The Contraction Mapping Theorem and the Implicit and Inverse Function Theorems

The Contraction Mapping Theorem

Theorem (The Contraction Mapping Theorem) Let $B_a = \{ \vec{x} \in \mathbb{R}^d \mid ||\vec{x}|| < a \}$ denote the open ball of radius a centred on the origin in \mathbb{R}^d . If the function

$$\vec{g}: B_a \to \mathbb{R}^d$$

obeys

(H1) there is a constant G < 1 such that $\|\vec{g}(\vec{x}) - \vec{g}(\vec{y})\| \le G \|\vec{x} - \vec{y}\|$ for all $\vec{x}, \vec{y} \in B_a$ (H2) $\|\vec{g}(\vec{0})\| < (1-G)a$

then the equation

 $\vec{x} = \vec{g}(\vec{x})$

has exactly one solution.

Discussion of hypothesis (H1): Hypothesis (H1) is responsible for the word "Contraction" in the name of the theorem. Because G < 1 (and it is crucial that G is strictly smaller than 1) the distance between the images $\vec{g}(\vec{x})$ and $\vec{g}(\vec{y})$ of \vec{x} and \vec{y} is strictly smaller than the original distance between \vec{x} and \vec{y} . Thus the function g contracts distances. Note that, when the dimension d = 1 and the function g is C^1 ,

$$|g(x) - g(y)| = \left| \int_{x}^{y} g'(t) \, dt \right| \le \left| \int_{x}^{y} |g'(t)| \, dt \right| \le \left| \int_{x}^{y} \sup_{t' \in B_{a}} |g'(t')| \, dt \right| = |x - y| \sup_{t' \in B_{a}} |g'(t')|$$

For a once continuously differentiable function, the smallest G that one can pick and still have $|g(x) - g(y)| \leq G|x - y|$ for all x, y is $G = \sup_{t' \in B_a} |g'(t')|$. In this case (H1) comes down to the requirement that there exist a constant G < 1 such that $|g'(t)| \leq G < 1$ for all $t' \in B_a$. For dimensions d > 1, one has a whole matrix $\mathcal{G}(\vec{x}) = \left[\frac{\partial g_i}{\partial x_j}(\vec{x})\right]_{1 \leq i,j \leq d}$ of first partial derivatives. There is a measure of the size of this matrix, called the norm of the matrix and denoted $\|\mathcal{G}(\vec{x})\|$ such that

$$\left\|\vec{g}(\vec{x}) - \vec{g}(\vec{y})\right\| \le \left\|\vec{x} - \vec{y}\right\| \sup_{\vec{t} \in B_a} \left\|\mathcal{G}(\vec{t})\right\|$$

Once again (H1) comes down to $\|\mathcal{G}(\vec{t})\| \leq G < 1$ for all $\vec{t} \in B_a$. Roughly speaking, (H1) forces the derivative of \vec{g} to be sufficiently small, which forces the derivative of $\vec{x} - \vec{g}(\vec{x})$ to be bounded away from zero.

If we were to relax (H1) to $G \leq 1$, the theorem would fail. For example, g(x) = x obeys |g(x) - g(y)| = |x - y| for all x and y. So G would be one in this case. But every x obeys g(x) = x, so the solution is certainly not unique.

Discussion of hypothesis (H2): If \vec{g} only takes values that are outside of B_a , then $\vec{x} = \vec{g}(\vec{x})$ cannot possibly have any solutions. So there has to be a requirement that $\vec{g}(\vec{x})$ lies in B_a for at least some values of $\vec{x} \in B_a$. Our hypotheses are actually somewhat stronger than this:

$$\|\vec{g}(\vec{x})\| = \|\vec{g}(\vec{x}) - \vec{g}(\vec{0}) + \vec{g}(\vec{0})\| \le \|\vec{g}(\vec{x}) - \vec{g}(\vec{0})\| + \|\vec{g}(\vec{0})\| \le G\|\vec{x} - \vec{0}\| + (1 - G)a$$

by (H1) and (H2). So, for all \vec{x} in B_a , that is, all \vec{x} with $\|\vec{x}\| < a$, $\|\vec{g}(\vec{x})\| < Ga + (1-G)a = a$. With our hypotheses $\vec{g} : B_a \to B_a$. Roughly speaking, (H2) requires that $\vec{g}(\vec{x})$ be sufficiently small for at least one \vec{x} .

