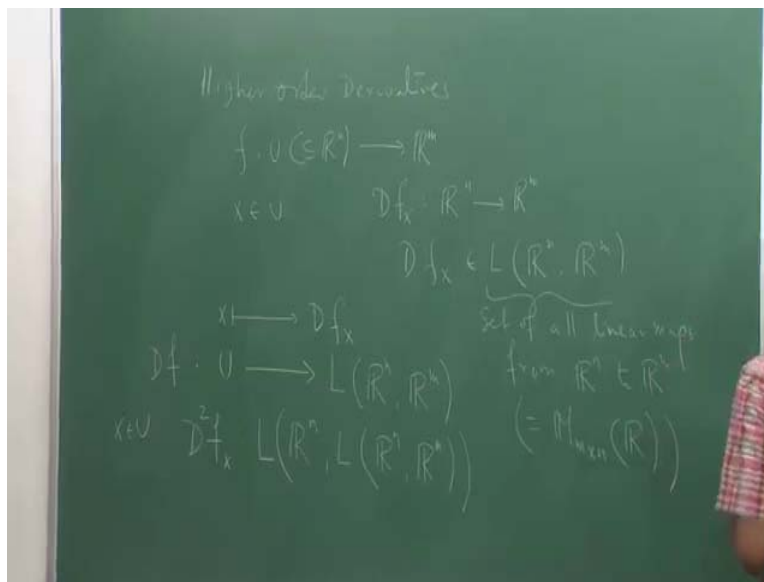


**Differential Calculus of Several Variables**  
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**Module 02**  
**Lecture No 10**  
**High Order Derivatives.**

Okay, I will come to the last lecture of this module. Here we will discuss about, well in several variables calculus you don't stop at taking first derivative, right. You then take second derivative and third derivative and finally arrive, finally you talk about function which has all derivatives and then you talk about Taylor's theorem and Taylor's formula. We will do that next week for several variables but for time being this lecture we concentrate on higher order derivatives.

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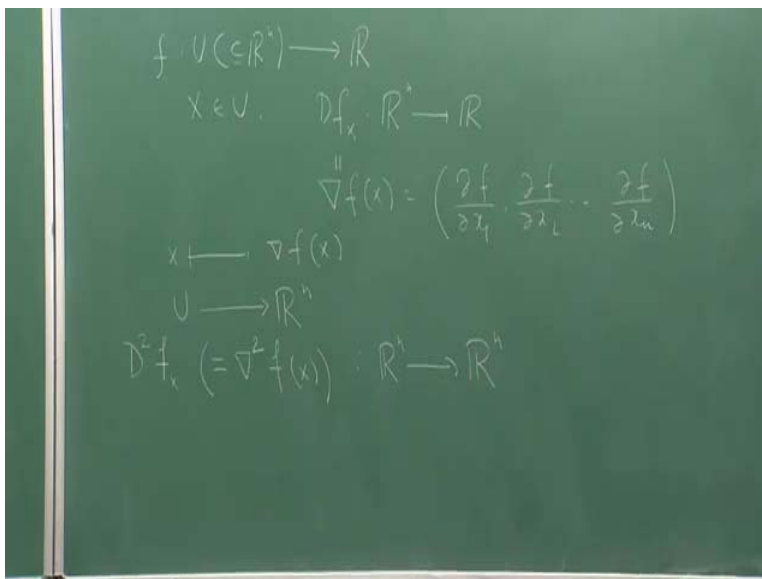
So the same setup,  $F$  is from  $U$  open connected set, maybe connectedness is not essential for this lecture  $\mathbb{R}^m$ , and we know we can define for some  $X$  in  $U$ , we can define this derivative,  $DF_X$  which is a linear map from  $\mathbb{R}^n$  to  $\mathbb{R}^m$ , let me write it in this way.  $DF_X$  belongs to  $L(\mathbb{R}^n, \mathbb{R}^m)$ , so this is the set of all linear maps from  $\mathbb{R}^n$  to  $\mathbb{R}^m$  and all in the, if I write in matrix form these are all, if I fix bases from  $\mathbb{R}^n$  and  $\mathbb{R}^m$  then this will give us all  $m$  cross matrixes, real matrixes.

