

MATH2010E LECTURE 12: IMPLICIT FUNCTION THEOREM

1. INTRODUCTION

Recall that we have already discussed the following situation: Let $F(x, y) = 0$ be an implicit function with F being a C^1 map from \mathbb{R}^2 to \mathbb{R} . Then we have the formula

$$(1.1) \quad \frac{dy}{dx} = -\frac{F_x}{F_y}$$

when $F_y \neq 0$. This shows us that y can be written as a function of x near a point p if and only if $F_y(p) \neq 0$.

Let us also recall that the way we obtain (1.1). Suppose there exists a variable s with $x = s$ and $y = y(s)$, we have

$$(1.2) \quad F_x + F_y \frac{dy}{dx} = 0$$

by using the chain rule. In the following paragraphs we will generalize this equation.

Let $F : \mathbb{R}^{m+n} \rightarrow \mathbb{R}^n$ be a C^1 function. So for any $x \in \mathbb{R}^m$, $y \in \mathbb{R}^n$, we can write $F(x, y) = (f_1(x, y), f_2(x, y), \dots, f_n(x, y))$ with all $f_i : \mathbb{R}^{m+n} \rightarrow \mathbb{R}$ are C^1 .

Now, let us suppose that there exist parameters s_1, \dots, s_n with $x_i = s_i$ and $y = y(s_1, \dots, s_n)$. Under this setting, we have

$$(1.3) \quad \begin{aligned} \frac{\partial F}{\partial s_i} &= \begin{pmatrix} \frac{\partial f_1}{\partial x_i} & \frac{\partial f_1}{\partial s_i} \\ \frac{\partial f_2}{\partial x_i} & \frac{\partial f_2}{\partial s_i} \\ \vdots & \vdots \\ \frac{\partial f_n}{\partial x_i} & \frac{\partial f_n}{\partial s_i} \end{pmatrix} + \begin{pmatrix} \frac{\partial f_1}{\partial y_1} \frac{\partial y_1}{\partial s_i} & \dots & \frac{\partial f_1}{\partial y_n} \frac{\partial y_n}{\partial s_i} \\ \frac{\partial f_2}{\partial y_1} \frac{\partial y_1}{\partial s_i} & \dots & \frac{\partial f_2}{\partial y_n} \frac{\partial y_n}{\partial s_i} \\ \vdots & \vdots & \vdots \\ \frac{\partial f_n}{\partial y_1} \frac{\partial y_1}{\partial s_i} & \dots & \frac{\partial f_n}{\partial y_n} \frac{\partial y_n}{\partial s_i} \end{pmatrix} \\ &= F_x + [F_y] \begin{pmatrix} \frac{\partial y_1}{\partial x_i} \\ \frac{\partial y_2}{\partial x_i} \\ \vdots \\ \frac{\partial y_n}{\partial x_i} \end{pmatrix} = 0 \end{aligned}$$

for any $i = 1, 2, \dots, n$. Here $[F_y]$ is a matrix value function defined as the following

$$(1.4) \quad [F_y] = \begin{pmatrix} \frac{\partial f_1}{\partial y_1} & \dots & \frac{\partial f_1}{\partial y_n} \\ \frac{\partial f_2}{\partial y_1} & \dots & \frac{\partial f_2}{\partial y_n} \\ \vdots & \vdots & \vdots \\ \frac{\partial f_n}{\partial y_1} & \dots & \frac{\partial f_n}{\partial y_n} \end{pmatrix}.$$

To obtain (1.1) from (1.2), divide the both sides of (1.1) by F_y when it is non zero. In this general case, the situation is similar. We have to "divide" (1.3) by $[F_y]$.

This idea leads the following theorem.