If we were to relax (H2) to $\|\vec{g}(\vec{0})\| \leq (1-G)a$, the theorem would fail. For example, let d = 1, pick any a > 0, 0 < G < 1 and define $g : B_a \to \mathbb{R}$ by g(x) = a(1-G) + Gx. Then g'(x) = G for all x and g(0) = a(1-G). For this g,

$$g(x) = x \quad \iff \quad a(1-G) + Gx = x \quad \iff \quad a(1-G) = (1-G)x \quad \iff \quad x = a$$

As x = a is not in the domain of definition of g, there is no solution.

Proof that there is at most one solution: Suppose that \vec{x}^* and \vec{y}^* are two solutions. Then

$$\begin{aligned} \vec{x}^* &= \vec{g}(\vec{x}^*), \ \vec{y}^* &= \vec{g}(\vec{y}^*) \implies \|\vec{x}^* - \vec{y}^*\| = \|\vec{g}(\vec{x}^*) - \vec{g}(\vec{y}^*)\| \\ \stackrel{\text{(H1)}}{\implies} &\|\vec{x}^* - \vec{y}^*\| \le G \|\vec{x}^* - \vec{y}^*\| \\ \implies & (1 - G) \|\vec{x}^* - \vec{y}^*\| = 0 \end{aligned}$$

As G < 1, 1 - G is nonzero and $\|\vec{x}^* - \vec{y}^*\|$ must be zero. That is, \vec{x}^* and \vec{y}^* must be the same.

Proof that there is at least one solution: Set

$$\vec{x}_0 = 0$$
 $\vec{x}_1 = \vec{g}(\vec{x}_0)$ $\vec{x}_2 = \vec{g}(\vec{x}_1)$ \cdots $\vec{x}_n = \vec{g}(\vec{x}_{n-1})$ \cdots

We showed in "Significance of hypothesis (H2)" that $\vec{g}(\vec{x})$ is in B_a for all \vec{x} in B_a . So $\vec{x}_0, \vec{x}_1, \vec{x}_2, \cdots$ are all in B_a . So the definition $\vec{x}_n = \vec{g}(\vec{x}_{n-1})$ is legitimate. We shall show that the sequence $\vec{x}_0, \vec{x}_1, \vec{x}_2, \cdots$ converges to some vector $\vec{x}^* \in B_a$. Since \vec{g} is continuous, this vector will obey

$$\vec{x}^* = \lim_{n \to \infty} \vec{x}_n = \lim_{n \to \infty} \vec{g}(\vec{x}_{n-1}) = \vec{g}\left(\lim_{n \to \infty} \vec{x}_{n-1}\right) = \vec{g}(\vec{x}^*)$$

In other words, \vec{x}^* is a solution of $\vec{x} = \vec{g}(\vec{x})$.

To prove that the sequence converges, we first observe that, applying (H1) numerous times,

$$\begin{aligned} \|\vec{x}_{m} - \vec{x}_{m-1}\| &= \|\vec{g}(\vec{x}_{m-1}) - \vec{g}(\vec{x}_{m-2})\| \\ &\leq G \|\vec{x}_{m-1} - \vec{x}_{m-2}\| &= G \|\vec{g}(\vec{x}_{m-2}) - \vec{g}(\vec{x}_{m-3})\| \\ &\leq G^{2} \|\vec{x}_{m-2} - \vec{x}_{m-3}\| &= G^{2} \|\vec{g}(\vec{x}_{m-3}) - \vec{g}(\vec{x}_{m-4})\| \\ &\vdots \\ &\leq G^{m-1} \|\vec{x}_{1} - \vec{x}_{0}\| &= G^{m-1} \|\vec{g}(\vec{0})\| \end{aligned}$$