So if you talk about second derivative you must consider this  $X$  going to  $DF_X$ , but now you will see this is the map from  $U$  to so  $DF$  if I call this map  $DF$ , this is the map from  $U$  to  $DF_X$  belongs to  $L$  of  $\mathbb{R}^n$  to  $\mathbb{R}^m$  which is itself a vector's space. If you now want to talk about the second derivative that is this square  $F$ , so  $X$  in  $U$ , this square  $F$  at  $X$  that is a derivative of this map, this will be a linear map from  $U$  is in  $\mathbb{R}^n$  to  $L$  of  $\mathbb{R}^n$  to  $\mathbb{R}^m$ .

Well, you see it is already matrix value, this fellow is already matrix. Now you are defining maps from  $\mathbb{R}^n$  to  $\mathbb{R}$  so it will be, again you can say it is a matrix, huge matrix where each entry is a matrix of order  $(n \times 1)$ . So total matrix will be  $M \times N$  into  $N$ . So this is very difficult to write down and people still do analysis but let us not bother too much about this thing because I think in matrix form it doesn't help much.

If you want to do some analysis you have to think of some other ways, maybe we encounter or may not in this course, but there is one thing if we take real valued function this becomes very easier.

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In the sense that suppose of  $F$  from  $U$  in  $\mathbb{R}^n$  to  $\mathbb{R}$ , real value and you know actually to talk about differentiable function in  $F$  you can write  $F$  as  $F_1 F_2 \dots F_m$  and you understand the properties or differentiability of each component  $F_i$  and then you can talk about derivative of  $F$  in terms of those. So enough to from all practical purpose if you want to talk about higher derivative you consider  $F$  from  $\mathbb{R}^n$  to  $\mathbb{R}$  and for  $\mathbb{R}^n$  to  $\mathbb{R}^m$  you start from here and then go up with the formula we have it.

But now this  $DF_x$  for  $x$  in  $U$ ,  $DF_x$  is a linear map from  $\mathbb{R}^n$  to  $\mathbb{R}$ , so this is a row vector which we have actually written as, actually it is we have fixed notation  $\text{Grad } F$  at  $x$  which is you know  $\frac{\partial F}{\partial x_1}, \frac{\partial F}{\partial x_2}, \dots, \frac{\partial F}{\partial x_n}$ , so on  $\frac{\partial F}{\partial x_1}, \dots, \frac{\partial F}{\partial x_n}$ , this is the reserved notation for  $\text{Grad}$ . So you see now  $x$  going to  $\text{Grad } F$  at  $x$ , this now a map from  $U$  which is in  $\mathbb{R}^n$  to  $\mathbb{R}^n$  again, so  $D^2$  of  $DF_x$  maybe we will write it as a special notation I don't want to use this notation because this is reserved for something else.

Okay, let me write for this course, I am not going to talk about this. This will be in a linear map from  $\mathbb{R}^N$  to  $\mathbb{R}^M$  and this I can write it as  $M$  cross  $N$  matrix, how, well,  $\text{Grad } F$  is from  $U$  to  $\mathbb{R}^N$ ,  $\text{Grad } F$  a vector in  $\mathbb{R}^N$ , now I will consider this is a function, so what I will do...

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I will write  $\text{Grad } F$  at  $X$  as, it is a  $\mathbb{R}^N$  to  $\mathbb{R}^N$ ,  $\text{del } F$  is map from  $\mathbb{R}^N$  to  $\mathbb{R}^N$  so I can write it as  $N$  component, we have done it before. Well each  $F_i$  is  $\text{Grad } F$  del  $X_i$ . Now I know what is the second derivative, derivative of this map, this is we have already known so that will be  $\text{del } F_i$ , so this will be  $\text{del } F_1$  del  $X_1$ ,  $\text{del } F_2$  del  $X_1$ , so on  $\text{del } F_N$  del  $X_1$ ,  $\text{del } F_1$  del  $X_2$ ,  $\text{del } F_2$  del  $X_2$ , del  $X_2$  so on  $\text{del } F_N$  del  $X_2$ ,  $\text{del } F_1$  del  $X_N$  so one  $\text{del } F_N$  del  $X_N$ . We know this from before because I have written. Actually this is Jacobian of this map,  $\text{del } F$  at  $X$ , correct.