Theorem 1.1. *Let $F \in C^1$. Suppose $[F_y]$ is invertible at a point p , then we can write y as a function of x near p and*

$$(1.5) \quad \frac{\partial y}{\partial x_i} = \begin{pmatrix} \frac{\partial y_1}{\partial x_i} \\ \frac{\partial y_2}{\partial x_i} \\ \vdots \\ \frac{\partial y_n}{\partial x_i} \end{pmatrix} = -[F_y]^{-1} F_x$$

One simple example we can think of is the implicit function of n -dimensional unit sphere S^n .

$$(1.6) \quad S^n = \{x_1^2 + x_2^2 + \cdots + x_n^2 - 1 = 0\}.$$

We can see that by the implicit function theorem: If $F_{x_i}(p)$ is non zero for some $i = 1, 2, \dots, n$, then x_i can be written as the function of other variables. So at $p = (0, 0, \dots, 1, 0, \dots, 0)$ which has 0 for all but i -th component, $F_{x_k}(p) = 0$ for all $k \neq i$ and $F_{x_i}(p) = 2$. In this case, we can conclude that x_i can be written as a function of other variables.

2. PROOF

Proof. Here we only prove the case that F is a C^∞ (This assumption can actually be changed to $F \in C^1$). Also, in our proof, we always write F as a column vector.

Let $p = (p_1, p_2) \in \mathbb{R}^{m+n}$. for any $x \in \mathbb{R}^m$ near p_1 , we can write down following formula by the error bound estimate.

$$(2.1) \quad 0 = F(x, y) = F(x, p_2) + [F_y](x, p_2)(y - p_2)^t + E_2(y)$$

where $|E_2(y)| \leq C|y - p_2|^2$.

Recall by the assumption in the statement of Theorem 1.1, the matrix $[F_y](p)$ is invertible, so for any x which is sufficiently close to p_1 , $[F_y](x, p_2)$ is invertible. Therefore, we have

$$(2.2) \quad (y - p_2)^t = [F_y]^{-1}(x, p_2)F(x, p_2) + [F_y]^{-1}(x, p_2)E_2(y).$$

Not that the last term $[F_y]^{-1}(x, p_2)E_2(y)$ is still bounded by some $C|y - p_2|^2$. We denote $[F_y]^{-1}(x, p_2)E_2(y)$ by $G(y - p_2)$. So by taking $y \in \mathbb{R}^n$ also sufficiently close to p_2 , we have $|G(y - p_2)| \leq \frac{1}{100}|y - p_2|$.

Now, (1.8) implies that

$$(2.3) \quad (I - G)(y - p_2) = [F_y]^{-1}(x, p_2)F(x, p_2).$$

Here we claim that $(I - G)$ gives us the 1-1 map near p_2 . So we can define the $(I - G)(y - p_2) = y' - p_2$ and obtain the map from x to y' near the point p . Therefore, we prove this theorem. \square

To show $(I - G)$ is 1-1, it is actually an implication of a fixed point theorem. I will prove this in a moment. However, we can easily be convinced by this claim, because I is 1-1 and G is a such small error term.

To prove that $I - G$ is one to one, we can see this from the inequality

$$(2.4) \quad |(I - G)(y_1 - p_2) - (I - G)(y_2 - p_2)| \geq |y_1 - y_2| - |G||y_1 - y_2| \geq |y_1 - y_2|.$$

To prove $I - G$ is onto, we take any q near p_2 fixed. Then we want to find y such that

$$(2.5) \quad G(y) + q = y.$$

Let us consider $B_\delta(p_2)$ with $\delta > 2 \operatorname{dist}(q, p_2)$. Then $G(y) + q \in B_\delta(p_2)$ for any $y \in B_\delta(p_2)$. Therefore, if we start with any $y_0 \in B_\delta(p_2)$ and consider the sequence

$$(2.6) \quad y_i = G(y_{i-1}) + q.$$

we can see that $|y_i - y_{i+1}| \leq \frac{1}{100}|y_{i-1} - y_i|$. So $\{y_i\}$ converges to some y with $y = G(y) + q$. This proves (1.11)