Remember that G < 1. So the distance $\|\vec{x}_m - \vec{x}_{m-1}\|$ between the $(m-1)^{\text{st}}$ and m^{th} entries in the sequence gets really small for m large. As

$$\vec{x}_n = \vec{x}_0 + (\vec{x}_1 - \vec{x}_0) + (\vec{x}_2 - \vec{x}_1) + \dots + (\vec{x}_n - \vec{x}_{n-1}) = \sum_{m=1}^n (\vec{x}_m - \vec{x}_{m-1})$$

(recall that $\vec{x}_0 = \vec{0}$) it suffices to prove that $\sum_{m=1}^n (\vec{x}_m - \vec{x}_{m-1})$ converges as $n \to \infty$. To do so it suffices to prove that $\sum_{m=1}^n ||\vec{x}_m - \vec{x}_{m-1}||$ converges as $n \to \infty$, which we do now.

$$\sum_{m=1}^{n} \left\| \vec{x}_m - \vec{x}_{m-1} \right\| \le \sum_{m=1}^{n} G^{m-1} \| \vec{g}(\vec{0}) \| = \frac{1 - G^n}{1 - G} \| \vec{g}(\vec{0}) \|$$

As *n* tends to ∞ , G^n converges to zero (because $0 \le G < 1$) and $\frac{1-G^n}{1-G} \|\vec{g}(\vec{0})\|$ converges to $\frac{1}{1-G} \|\vec{g}(\vec{0})\|$. Hence \vec{x}_n converges to some \vec{x}^* as $n \to \infty$. As

$$\|\vec{x}^*\| \le \sum_{m=1}^{\infty} \|\vec{x}_m - \vec{x}_{m-1}\| \le \frac{1}{1-G} \|\vec{g}(\vec{0})\| < \frac{1}{1-G} (1-G)a = a$$

 \vec{x}^* is in B_a .

Generalization: The same argument proves the following generalization:

Let X be a complete metric space, with metric d, and $g: X \to X$. If there is a constant $0 \leq G < 1$ such that

$$d(g(x), g(y)) \le G d(x, y)$$
 for all $x, y \in X$

then there exists a unique $x \in X$ obeying g(x) = x.

Aliases: The "contraction mapping theorem" is also known as the "Banach fixed point theorem" and the "contraction mapping principle".

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The Implicit Function Theorem

As an application of the contraction mapping theorem, we now prove the implicit function theorem. Consider some C^{∞} function $\vec{f}(\vec{x}, \vec{y})$ with \vec{x} running over \mathbb{R}^n , \vec{y} running over \mathbb{R}^d and \vec{f} taking values in \mathbb{R}^d . Suppose that we have one point (\vec{x}_0, \vec{y}_0) on the surface $\vec{f}(\vec{x}, \vec{y}) = 0$. In other words, suppose that $\vec{f}(\vec{x}_0, \vec{y}_0) = 0$. And suppose that we wish to solve $\vec{f}(\vec{x}, \vec{y}) = 0$ for \vec{y} as a function of \vec{x} near (\vec{x}_0, \vec{y}_0) . First observe that for each fixed \vec{x} , $\vec{f}(\vec{x}, \vec{y}) = 0$ is a system of d equations in d unknowns. So at least the number of unknowns matches the number of equations. By way of motivation, let's expand the equations in powers of $\vec{x} - \vec{x}_0$ and $\vec{y} - \vec{y}_0$. The i^{th} equation (with $1 \le i \le d$) is then

$$0 = f_i(\vec{x}, \vec{y}) = f_i(\vec{x}_0, \vec{y}_0) + \sum_{j=1}^n \frac{\partial f_i}{\partial x_j} (\vec{x}_0, \vec{y}_0) (\vec{x} - \vec{x}_0)_j + \sum_{j=1}^d \frac{\partial f_i}{\partial y_j} (\vec{x}_0, \vec{y}_0) (\vec{y} - \vec{y}_0)_j + \text{h.o.}$$

where h.o. denotes terms of degree at least two. Equivalently

$$A(\vec{y} - \vec{y}_0) = b$$

where A denotes the $d \times d$ matrix $\left[\frac{\partial f_i}{\partial y_j}(\vec{x}_0, \vec{y}_0)\right]_{1 \le i,j \le d}$ of first partial \vec{y} derivatives of \vec{f} at (\vec{x}_0, \vec{y}_0) and

$$b_i = -\sum_{j=1}^n \frac{\partial f_i}{\partial x_j} (\vec{x}_0, \vec{y}_0) (\vec{x} - \vec{x}_0)_j - \text{h.o.}$$

For (\vec{x}, \vec{y}) very close to (\vec{x}_0, \vec{y}_0) the higher order contributions h.o. will be very small. If we approximate by dropping h.o. completely, then the right hand side \vec{b} becomes a constant (remember that are trying to solve for \vec{y} when \vec{x} is viewed as a constant) and there is a unique solution if and only if A has an inverse. The unique solution is then $\vec{y} = \vec{y}_0 + A^{-1}\vec{b}$.