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$$f: U \subseteq \mathbb{R}^n \rightarrow \mathbb{R}$$

$$\nabla^2 f(x) = \begin{pmatrix} \frac{\partial^2 f}{\partial x_1^2} & \frac{\partial^2 f}{\partial x_1 \partial x_2} & \frac{\partial^2 f}{\partial x_1 \partial x_3} \\ \frac{\partial^2 f}{\partial x_2 \partial x_1} & \frac{\partial^2 f}{\partial x_2^2} & \frac{\partial^2 f}{\partial x_2 \partial x_3} \\ \frac{\partial^2 f}{\partial x_3 \partial x_1} & \frac{\partial^2 f}{\partial x_3 \partial x_2} & \frac{\partial^2 f}{\partial x_3^2} \end{pmatrix}$$

speculation

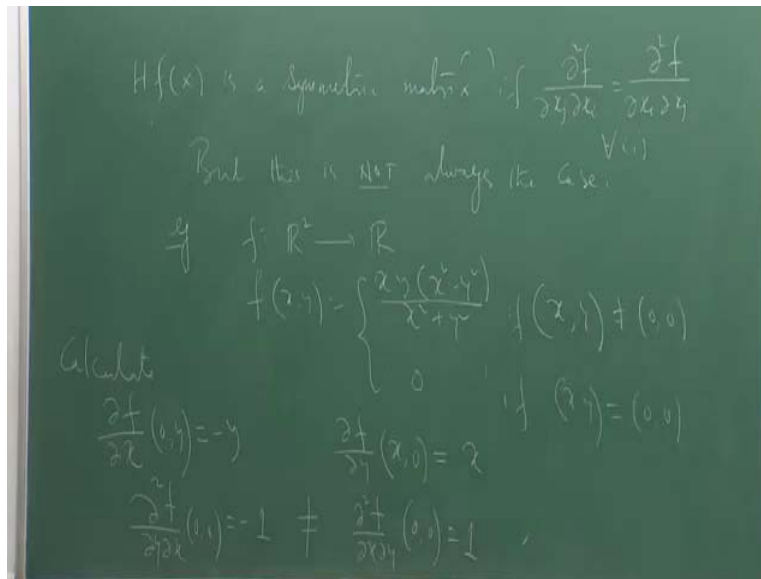
$$= \left( \frac{\partial^2 f}{\partial x_i \partial x_j} \right)_{\substack{i=1 \\ j=1}}^n$$

$(= H_f(x))$   
Hessian of  $f$  at  $x$

But now I know what is FI, so this matrix will be, I can write it as, I don't have place to write here, maybe I go back to that board. So let me keep the setup, so Grad square F at X is, now I write what is definition of FI, F1 is Grad F del X1, so del square F, del X1 del X1, del X1 square, del F2 is, del F del X2, so that is del X1 del X2 so on, del X del X1 del XN, next del F del X1 del X2, del square, del square F del X2 square, so one del square F del X2 del XN, del square F del X1 del XN so one del square F del XN square.

Which is written as del FI, sorry, del F, del X JXI, I equal to 1 to N, J equal to 1 to N. Some books use a special notation for this, special notation for this we will use it in our next calculation next time, it is called H F at X and written as Hession. Okay, so if you don't remember which way to follow del XJ or del Xi, always go back to this way, that you write del FX is equal to F1 F2 FN, FI equal to this thing and then apply the derivative formula, so there is nothing much to remember here. In one minute you can just write it down if you know, how to write a derivative of a map from RN to RM by component wise. Now this matrix has this property. You see 1 2 (( ))(11:25) del X2 del X1, and 21 (( ))(11:29) del X1 del X2 so order is changed.

