Some discussion and/or hints on assignment 07 .
There may be misprints, so use with care.

## 1. The unix/linux command line

## 2. Newton's method for finding a minimum

(a) Consider the single-variable function

$$
f(x)=1+x^{4 / 3}
$$

which has a single minimum at $x=0$. Write down the iteration equation for Newton' method.
The iterations do not converge. By sketching the derivative $f^{\prime}(x)$, explain graphically why.

## Discussion/Hint $\longrightarrow$

$$
f^{\prime}(x)=(4 / 3) x^{1 / 3} ; \quad f^{\prime \prime}(x)(4 / 9) x^{-2 / 3} .
$$

So the iteration equation is

$$
x_{k+1}=x_{k}-f^{\prime}\left(x_{k}\right) / f^{\prime \prime}\left(x_{k}\right)=x_{k}-3 x_{k}=-2 x_{k}
$$

What a simple iteration equation. If you start from $x=1$ you get $1,-2,4,-8,16, \ldots$ Never converges to $x=0$.
If you plot $f^{\prime}(x)$, you should be able to see this graphically, if you know what Newton's iteration is trying to do. For root-finding, the Newton-Raphson algorithm approximates the function $f(x)$ at each step by it's tangent at that point. Please look up how this works graphically, e.g, wikipedia Newton's method.
For minimization, the algorithm approximates the derivative $f^{\prime}(x)$ at each step by its tangent. So if you have plotted $f^{\prime}(x)$, you should be able to graphically see how the iteration proceeds:


Finally, another way to look at this: For a single-variable iterative scheme

$$
x_{k+1}=g\left(x_{k}\right)
$$

you can show graphically or algebraically that, if $g^{\prime}(x) \in(-1,1)$, there is convergence, if $g^{\prime}(x)$ is outside this range, there is no convergence. E.g., see
http://wwwf.imperial.ac.uk/metric/metric_public/ numerical_methods/iteration/fixed_point_iteration.html
In our case, $g(x)=-2 x$, so $g^{\prime}(x)=-2$ which is outside $(-1,1)$. Therefore the iteration will not converge.
Comment 1: If $g^{\prime}(x) \in(-1,1)$ for some $x$ and not for some other values of $x$, it's more complicated, but our case is simple.
Comment 2: these considerations are more general than Newton's iteration, and generally valid for any fixed-point iteration.

(b) We want to find the location of the minimum of the function of 2 variables

$$
f(x, y)=x^{2}+x y+y^{2}+3 x
$$

using Newton's method. Set up the iteration equations. You will have to invert a $2 \times 2$ matrix.
Because the function is quadratic, the iteration should converge in a single step. Starting from any initial point (you can choose), show that the iteration converges in a single step.

Discussion/Hint $\longrightarrow$

The Hessian turns out to be a constant matrix, not a function of ( $\mathrm{x}, \mathrm{y}$ ), because the function is quadratic. Once you invert the Hessian and calculate

$$
H^{-1} \nabla f
$$

you get the vector

$$
\binom{x+2}{y-1}
$$

So that the iteration equations are

$$
\binom{x_{k+1}}{y_{k+1}}=\binom{x_{k}}{y_{k}}-\binom{x+2}{y-1}
$$

which simplifies to

$$
x_{k+1}=-2 ; \quad y_{k+1}=1 .
$$

This does not even depend on what the current value of the iterates are - the next value will always be $(-2,1)$. In other words, the minimum is reached in a single iteration!
This is not surprising because we are dealing with a quadratic function, for which Newton's iteration is exact.
(c) I have a multidimensional minimization problem and calculating the inverse of the Hessian $\left(\mathbb{H}^{-1}\right)$ is too hard for me. As a very crude approximation, I replace $\mathbb{H}^{-1}$ by $\lambda \mathbb{I}$, where $\lambda$ is a small number and $\mathbb{I}$ is the unit matrix. The resulting algorithm is then equivalent to a widely used algorithm. Which one?

## Discussion/Hint $\longrightarrow$

You should be able to show that you end up with the "gradient descent" algorithm.

## 3. Statistical Mechanics

Note: Some of the following is worked out in the student projects linked to on the webpage, under "Ising model".
Remember $Z=\sum_{\alpha} e^{-\beta E_{\alpha}}$, where $E_{\alpha}$ is the energy of the configuration $\alpha$. At thermal equilibrium, each configuration appears with probability $P_{\alpha}=\frac{1}{Z} e^{-\beta E_{\alpha}}$.
(a) Show that the system energy and its square has expectation values

$$
\langle E\rangle=\frac{1}{Z} \frac{\partial Z}{\partial \beta}=\frac{\partial}{\partial \beta} \ln Z \quad \text { and } \quad\left\langle E^{2}\right\rangle=\frac{1}{Z} \frac{\partial^{2} Z}{\partial \beta^{2}}
$$

## Discussion/Hint $\longrightarrow$

The crucial point for this problem is:
If $e^{-\beta E_{a}}$ is the probability (up to normalization) of the configuration $a$, then any quantity $x$ has the expectation value:

$$
\langle x\rangle=\frac{1}{Z} \sum_{a} x_{a} e^{-\beta E_{a}}
$$

Here $1 / Z$ serves as the normalization. $Z$ is called the partition function.
So for example

$$
\begin{aligned}
\langle E\rangle & =\frac{1}{Z} \sum_{a} E_{a} e^{-\beta E_{a}} \\
\left\langle E^{2}\right\rangle & =\frac{1}{Z} \sum_{a}\left(E_{a}\right)^{2} e^{-\beta E_{a}}
\end{aligned}
$$

Taking derivatives of $Z=\sum_{\alpha} e^{-\beta E_{\alpha}}$ with respect to $\beta$ should give the desired relations.
(b) Hence show that the specific heat

$$
C_{v}=\frac{\partial\langle E\rangle}{\partial T}
$$

can be written as $C_{v}=\beta^{2}\left(\left\langle E^{2}\right\rangle-\langle E\rangle^{2}\right)$. I am probably setting the Boltzmann constant to unity here.

## Discussion/Hint $\longrightarrow$

An exercise in taking derivatives. The relevant definitions for $\langle E\rangle$ and $\left\langle E^{2}\right\rangle$ are above.
(c) Perform the corresponding derivation for the magnetic susceptibility. You might have to remember that the configuration energy contains a term $-B M_{\alpha}$, where $B$ is the magnetic field (often written as $H$ ) and $M_{\alpha}$ is the total magnetization of configuration $\alpha$.

## Discussion/Hint $\longrightarrow$

You could define $E_{\alpha}=A_{\alpha}-B M_{\alpha}$, to help remember that the configuration energy contains a term $-B M_{\alpha}$. The $A_{\alpha}$ part of the configuration energy does not depend on $B$. The definitions of expectation values are

$$
\begin{aligned}
\langle M\rangle & =\frac{1}{Z} \sum_{a} M_{\alpha} e^{-\beta E_{\alpha}} \\
\left\langle M^{2}\right\rangle & =\frac{1}{Z} \sum_{a}\left(M_{\alpha}\right)^{2} e^{-\beta E_{\alpha}}
\end{aligned}
$$

One can now proceed to calculate

$$
\chi=\frac{\partial\langle M\rangle}{\partial B}
$$

and express the resulting expression in terms of $\langle M\rangle$ and $\left\langle M^{2}\right\rangle$.