Now return to the problem of solving $\vec{f}(\vec{x}, \vec{y}) = 0$, without making any approximations. Assume that the matrix A exists and has an inverse. When d = 1, A is invertible if and only if $\frac{\partial f}{\partial y}(x_0, \vec{y}_0) \neq 0$. For d > 1, A is invertible if and only if 0 is not an eigenvalue of Aor, equivalently, if and only if det $A \neq 0$. In any event, assuming that A^{-1} exists,

$$\vec{f}(\vec{x},\vec{y}) = 0 \quad \iff \quad A^{-1}\vec{f}(\vec{x},\vec{y}) = 0 \quad \iff \quad \vec{y} - \vec{y}_0 = \vec{y} - \vec{y}_0 - A^{-1}\vec{f}(\vec{x},\vec{y})$$

(If you expand in powers of $\vec{x} - \vec{x}_0$ and $\vec{y} - \vec{y}_0$, you'll see that the right hand side is exactly $A^{-1}\vec{b}$, including the higer order contributions.) This re-expresses our equation in a form to which we may apply the contraction mapping theorem. Precisely, rename $\vec{y} - \vec{y}_0 = \vec{z}$ and define $\vec{g}(\vec{x}, \vec{z}) = \vec{z} - A^{-1}\vec{f}(\vec{x}, \vec{z} + \vec{y}_0)$. Then

$$\vec{f}(\vec{x}, \vec{y}) = 0 \quad \iff \quad \vec{y} = \vec{y}_0 + \vec{z} \text{ and } \vec{g}(\vec{x}, \vec{z}) = \vec{z}$$

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Fix any \vec{x} sufficiently near \vec{x}_0 . Then $\vec{g}(\vec{x}, \vec{z})$ is a function of \vec{z} only and one may apply the contraction mapping theorem to it.

We must of course check that the hypotheses are satisfied. Observe first, that when $\vec{z} = \vec{0}$ and $\vec{x} = \vec{x}_0$, the matrix $\left[\frac{\partial g_i}{\partial z_j}(\vec{x}_0, \vec{0})\right]_{1 \le i,j \le d}$ of first derivatives of \vec{g} is exactly $1 - A^{-1}A$, where 1 is the identity matrix. The identity 1 arises from differentiating the term \vec{z} in $\vec{g}(\vec{x}_0, \vec{z}) = \vec{z} - A^{-1}\vec{f}(\vec{x}_0, \vec{z} + \vec{y}_0)$ and $-A^{-1}A$ arises from differentiating $-A^{-1}\vec{f}(\vec{x}_0, \vec{z} + \vec{y}_0)$. So $\left[\frac{\partial g_i}{\partial z_j}(\vec{x}_0, \vec{0})\right]_{1 \le i,j \le d}$ is exactly the zero matrix. For (\vec{x}, \vec{z}) sufficiently close to $(\vec{x}_0, \vec{0})$, the matrix $\left[\frac{\partial g_i}{\partial z_j}(\vec{x}, \vec{z})\right]_{1 \le i,j \le d}$ will, by continuity, be small enough that (H1) is satisfied. This is because, for any $\vec{u}, \vec{v} \in \mathbb{R}^d$, and any $1 \le i \le d$,

$$g_i(\vec{x}, \vec{u}) - g_i(\vec{x}, \vec{v}) = \int_0^1 \frac{d}{dt} g_i\left(\vec{x}, t\vec{u} + (1-t)\vec{v}\right) dt = \sum_{j=1}^d \int_0^1 \left(u_j - v_j\right) \frac{\partial g_i}{\partial z_j} \left(\vec{x}, t\vec{u} + (1-t)\vec{v}\right) dt$$