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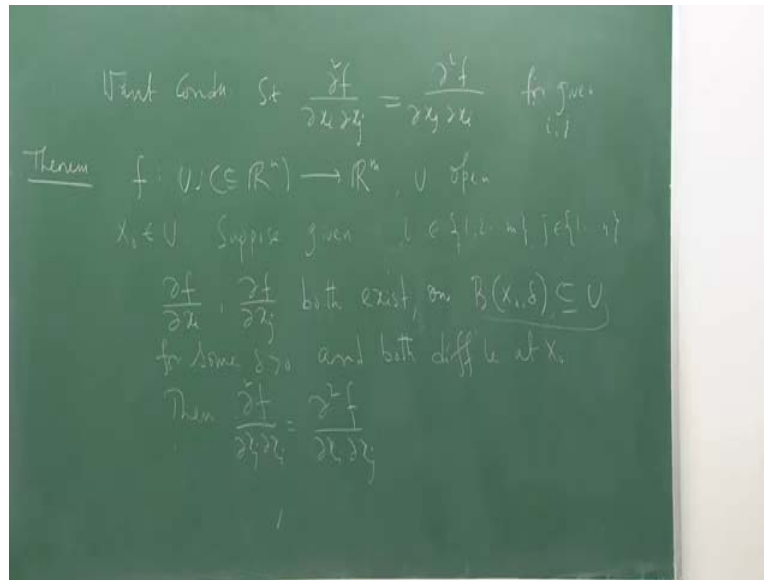
So what I can see from here is that this matrix  $H$  is a symmetric matrix if the square of the mixed partial derivatives are equal to the square of the mixed partial derivatives for all  $i, j$ . So if the mixed partial derivatives are equal, they are called mixed partial derivatives. They are two different components involved, if changing the order are equal then the matrix becomes symmetric.

But this is not always the case. For example, I give you a very elementary example, let us say  $f$  from entire  $\mathbb{R}^2$  to  $\mathbb{R}$ ,  $f$  of  $(x,y)$  equal to  $x^2 - y^2$  divided by  $x^2 + y^2$  when  $x$  and  $y$  both are not equal to 0, and 0 at the origin. What you can calculate here, so do this calculation yourself that the mixed partial derivative of  $f$  with respect to  $x$ , this is equal to, you just calculate it, the mixed partial derivative of  $f$  with respect to  $x$  equal to, well let us calculate it doesn't matter.

Let us calculate it at  $(0,0)$ , this will be equal to  $-y$ . So the mixed partial derivative of  $f$  with respect to  $y$  and  $x$  at  $(0,0)$  so you verify this calculation is equal to  $-1$ , whereas the mixed partial derivative of  $f$  with respect to  $x$  and  $y$  at  $(0,0)$ , this will be  $x$ , so the mixed partial derivative of  $f$  with respect to  $x$  and  $y$  this will be equal to  $1$ , clearly these two are not equal so the mixed partial derivative of  $f$  with respect to  $x$  and  $y$  at  $(0,0)$  they are not equal, one is  $-1$  and the other is  $1$ . You do this calculation very easily (14:31) to do the derivative.

But this is not a very nice situation for us, to go ahead with calculation to go ahead with calculus, we want the mixed partial derivatives to be equal so that I get this matrix symmetric. It becomes very handy when you, next time we talk about Taylor's theorem and also when you talk about maximum and minimum real valued function. So come up with certain criteria to check maximum and minimum this symmetric is essential otherwise it gets total mess.

