

Optimization with side constraints

Philipp Warode

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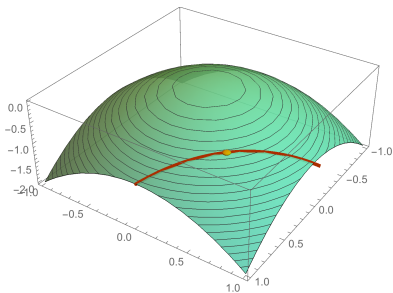


We want to maximize

$$\max -x^2 - y^2$$

with the side constraint

$$x + y = 1$$



- Reduce numbers of variables by inserting side constraints in the objective function

Example:

Side constraint:

$$x + y = 1 \Leftrightarrow y = 1 - x$$

Objective function:

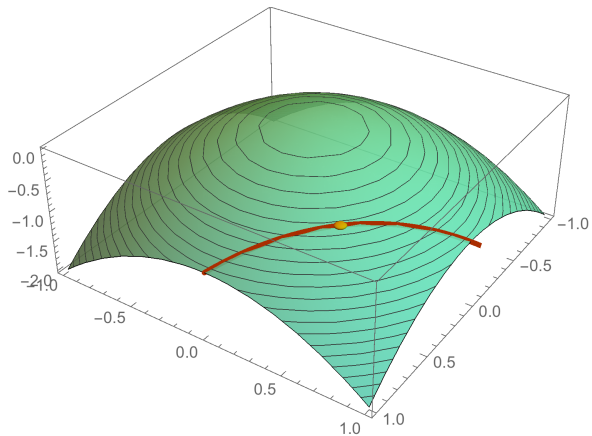
$$\max -x^2 - y^2 = \max -x^2 - (1 - x)^2$$

- Not always possible, e.g. if the side constraint can't be solved uniquely:

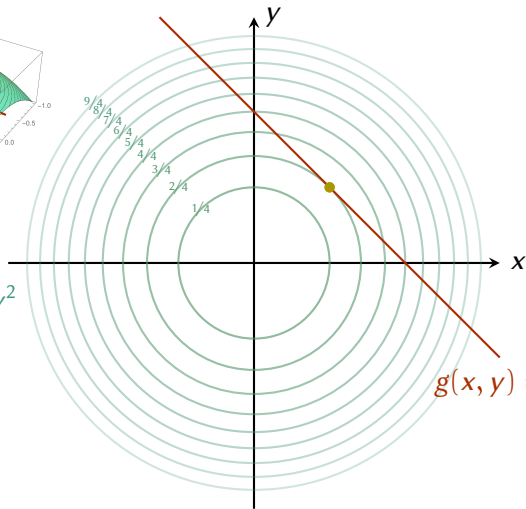
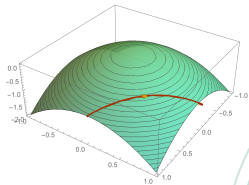
$$x^2 + y^2 = 1$$



Lagrange Multipliers



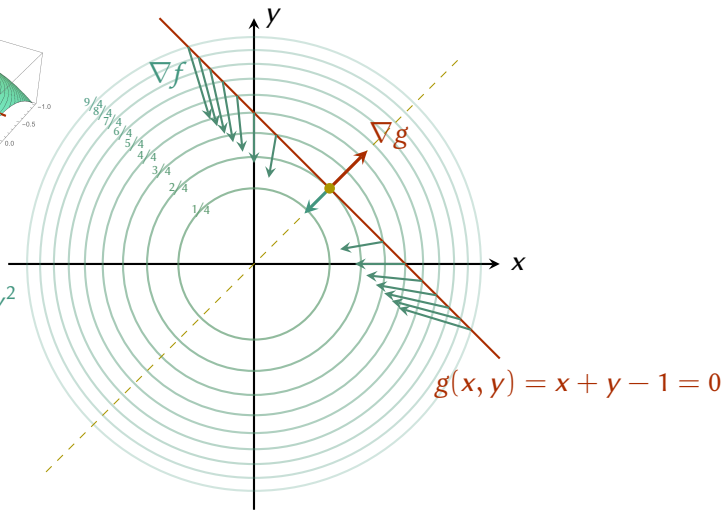
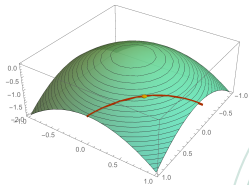
Lagrange Multipliers



$$f(x, y) = -x^2 - y^2$$

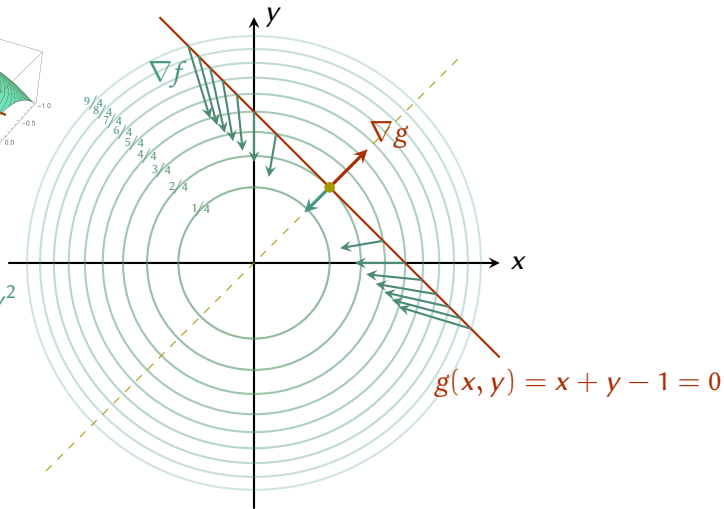
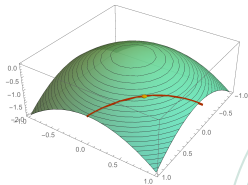
$$g(x, y) = x + y - 1 = 0$$

Lagrange Multipliers



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Lagrange Multipliers



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- Necessary condition for local optimum: $\nabla f = \lambda \nabla g$

Theorem

Let $\mathbf{x}^{(0)} = (x_n^{(0)}, \dots, x_n^{(0)})$ be an optimal solution of

$$\begin{aligned} \max \quad & f(\mathbf{x}) \\ \text{s.t.} \quad & g_j(\mathbf{x}) = 0 \quad \forall j \in \{1, \dots, m\} \end{aligned}$$

and f, g partially differentiable with $\nabla g_j(\mathbf{x}^{(0)}) \neq 0$ for $j = 1, \dots, m$ then there are $\lambda_1, \dots, \lambda_m$ such that

$$\nabla f(\mathbf{x}^{(0)}) + \sum_{j=1}^m \lambda_j \nabla g_j(\mathbf{x}^{(0)}) = 0.$$



1 Create Lagrange function

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$$\frac{\partial}{\partial x_i} \mathcal{L}(\mathbf{x}, \lambda) = \frac{\partial}{\partial x_i} f(\mathbf{x}) + \sum_{j=1}^m \lambda_j \frac{\partial}{\partial x_i} g_j(\mathbf{x})$$

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3 Solve the system of equations

$$\frac{\partial}{\partial x_i} \mathcal{L}(x, \lambda) = 0 \text{ for all } i \text{ and } \frac{\partial}{\partial \lambda_j} \mathcal{L}(x, \lambda) = 0 \text{ for all } j$$

