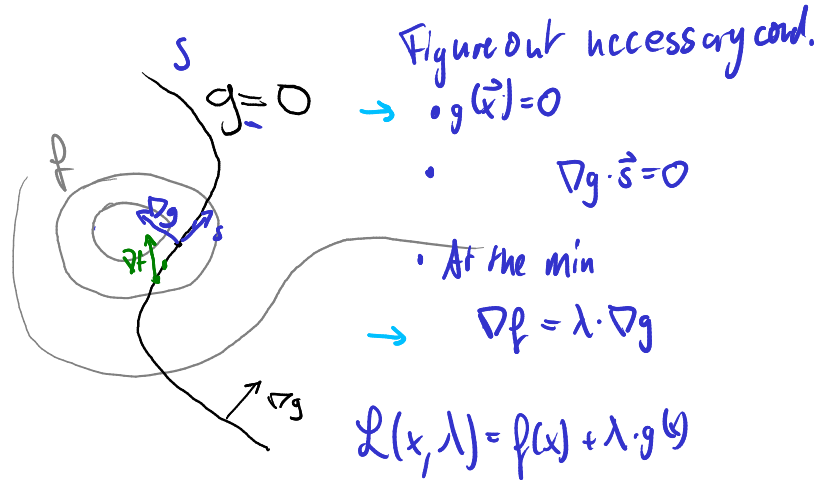


Lagrange Multipliers



- Seen: Need

$$-\nabla f(\mathbf{x}) = J_g^T \lambda$$

at the (constrained) optimum.

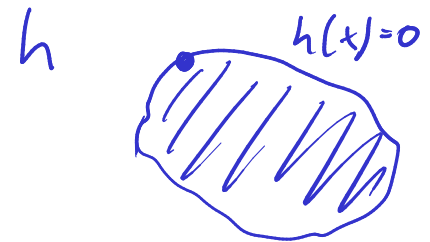
Idea: Turn constrained optimization problem for \mathbf{x} into an *unconstrained* optimization problem for (\mathbf{x}, λ) . How?

Demo: Sequential Quadratic Programming

Inequality-Constrained Optimization

Want \mathbf{x}^* so that

$$f(\mathbf{x}^*) = \min_{\mathbf{x}} f(\mathbf{x}) \quad \text{subject to} \quad \underbrace{\mathbf{g}(\mathbf{x}) = \mathbf{0}} \quad \text{and} \quad \underbrace{\mathbf{h}(\mathbf{x}) \leq \mathbf{0}} \quad h(x) \leq 0$$



This is **inequality-constrained optimization**. Develop a necessary condition for a minimum.

Define Lagrangian:

$$\mathcal{L}(\mathbf{x}, \lambda_1, \lambda_2) := f(\mathbf{x}) + \lambda_1^T \mathbf{g}(\mathbf{x}) + \lambda_2^T \mathbf{h}(\mathbf{x})$$

- Some inequality constraints may not be “active”
(active $\Leftrightarrow h_i(\mathbf{x}^*) = 0 \Leftrightarrow$ at ‘boundary’ of ineq. constraint)
(Equality constraints are always ‘active’)
- If h_i inactive ($h_i(\mathbf{x}^*) < 0$), must force $\lambda_{2,i} = 0$.

Otherwise: Behavior of h could change location of minimum of \mathcal{L} .
Use complementarity condition

$$h_i(\mathbf{x}^*) \lambda_{2,i} = 0.$$

Assuming J_g and $J_{h,\text{active}}$ have full rank, this set of conditions is *necessary*:

$$(*) \quad \nabla_{\mathbf{x}} \mathcal{L}(\mathbf{x}^*, \lambda_1^*, \lambda_2^*) = \mathbf{0}$$

$$(*) \quad \mathbf{g}(\mathbf{x}^*) = \mathbf{0}$$

$$\mathbf{h}(\mathbf{x}^*) \leq \mathbf{0}$$

$$\lambda_2 \geq \mathbf{0}$$

$$(*) \quad \mathbf{h}(\mathbf{x}^*) \cdot \lambda_2 = 0$$

These are called the **Karush-Kuhn-Tucker** ('KKT') conditions.

Computational approach: Solve (*) equations by Newton.

7 Interpolation

Interpolation: Setup

Given: $(x_i)_{i=1}^N, (y_i)_{i=1}^N$

Wanted: Function f so that $f(x_i) = y_i$

- How is this not the same as function fitting? (from least squares)

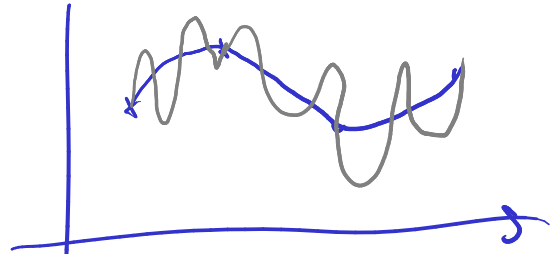
because; we exactly hit the values

- Does this problem have a unique answer?

no

- Why is this important?

because; calculus.



Making the Interpolation Problem Unique

- How can we cut down the set of possible answers to *exactly one*?

$$f(x) = \sum_{j=1}^{N_{\text{func}}} \alpha_j p_j(x)$$

p_0 : —
 p_1 : /
 p_2 : ∪

$$y_i = f(x_i) = \sum_{j=1}^{N_{\text{func}}} \alpha_j \underbrace{p_j(x_i)}_{V_{ij}} \quad (\Leftrightarrow) \quad V \vec{\alpha} = \vec{y}$$

$$V \begin{pmatrix} \text{coefficient} \\ \text{vec.} \end{pmatrix} = \begin{pmatrix} \text{values } \vec{y} \\ \text{at interp.} \\ \text{nodes } (x_i) \end{pmatrix}$$

↑ generalized Vandermonde
matrix

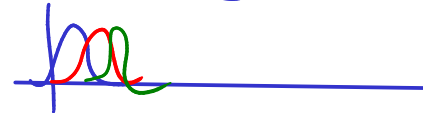
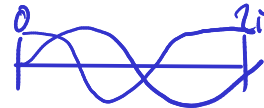
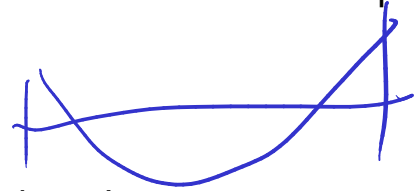
conditioning of interpolation; same as solving $V \vec{\alpha} = \vec{y}$

Modes and Nodes (aka Functions and Points)

Both function basis and point set are under our control. What do we pick?

Ideas for functions:

- \rightarrow Monomials $1, x, x^2, x^3, x^4, \dots$
- Functions that make $\mathbf{V} = \mathbf{I} \rightarrow$ 'Lagrange basis'
- Functions that make \mathbf{V} triangular \rightarrow 'Newton basis'
- Splines (piecewise polynomials)
- Orthogonal polynomials
- Sines and cosines
- 'Bumps' ('Radial Basis Functions')



Ideas for points:

- \rightarrow Equispaced





- 'Edge-Clustered' (so-called Chebyshev/Gauss/... nodes)
 - But first: Why *not* monomials on equispaced points?
 - Why not equispaced?

Lagrange Interpolation

- Find a basis so that $V = I$, i.e.

$$\varphi_j(x_i) = \begin{cases} 1 & i=j, \\ 0 & \text{otherwise.} \end{cases}$$