of machine cells.

Now, let us also try to understand the part assignment rule as a clustering rule let me explain that.

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Now, let us go back and let us write thus these 2 machine groups 1 3 4, 2 5 6. Now when we looked at the part assignment rule we said that part 1 requires 1 3 4 and 6. So, maximum is 1 3 4 here and it will create 1 intercell move. Now what we can do is now there are 8 parts now the part assignment rule can be seen as another clustering way by which these 8 parts, which are 8 points looking at the transpose of the matrix each part can be seen as a point in a 6 dimensional binaries space 0 1 space, now the part assignment rule can be seen as another cluster these 8 parts around the 2 groups and putting each part into the group which has smallest distance, the way I introduced the part assignment rule I introduced it as a way by which you take a part and put it into a group where it visits maximum number of machines.

Now, I am going to modify this redefine the part assignment rule again in the context of clustering and show how it is actually a way to cluster these 8 parts to these 2 groups. Now once we have formed these 2 groups let us say that these 2 groups are represented by 2 seed points the group itself is represented by 2 by a seed point.

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So, this will give a seed point S 1 with 1 0 1 1 0 0 and this will give a seed point S 2 with 0 1 0 0 1 1, now 1 3 and 4 gives me a seed point with 1 3 and 4 positions having a 1 and the other positions having a 0 2 5 and 6 will give me another seed with positions 2 5 and 6 having 1 and the rest of them having 0, now the nice thing about this seeds is that since each machine will figure only in 1 group each column will have 1 only in 1 place. So, now, I go back and take the first part the first part is 1 0 1 1 0 1. So, the first part P 1 and let me call it look at the column for say is 1 0 1 1 0 1.

Now, I find the distance between this and this and the distance between this and this. So, distance between seed S 1 and part P 1 is equal to the number of 0 1 or 1 0 pairs will constitute a distance of 1. So, this is a 1 1 pair 0 distance 0 distance 0 distance 0 distance 0 distance 0 distance 1 distance this will give me 1 distance. So, distance is equal to 1 let me repeat 1 and 1. So, 1 1 part distance is 0 0 0 pair distance is 0 1 1 pair distance is 0 1 1 pair distance is 0 1 1 pair distance is 0 0 1 pair distance is 1 now d S 2, P 1 is equal to 0 1 pair distance is 1 1 0 pair distance is 1 o total 2 0 1 pair, 3 0 1 pair, 4 1 0 pair, 5 1 1 0. So, total distance is 5.

So, distance between part 1 and seed 1 or group 1 is 1 distance between part 1 and seed 2 or group 2 is 5 part 1 will go to the group with which it has minimum distance. So, part 1 will go here let me show 1 more illustration and not all the 8 of them let me show one more illustration to understand this.

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So, let us write P 2 except that I am not writing them as column vectors I am writing everything consistently as a row vector 1 could write it as a column vector and map it. So, part 2 is a $0 \ 1 \ 0 \ 0 \ 1 \ 1 \ 0 \ 0 \ 1 \ 1$ is part 2. So, d S 1, P 2 is equal to 1 0 pair 1 0 1 pair 1 plus 1 2, 1 0 pair 2 plus 1 3, 1 0 pair 3 plus 1 4, 0 1 pair 4 plus 1 5, 0 1 pair 5 plus 1 6 0 0 0 1 1 0 0 0 0 0 0 1 1 0 1 1 0 1 1 0 identical so distances 0. So part 2 will go to seed 2 our group 2 with which it has to minimum distance so part two will come here. Like this we can complete it we will get the same solution 1 4 5 6, 2 3 7 8.

So our part assignment rule is essentially clustering procedure, where the part is assigned to the group with minimum distance. So the same rule can be looked in looked at in two ways if we say that each part will go to the machine group where it visits maximum machines automatically it will have minimum distance with that group. So, in simple terms the part assignment rule assigns parts to machine groups where it visits maximum number of machines, subsequent rule qualifies it better to say that in the event of it being equal or there is a tie it will visit the group with the smallest size.

It is seen as a clustering way by which part is now seen as a vector with zeros and ones and each of this group can be written as a seed and then the part vector is mapped with the seeds and then you find out which seed it has minimum distance and the part goes to that seed. So, this is the same as finding out which group it has maximum machines or which group it has maximum similarity and it goes to that group. So, the part assignment rule is a very simple way of clustering parts or assigning parts to machine groups.

So, this is how a non-hierarchical clustering algorithm works for cell formation. So, given number of groups first compute a distance matrix based on this distance rule.

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Now here the distance matrix is given similarity is not given based on this rule where dij is equal to summed over k absolute value of aik minus based on this rule, find out as many seed points as the number of groups required if more groups are required make sure that the seed points distance amongst the seed points is maximum. For example, if we need 3 groups and if had chosen 1 3 5 and 1 let us say it then we have to ensure that distance between 3 to 5 is large distance between 1 to 5 is large distance between 1 to 3 is also large.

So, that is where the real difficulty comes in finding out the correct seed points because the seed point should be chosen such that the distance amongst them all the distances are large. If seed points are chosen the 2 of them are nearby then they will attract points in a different manner and we may not get the correct set of groups, but then choose the seed points cluster the machines or rows with the seed points get machine groups either apply the part assignment rule or cluster the parts around machine groups the manner that it was described here get the part groups and while getting the part groups compute the intercell moves for a given number of groups. We also have to bear in mind that after this we have to find out ways by which the intercell moves can be reduced. So, that the implementation can be carried out, but the moment we start analyzing this with 0 1 matrices we will be concerned about minimizing the intercell moves, but we have to understand that the problem does not stop there it we have to now try and minimize the intercell moves through the ways that we had described earlier which is operation subcontracting part subcontracting, machine duplication, change in process plans etcetera.

Now that we have seen some algorithms for cell formation now are they do they provide the best solution or is there a scope for using optimization to try and get the best solution can we formulate these problems as proper optimization problems. So, far we have seen them as clustering problems can we formulate and solve them as optimization problems that approach we will seen in the next lecture.