Nonlinear Optimization Lecture 21 Garrick Aden-Buie Thursday, April 7, 2016

Review

• $VI(F,\Omega)$

$$-y \in \Omega, F(y)^T(x-y) \ge 0 \ \forall x \in \Omega$$

- *NCP*(*F*)
 - $-F(y)^T y = 0$
 - $-F(y) \ge 0$
 - $-y \ge 0$
- $FPP_{\min}(F,\Omega)$

$$-y \in P_{\Omega}[y - F(y)]$$

 $-y \in \Omega$

Theorem

If $\Omega = \mathbb{R}^n_+[^1]$ then $VI(F,\Omega) \Leftrightarrow NCP(F)$.

Proof (\Rightarrow) . If y is a solution of $VI(F,\Omega)$, then y is a solution of NCP(F).

$$F(y)^T(x-y) \ge 0 \ \forall x \in \mathbb{R}^n_+$$

- i. $x = 0 \in \mathbb{R}^n_+$: $F(y)^T(-y) \ge 0$
- ii. $x = 2y \in \mathbb{R}^n_+$: $F(y)^T y \ge 0$
- iii. (i) & (ii) $\Rightarrow F(y)^T y = 0$. Now we need to show that $F(y) \ge 0$.

Suppose not: $F(y) \not\geq 0 \Rightarrow \exists j \in 1,...,n$ such that $F_j(y) < 0$, which is to say that F(y) is not non-negative.

$$F(y)^{T}(x - y) = \sum_{i=1}^{n} F_{i}(y)(x_{i} - y_{i}) \ge 0$$

$$\text{Pick } x = \begin{bmatrix} y_{1} \\ \vdots \\ x_{j} = \infty \\ \vdots \\ y_{n} \end{bmatrix}$$

Now, then $x_i - y_i = 0$ for all elements that are not x_j , but then x_j forces $F_j(y)(x_j - y_j) < 0$, so contradiction.

Proof (\Leftarrow). If y is a solution to NCP(F), then y is also a solution to $VI(F,\Omega)$. $F(y) \ge 0, y \ge 0, F(y)^T y = 0$. Then we choose an $x \in \Omega$ which will by definition be non-negative and observe the following

$$F(y)^T x \ge 0 \quad \forall x \in \Omega$$

$$\Rightarrow F(y)^T x - F(y)^T y \ge 0 \quad \forall x \in \Omega$$

$$\Rightarrow F(y)^T (x - y) \ge 0 \quad \forall x \in \Omega$$

Theorem

 $\Omega \subset \mathbb{R}^n$ convex, nonempty, closed. Then $FPP_{\min}(F,\Omega) \Leftrightarrow VI(F,\Omega)$.

Proof. $P_{\Omega}[y - F(y)]$ requires a solution to

$$\min_{x} \quad \|(y - F(y)) - x\|$$
s.t. $x \in \Omega$

Without loss of generality we can rewrite as

$$\begin{aligned} & \min_{x} & & \frac{1}{2} \| (y - F(y)) - x \|^2 \\ & \text{s.t.} & & x \in \Omega \end{aligned}$$

Which is also the same as

$$\min_{x} \quad \frac{1}{2} (y - F(y) - x)^{T} (y - F(y) - x) = Z(x; y)$$
s.t $x \in \Omega$

Now, we can rewrite this as the KKT conditions, which are sufficient conditions given the convexity of Ω , although in this case we'll use the VI-type optimality:

$$\Leftrightarrow \nabla_x Z(x^*; y)^T (x - x^*) \ge 0 \ \forall x \in \Omega$$

But note that x, x^* , and y are all the same at the end, because we are solving the Fixed-Point Problem.

Note that in the simple case if we have Ω convex, then $\min f(x)$ s.t. $x \in \Omega \Leftrightarrow \nabla f(x^*)^T (x - x^*) \geq 0 \ \forall x \in \Omega$. So in this case, note that

$$\nabla_x Z(x^*;y) = -(y - F(y) - x^*)$$
 (Note that $\nabla_x Z(x^*;y) = \nabla_x Z(x;y)|_{x=x^*}$)
 $\Leftrightarrow -(y - F(y) - x^*)^T (x - x^*) \ge 0$ $\forall x \in \Omega$

At this point we have shown that $FPP_{\min}(F\Omega) \Rightarrow VI(F,\Omega)$, and we have that $y=x^*$.

The next step is to show that $VI(F,\Omega) \Rightarrow FPP_{\min}(F,\Omega)$. Start from the condition $F(y)^T(x-y) \ge 0 \ \forall x \in \Omega$ (1). We also have $-(y-F(y)-x^*)^T(x-x^*) \ge 0$ (2) which gives x^* as a result of the projection.

So from the side of (1), y is a VI solution and x^* is a projection result from a given y. So we pick $x = x^*$. This gives $F(y)^T(x^* - y) \ge 0$.

Then from (2), pick $x = y \Rightarrow -(y - x^*)^T (y - x^*) + F(y)^T (y - x^*) \ge 0 \Rightarrow 0 \ge F(y)^T (y - x^*) \ge (y - x^*)^T (y - x^*) \ge 0$. Notice that $(y - x^*)^T (y - x^*)$ is sandwiched between 0 and 0, so y needs to be x^* .

Overall, the proof starts with knowing that at the end x, y, and x^* are all the same, but starting from the assumption that they may be different.

Existence (of Fixed-Point)

Brower's Fixed-Point Theorem

If Ω is a convex, nonempty and compact set and F(x) is continuous on Ω , then the fixed-point problem

$$x = F(x)$$
$$x \in \Omega$$

has a solution.

Theorem

- Ω convex, nonempty, compact
- F(x) continuous on Ω
- Then $VI(F,\Omega)$ has a solution

Proof. $VI(F,\Omega) \Leftrightarrow FPP_{\min}(F,\Omega)$. Then $y = P_{\Omega}(y - F(y))$, or equivalently y = G(y). If we can show that G(y) is continuous, then we are done. From advanced linear algebra (and commonly taught in advance linear algebra courses), the projection operator is continuous, so G(y) is continuous.

Theorem: Nash Game

$$\max u_i(x^i; x^{-i})$$

If

- u_i is pseudo-concave with respect to x^i for all x^{-i} .
- $\Omega = \prod_{i=1}^{N} \Omega_i$ is convex, compact, nonempty

Then there exists a Nash equilibrium.

Uniqueness

- Optimization: strictly pseudoconvex
- Nash equilibrium: strictly monotone

Definition

- $F: \mathbb{R}^n \to \mathbb{R}^n$
- F is (strictly) monotone on Ω if

$$[F(y^{1}) - F(y^{2})]^{T} (y^{1} - y^{2}) \ge (>)0$$
$$\forall y^{1}, y^{2} \in \Omega \ (y^{1} \ne y^{2})$$

Theorem

If $y \in \Omega \subset \mathbb{R}^n$ is a solution of $VI(F,\Omega)$ and $F(\cdot)$ is strictly monotone

Then y is the unique solution.