Continuous Maths HT 2019: Problem Sheet 2

Optimization, Convexity, Langrage Multipliers, and Numerical Integration

- **2.1** Find and classify the stationary points of these functions:
 - (a) $g(x,y) = \exp(x^3 3x) \exp(y^3 3y)$,
 - (b) $h(x, y, z) = \frac{1}{2}x^2 + y^2 + \frac{27}{2}z^2 xy + xz + 4yz x y 11z$.
- **2.2** Let \boldsymbol{a} be a vector with $a_i > 0$, $\sum_i a_i = 1$. Using the facts in the lecture notes (or otherwise), show that that matrix $\boldsymbol{\Delta_a} \boldsymbol{aa}^T$, where $\boldsymbol{\Delta_a}$ is the diagonal matrix with \boldsymbol{a} on the diagonal, is positive semidefinite.

Deduce that the log-sum-exp function, $l(\mathbf{x}) = \ln(\sum_{i=1}^{n} \exp(x_i))$, is convex.

- **2.3** Here is an application from economics. A factory makes a product out of three infinitely-divisible ingredients X, Y, and Z. The ingredients cost p, q, and r pounds per kg, respectively, with p, q, r > 0 all different, and the factory has a budget of B > 0 pounds. The value of the product is some function g(x, y, z) of the weight of the ingredients.
 - (a) Formulate, as constrained optimization in standard form, the problem that the factory wishes to maximize the value of their product, within their budget.
 - (b) Solve the problem in the case when g(x, y, z) = xyz. Be careful not to divide by zero, or assume that a constraint is slack when it might be tight (or vice versa).
 - (c) Now solve in the case when $g(x, y, z) = \exp(x + y + z)$.
- **2.4** Here is an example from image retrieval and machine learning. We have objects O_1, \ldots, O_n for which we have computed some measure of pairwise distance (or weights), $w_{ij} = w_{ji}$ denoting the distance between O_i and O_j . We wish to assign each O_i a scalar x_i such that objects that have a low distance are assigned scalars that are close. After fixing scale and location, we arrive at the constrained optimization problem

$$\underset{x_1,\dots,x_n}{\text{minimize}} \ E(\boldsymbol{x}) = \sum_i \sum_j w_{ij} (x_i - x_j)^2 \text{ subject to } \sum_i x_i^2 = 1, \ \sum_i x_i = 0.$$

(a) Show that another way to write the objective function is

$$E(\boldsymbol{x}) = 2\boldsymbol{x}^T(\mathbf{D} - \mathbf{W})\boldsymbol{x},$$

where **W** is the symmetric matrix (w_{ij}) , and **D** is a diagonal matrix that satisfies $\mathbf{1}^T \mathbf{D} = \mathbf{1}^T \mathbf{W}$. Also write the constraints as vector equations.

- (b) By considering the original problem, show that $\mathbf{D} \mathbf{W}$ is positive semidefinite.
- (c) Show that the first-order condition, for a stationary point of the Lagrangian, is

$$4(\mathbf{D} - \mathbf{W})x - 2\lambda x - \mu \mathbf{1} = \mathbf{0}. \quad (*)$$

By applying $\mathbf{1}^T$ to (*), show that $\mu = 0$.

(d) Show that every solution \boldsymbol{x} of (*) is an eigenvector of $\mathbf{D} - \mathbf{W}$, and that as long as the constraints are satisfied $E(\boldsymbol{x}) = 2\nu$, where ν is the corresponding eigenvalue. Show also that $\mathbf{1}^T \boldsymbol{x} = 0$ unless $\nu = 0$.

- (e) Deduce that the solution to the optimization problem is the unit eigenvector of $\mathbf{D} \mathbf{W}$ with the *second*-smallest eigenvalue.
- **2.5** Let $f(x) = \exp(\exp x)$. Using the error bounds in the lecture notes, find the smallest number of strips guaranteed to find $\int_0^1 f(x) dx$ to within 10^{-6} using (a) the Midpoint rule, (b) the Trapezium rule, and (c) Simpson's rule.
- **2.6** We will derive another method of numerical integration. For one strip [0, 2l], we approximate f(x) by its third-order Taylor polynomial about x = l:

$$\hat{f}_3(x) = f(l) + (x - l)\frac{\mathrm{d}f}{\mathrm{d}x}(l) + \frac{(x - l)^2}{2}\frac{\mathrm{d}^2f}{\mathrm{d}x^2}(l) + \frac{(x - l)^3}{6}\frac{\mathrm{d}^3f}{\mathrm{d}x^3}(l).$$

Then we approximate $\int_0^{2l} f(x) dx$ by $A_1[f, 0, 2l] = \int_0^{2l} \hat{f}_3(x) dx$.

- (a) Verify that $A_1[f, 0, 2l] = 2lf(l) + \frac{1}{3}l^3 \frac{d^2f}{dx^2}(l)$.
- (b) Use Taylor's theorem to bound $\hat{f}_3(x) f(x)$ in terms of x, l,

$$\underline{D_4} = \min_{\xi \in (0,2l)} \left| \frac{\mathrm{d}^4 f}{\mathrm{d}x}(\xi) \right|, \quad \text{and} \quad \overline{D_4} = \max_{\xi \in (0,2l)} \left| \frac{\mathrm{d}^4 f}{\mathrm{d}x}(\xi) \right|.$$

(c) Derive upper and lower bounds on the error of the single-strip integral

$$\operatorname{err}(A_1)[f, 0, 2l] = A_1[f, 0, 2l] - \int_0^{2l} f(x) \, \mathrm{d}x,$$

in terms of l, $\underline{D_4}$, and $\overline{D_4}$.

- (d) Derive the corresponding composite method that uses n equal-sized strips to approximate $\int_a^b f(x) dx$, and give error bounds for the composite rule.
- (e) How does this method compare with Simpson's rule, in terms of accuracy and speed?
- **2.7** Compute $\int_0^1 x^2 dx$ exactly, and then estimate it using the Midpoint and Trapezium rules, using two strips. Compute $\int_0^1 x^4 dx$ exactly, and then estimate it using Simpson's rule and the method of question **2.6**, using two strips.

Compare the error of your approximations with the error bounds derived in the lecture notes and question **2.6**. What do these results tell you?

2.8 Write a program to estimate $\int_0^2 x^{3/2} dx$ using Simpson's rule with n strips, for $n = 2^1, 2^2, 2^3, \dots, 2^{24}$ (or n up to as large as your computer can handle). Draw a table or plot a graph of the observed error: the results are not quite as predicted by the error bound in the lecture notes. Explain this phenomenon.