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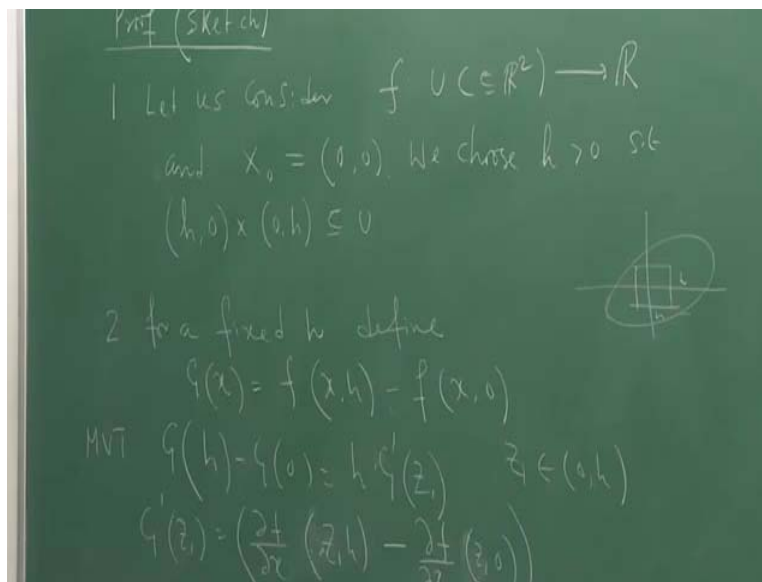
So we actually want condition for equality of mixed partial derivative. So we want condition such that  $\frac{\partial^2 f}{\partial x_i \partial x_j} = \frac{\partial^2 f}{\partial x_j \partial x_i}$  and  $\frac{\partial^2 f}{\partial x_i \partial x_j} = \frac{\partial^2 f}{\partial x_j \partial x_i}$  for given  $i, j$ . Let me state it as a theorem. I state it for  $f$  from  $U$ , I state it more general,  $\mathbb{R}^n$  into  $\mathbb{R}^m$ ,  $U$  is open connected state but open is enough here. Condition says, so let's fix a point, I want to always check at a point, suppose given  $i$  and  $j$ , given  $i$  from  $1$  to  $m$  and  $j$  from  $1$  to  $n$ ,  $\frac{\partial f}{\partial x_i}, \frac{\partial f}{\partial x_j}$  both exist on a ball around  $x_0$ . That is for all points in the ball around  $x_0$  for some  $\delta$ .

See when  $x_0$  not in  $U$  and  $U$  is open there will be always a ball but I want a ball such that this  $\frac{\partial f}{\partial x_i}$  and  $\frac{\partial f}{\partial x_j}$  both exist on the entire ball, not only at  $x_0$ , on the entire ball for some  $\delta$  greater than  $0$  and both differentiable at  $x_0$ , that is  $\frac{\partial f}{\partial x_i}$  and  $\frac{\partial f}{\partial x_j}$  differentiable at  $x_0$ . Then  $\frac{\partial^2 f}{\partial x_i \partial x_j} = \frac{\partial^2 f}{\partial x_j \partial x_i}$  equal to  $\frac{\partial^2 f}{\partial x_j \partial x_i}$ , mixed partial derivative at equal.

So what is the condition they must be of course, this must two must exist so they must be differentiable at  $x_0$ , but the condition is there both exist. I missed most important, and continuous. Why I did not write because I am saying that there is a differentiable but differentiable  $x_0$  means it is already continuous at  $x_0$  but I want it continuous on the entire  $B(x_0, \delta)$ , but, if anyways, you can have this or may not have this, continuity of  $x_0$  is not enough.

But it has to exist on the entire ball that is important, so you add  $N$  continuous or not it does not make any difference, that is what I mean. Okay, the proof is little long and the proof is not going to, we are not going to use the entire idea of the proof anyway. But still you need a proof once you write a statement.

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So what I write here is proof, but I will write a sketchy proof. I will give you the idea of the proof you complete the lines in between. Okay. Do the sketching and you go like this. First may your reduction that I am only concerned about 2, XI given XI and XJ, so let us only consider because nothing to be changed for R1 and RM, F from You in R2 because two variables are involved at R. For RM what you do you apply component wise, two variables are involved do R2 is enough. If we have RN you do component wise.

Okay and without loss of generality (20:09) your  $x$  not is  $0, 0$ , this is just to make the calculation easy, because  $U$  is any set in  $\mathbb{R}^2$ , here is the origin but you can always shift origin such a way that  $0, 0$  belongs here. There is a transformation of origin and that does not change any property differentiability, continuity anything.