so that

$$\left| g_i(\vec{x}, \vec{u}) - g_i(\vec{x}, \vec{v}) \right| \le d \| \vec{u} - \vec{v} \| \max_{\substack{0 \le t \le 1 \\ 1 \le j \le d}} \left| \frac{\partial g_i}{\partial z_j} (\vec{x}, t\vec{u} + (1-t)\vec{v}) \right|$$

and

$$\left\|\vec{g}(\vec{x},\vec{u}) - \vec{g}(\vec{x},\vec{v})\right\| \le \Gamma \|\vec{u} - \vec{v}\| \quad \text{with} \quad \Gamma = d^2 \max_{\substack{0 \le t \le 1\\ 1 \le j \le d}} \left|\frac{\partial g_i}{\partial z_j} \left(\vec{x}, t\vec{u} + (1-t)\vec{v}\right)\right|$$

By continuity, we may choose a > 0 small enough that $\Gamma \leq \frac{1}{2}$ whenever $\|\vec{x} - \vec{x}_0\|$, $\|\vec{u}\|$ and $\|\vec{v}\|$ are all smaller than a. Also observe that $\vec{g}(\vec{x}_0, \vec{0}) = -A^{-1}\vec{f}(\vec{x}_0, \vec{y}_0) = \vec{0}$. So, once again, by continuity, we may choose 0 < a' < a so that $\|\vec{g}(\vec{x}, \vec{0})\| < \frac{1}{2}a$ whenever $\|\vec{x} - \vec{x}_0\| < a'$.

We conclude from the contraction mapping theorem that, assuming A is invertible, there exist a, a' > 0 such that, for each \vec{x} obeying $\|\vec{x} - \vec{x}_0\| < a'$, the system of equations $\vec{f}(\vec{x}, \vec{y}) = 0$ has exactly one solution, $\vec{y}(\vec{x})$, obeying $\|\vec{y}(\vec{x}) - \vec{y}_0\| < a$. That's the existence and uniqueness part of the

Theorem (Implicit Function Theorem) Let $n, d \in \mathbb{N}$ and let $U \subset \mathbb{R}^{n+d}$ be an open set. Let $\vec{f}: U \to \mathbb{R}^d$ be C^{∞} with $\vec{f}(\vec{x}_0, \vec{y}_0) = 0$ for some $\vec{x}_0 \in \mathbb{R}^n$, $\vec{y}_0 \in \mathbb{R}^d$ with $(\vec{x}_0, \vec{y}_0) \in U$. Assume that det $\left[\frac{\partial f_i}{\partial y_j}(\vec{x}_0, \vec{y}_0)\right]_{1 \leq i,j \leq d} \neq 0$. Then there exist open sets $V \subset \mathbb{R}^d$ and $W \subset \mathbb{R}^n$ with $\vec{x}_0 \in W$ and $\vec{y}_0 \in V$ such that

for each $\vec{x} \in W$, there is a unique $\vec{y} \in V$ with $\vec{f}(\vec{x}, \vec{y}) = 0$.

If the \vec{y} above is denoted $\vec{Y}(\vec{x})$, then $\vec{Y}: W \to \mathbb{R}^d$ is C^{∞} , $\vec{Y}(\vec{x}_0) = \vec{y}_0$ and $\vec{f}(\vec{x}, \vec{Y}(\vec{x})) = 0$ for all $\vec{x} \in W$. Furthermore

$$\frac{\partial \vec{Y}}{\partial \vec{x}}(\vec{x}) = -\left[\frac{\partial \vec{f}}{\partial \vec{y}}\left(\vec{x}, \vec{Y}(\vec{x})\right)\right]^{-1} \frac{\partial \vec{f}}{\partial \vec{x}}\left(\vec{x}, \vec{Y}(\vec{x})\right) \tag{1}$$

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where $\frac{\partial \vec{Y}}{\partial \vec{x}}$ denotes the $d \times n$ matrix $\left[\frac{\partial Y_i}{\partial x_j}\right]_{\substack{1 \leq i \leq d \\ 1 \leq j \leq n}}, \frac{\partial \vec{f}}{\partial \vec{x}}$ denotes the $d \times n$ matrix of first partial derivatives of \vec{f} with respect to \vec{x} and $\frac{\partial \vec{f}}{\partial \vec{y}}$ denotes the $d \times d$ matrix of first partial derivatives of \vec{f} with respect to \vec{y} .