So we choose, we want to go into (20:41) hypothesis so some  $H$  greater than  $0$  such that  $H > 0$  cross  $0, H$ , this set is in  $U$ , so here is my  $U$  from You around origin I choose  $H$  such that this square of length  $H$  and height  $H$ , this is completely named. With that what you do, for a fixed  $H$  define  $G$  of  $x$  equal to  $F$  of  $x, H$  minus  $F$  of  $x, 0$ .

Then we apply Mean Value theorem to get, this is equal to  $H$  into  $G'$  prime at some  $Z_1$ , right.  $Z_1$  is  $0$  to  $H$ , but immediately you can write  $G'$  prime  $Z_1$  equal to  $\frac{\partial F}{\partial x}$  at  $Z_1, H$  minus  $\frac{\partial F}{\partial x}$  at  $Z_1, 0$  and apply the definition of what is  $\frac{\partial F}{\partial x}$ ? That was my second step. See verify all those steps, I am not writing the entire proof.

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$$3. \frac{\partial^2 f}{\partial z^2}(z, h) - \frac{\partial^2 f}{\partial z^2}(z, 0) - \frac{\partial^2 f}{\partial z^2}(0, 0)z + h \frac{\partial^2 f}{\partial z^2}(0, 0) + (12 \dots) E_1(h)$$

$$E_1(h) \rightarrow 0 \text{ as } h \rightarrow 0$$

$$4. \frac{f(h) - f(0)}{h^2} \xrightarrow{h \rightarrow 0} \frac{\partial^2 f}{\partial z^2}(0, 0) \left\{ \begin{array}{l} f(h) - f(0) \\ = g_1(h) - g_1(0) \end{array} \right.$$

$$5. g_1(h) = f(h, 0) - f(0, 0)$$

$$\frac{g_1(h) - g_1(0)}{h^2} \xrightarrow{h \rightarrow 0} \frac{\partial^2 f}{\partial z^2}(0, 0)$$

Third step is you again write  $\frac{\partial^2 f}{\partial x^2}$  as applying MVT  $\frac{\partial^2 f}{\partial x^2}$  at  $(0, 0)$  at  $Z$ , not applying, applying the condition of derivative, sorry, applying this is differentiable,  $\frac{\partial^2 f}{\partial x^2}$  at  $(0, 0)$  as  $\frac{\partial^2 f}{\partial x^2}$  at  $(0, 0)$  plus  $H$  into  $\frac{\partial^2 f}{\partial x^2}$  at  $(0, 0)$  plus mod  $Z$   $H$  into  $(0, 0)$  (23:58)  $U$  and  $H$ ,  $U$  and  $H$  will go to 0 as  $H$  goes to 0 because as  $H$  goes to 0  $Z$  also goes to 0,  $Z$  is between 0 and  $H$ .

Okay, from that what we do, we calculate  $G(H) - G(0)$  it will come out to be  $\frac{\partial^2 f}{\partial x^2}$  del, okay, let me skip this step because this need some technicality, what I actually want to show is that this divided by  $H^2$  this goes to  $\frac{\partial^2 f}{\partial x^2}$  by  $\frac{\partial^2 f}{\partial x^2}$  at  $(0, 0)$ . And what you do in the next step you repeat the entire thing by defining  $G_1(Y) = f(H, Y) - f(H, 0)$ , so here I take  $XH$   $XO$  with  $X$  and I did  $G_1$  and  $G_2$ .

And you again show by the same step  $G_1(H) - G_1(0)$  divided by  $H^2$ , it will be just ultra, just other way round, sorry, this goes to 0, this thing as  $H$  goes to 0, this as  $H$  goes to 0 and final observation is  $G(H) - G(0) = G_1(H) - G_1(0)$ , so this two Limits will be equal because numerator are equal denominators are  $H^2$ , so there is the idea of the proof. You fill up the details.

Thank you!