Proof: We have already proven the existence and uniqueness part of the theorem.

The rest will follow once we know that $\vec{Y}(\vec{x})$ has one continuous derivative, because then differentiating $\vec{f}(\vec{x}, \vec{Y}(\vec{x})) = 0$ with respect to \vec{x} gives

$$\frac{\partial \vec{f}}{\partial \vec{x}} (\vec{x}, \vec{Y}(\vec{x})) + \frac{\partial \vec{f}}{\partial \vec{y}} (\vec{x}, \vec{Y}(\vec{x})) \frac{\partial \vec{Y}}{\partial \vec{x}} (\vec{x}) = \vec{0}$$

which implies (1). (The inverse of the matrix $\frac{\partial \vec{f}}{\partial \vec{y}}(\vec{x}, \vec{Y}(\vec{x}))$ exists, for all \vec{x} close enough to \vec{x}_0 , because the determinant of $\frac{\partial \vec{f}}{\partial \vec{y}}(\vec{x}, \vec{y})$ is nonzero for all (\vec{x}, \vec{y}) close enough to (\vec{x}_0, \vec{y}_0) , by continuity.) Once we have (1), the existence of, and formulae for, all higher derivatives follow by repeatedly differentiating (1). For example, if we know that $\vec{Y}(\vec{x})$ is C^1 , then the right of (1) is C^1 , so that $\frac{\partial \vec{Y}}{\partial \vec{x}}(\vec{x})$ is C^1 and $\vec{Y}(\vec{x})$ is C^2 .

We have constructed $\vec{Y}(\vec{x})$ as the limit of the sequence of approximations $\vec{Y}_n(\vec{x})$ determined by $\vec{Y}_0(\vec{x}) = \vec{y}_0$ and

$$\vec{Y}_{n+1}(\vec{x}) = \vec{Y}_n(\vec{x}) - A^{-1} \vec{f}(\vec{x}, \vec{Y}_n(\vec{x}))$$
(2)

Since $\vec{Y}_0(\vec{x})$ is C^{∞} (it's a constant) and \vec{f} is C^{∞} by hypothesis, all of the $\vec{Y}_n(\vec{x})$'s are C^{∞} by induction and the chain rule. We could prove that $\vec{Y}(\vec{x})$ is C^1 by differentiating (2) to get an inductive formula for $\frac{\partial \vec{Y}_n}{\partial \vec{x}}(\vec{x})$ and then proving that the sequence $\left\{\frac{\partial \vec{Y}_n}{\partial \vec{x}}(\vec{x})\right\}_{n \in \mathbb{N}}$ of derivatives converges uniformly.

Instead, we shall pick any unit vector $\hat{e} \in \mathbb{R}^n$ and prove that the directional derivative of $\vec{Y}(\vec{x})$ in direction \hat{e} exists and is given by formula (1) multiplying the vector \hat{e} . Since the right hand side of (1) is continuous in \vec{x} , this will prove that $\vec{Y}(\vec{x})$ is C^1 . We have $\vec{f}(\vec{x} + h\hat{e}, \vec{Y}(\vec{x} + h\hat{e})) = 0$ for all sufficiently small $h \in \mathbb{R}$. Hence

$$\begin{aligned} 0 &= \vec{f} \left(\vec{x} + h\hat{e} \,, \, \vec{Y}(\vec{x} + h\hat{e}) \, \right) - \vec{f} \left(\vec{x} \,, \, \vec{Y}(\vec{x}) \, \right) \\ &= \vec{f} \left(\vec{x} + th\hat{e} \,, \, t\vec{Y}(\vec{x} + h\hat{e}) + (1 - t)\vec{Y}(\vec{x}) \, \right) \Big|_{t=0}^{t=1} \\ &= \int_0^1 \frac{d}{dt} \vec{f} \left(\vec{x} + th\hat{e} \,, \, t\vec{Y}(\vec{x} + h\hat{e}) + (1 - t)\vec{Y}(\vec{x}) \, \right) \, dt \\ &= h \int_0^1 \frac{\partial \vec{f}}{\partial \vec{x}} \hat{e} \, dt + \int_0^1 \frac{\partial \vec{f}}{\partial \vec{y}} [\vec{Y}(\vec{x} + h\hat{e}) - \vec{Y}(\vec{x})] \, dt \end{aligned}$$

where the arguments of both $\frac{\partial \vec{f}}{\partial \vec{x}}$ and $\frac{\partial \vec{f}}{\partial \vec{y}}$ are $(\vec{x} + th\hat{e}, t\vec{Y}(\vec{x} + h\hat{e}) + (1 - t)\vec{Y}(\vec{x}))$. Recall that $\frac{\partial \vec{f}}{\partial \vec{x}}$ is the $d \times n$ matrix $\left[\frac{\partial f_i}{\partial x_j}\right]_{\substack{1 \le i \le d \\ 1 \le j \le n}}$, \hat{e} is an n component column vector, $\frac{\partial \vec{f}}{\partial \vec{y}}$ is the $d \times d$

matrix $\left[\frac{\partial f_i}{\partial y_j}\right]_{\substack{1 \le i \le d \\ 1 \le d \le n}}$, and \vec{Y} is a *d* component column vector. Note that $\left[\vec{Y}(\vec{x} + h\hat{e}) - \vec{Y}(\vec{x})\right]$ is independent of *t* and hence can be factored out of the second integral. Dividing by *h* gives

$$\frac{1}{\hbar}[\vec{Y}(\vec{x}+h\hat{e})-\vec{Y}(\vec{x})] = -\left[\int_0^1 \frac{\partial \vec{f}}{\partial \vec{y}} dt\right]^{-1} \int_0^1 \frac{\partial \vec{f}}{\partial \vec{x}} \hat{e} dt$$
(3)

Since

$$\lim_{h \to 0} \left(\vec{x} + th\hat{e} \,,\, t\vec{Y}(\vec{x} + h\hat{e}) + (1 - t)\vec{Y}(\vec{x}) \, \right) = \left(\vec{x} \,,\, \vec{Y}(\vec{x}) \, \right)$$

uniformly in $t \in [0, 1]$, the right hand side of (3) — and hence the left hand side of (3) — converges to

$$-\left[\frac{\partial \vec{f}}{\partial \vec{y}}\left(\vec{x},\vec{Y}(\vec{x})\right)\right]^{-1}\frac{\partial \vec{f}}{\partial \vec{x}}\left(\vec{x},\vec{Y}(\vec{x})\right)\hat{e}$$

as $h \to 0$, as desired.

The Inverse Function Theorem

As an application of the implicit function theorem, we now prove the inverse function theorem.

Theorem (Inverse Function Theorem) Let $d \in \mathbb{N}$ and let $U \subset \mathbb{R}^d$ be an open set. Let $\vec{F}: U \to \mathbb{R}^d$ be C^{∞} with det $\left[\frac{\partial F_i}{\partial y_j}(\vec{y_0})\right]_{1 \le i,j \le d} \ne 0$ for some $\vec{y_0} \in U$. Then there exists an open set $V \subset U$ with $\vec{y_0} \in V$ such that the restriction $\vec{F} \mid V$ of \vec{F} to V maps V one-to-one onto the open set $\vec{F}(V)$ and $(\vec{F} \mid V)^{-1}$ is C^{∞} . Furthermore, If we denote $(\vec{F} \mid V)^{-1}$ by \vec{Y} , then

$$\frac{\partial \vec{Y}}{\partial \vec{x}}(\vec{x}) = \left[\frac{\partial \vec{F}}{\partial \vec{y}}(\vec{Y}(\vec{x}))\right]^{-1} \tag{2}$$

Proof: Apply the implicit function theorem with n = d, $\vec{f}(\vec{x}, \vec{y}) = \vec{F}(\vec{y}) - \vec{x}$, $\vec{x}_0 = \vec{F}(\vec{y}_0)$ and U replaced by $\mathbb{R}^d \times U$.