Something something computational QUANTUM CHEMISTRY SOMETHING SOMETHING NEURAL NETWORKS

by

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Abstract

I havent done much worthwhile but hopefully I can bullshit my way into not failing.

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Chapter 1

Introduction

After being deveolped and pioneered in conjunction with nuclear physics during World War II, computer modelling and numerical experiments have become ubiquitous in the natural sciences. The list of areas in which simulations have been used to produce significant new results encompass now pretty much all of them [citation needed]. Today computer simulations play as natural a part of the hard sciences as laboratory experiments and theory. In most cases all three are used in order to glean new scientific insight. ((examples here?))

The advent of computer simulations during the last several decades have in particular made it possible to study moderately sized quantum mechanical systems from first principles. As our ability to solve—in closed form—the governing equations of quantum mechanics (QM) vanishes extremely quickly as the number of constituent particles exceed just a few, numerics are used to augment the proverbial *pen and paper*. It is striking that the underlying theory for all of chemistry and most of physics have been known for almost a century but the problem preventing us from essentially *solving* chemistry is almost purely computational: the equations resulting from the exact application of this theoretical framework are way too difficult to solve.

Any approximative scheme which aims to solve the many-body Schrödinger equation from scratch subject to some (more or less) well-defined simplifications is called an *ab initio* method. Working from first principles the aim of such algorithms extract information from a theoretical QM system in a reasonable amount of time. In order to accomplish this, a number of complicating intricacies need to be disregarded. The magnitude of the simplifications—essentially the number and importance of complicating factors dropped—determine both the efficacy and the efficiency of the method: More simplifications made allow solutions to be found for larger systems (albeit less precise solutions), whereas extremely precise solutions can be found for small systems if very few simplifications are employed.

Despite tremendous increases in available numerical computational power in the latter half of the previous-, and the early parts of the current century, any such approximate scheme used is still heavily limited w.r.t. the system size. In practice, most methods are limited to systems of containing on the order of between 10^2 (for high-

2 Introduction Chapter 1

precision methods such as CI, CC, DMC, etc.) and 10^5 electrons (for faster HF and DFT methods) [1, 2, 3]. Extracting information from larger systems neccessitate the use of classical or semi-classical algorithms, such as molecular dynamics (MD). Using MD, the time evolution of up to around 10^7 particles can feasibly be simulated over the order of nano seconds [4, 5]. Corresponding large-scale cosmological N-body simulations have been run for as many as 10^{11} particles [6, 7]. As macroscopic objects contain on the order of 10^{23} atoms, we are ostensibly a long way away from even classically modelling the constituent particles directly. In this region, continuum models are used.

1.1 Quantum and classical dynamics

As previously noted, solving the Schrödinger equation (SE) exactly by hand is impossible in the overwhelming majority of interesting cases. However, methods which can get close to the exact solution exists. Full Configuration Interaction (FCI) or direct diagonalization of the Hamiltonian is exact in the limit of an infinite orbital basis set but suffers from an exponential complexity scaling (in system *and* basis size) [8]. The related Configuration Interaction (CI) and Coupled Cluster (CC) approaches both truncate the FCI expansion of Slater determinants, thus gaining speed but loosing some accuracy [9, 10]. Diffusion Monte Carlo (DMC) techniques can in principle provide the exact solution to the SE by imaginary-time evolution of an initial wave function guess [11, 12]. In practice, DMC methods are highly dependent on this ansatz and thus require as input the results of less accurate method but faster methods. One example may be the Variational Monte Carlo (VMC) method: conceptually simpler and faster than DMC, but not as accurate [12, 13, 14].

The Hartree-Fock (HF) framework—which provides an efficient but not enormously accurate result—has seen extensive use since its inception in 1930 [15, 16, 17]. However, by far the most popular approximation is Density Functional Theory (DFT), developed by W. Kohn and L. J. Sham in 1965 [18, 19]. Between 1980 and 2010, DFT was the most active field in physics with eight out of the top ten most cited papers being on the subject [20].

"This is where multiscale modeling comes in. By considering simultaneously models at different scales, we hope to arrive at an approach that shares the efficiency of the macro- scopic models as well as the accuracy of the microscopic models." Weinan: Prinicples of Multiscale modelling side viii

1.2 Neural networks in molecular dynamics

Neural networks can parameterize the data from millions of electronic structure calculations and in theory provide accuracy close to the direct quantum mechanical calculations at a fraction of the calculational cost. Section 1.4 Goals 3

1.3 Goals

The goals of the thesis are as follows:

1.4 Structure of the thesis

This thesis is split into four parts. The first part, *foundational theory* presents an overview of classical mechanics (very briefly) and quantum mechanics as relevant for molecular dynamics and electronic structure calculations. In addition, the basics of machine learning and artifical neural networks are presented. Part one lays the groundwork and establishes most of the notation used later in part two: *Advanced theory*. Here, the different approximative schemes for solving the quantum equations of motion are presented. Alongside them is the theory of molecular dynamics simulations and advanced topics in neural networks.

The penultimate part contains information w.r.t. the concrete implementation of frameworks described in part two. Key parts of each code base are outlined in detail. Also contained in part three are validation tests of each implementation. Lastly, results for the full work-flow utilizing all the developed programs are presented.

The thesis ends with part four, containing conclusions and prospect for future work.

Part I Foundational theory

Part II Conclusions and future work

Appendices

Appendix A

Natural units: Hartree atomic units

When working within a specific branch of physics, it is often useful to deviate from the every-day SI units of measurements and instead use units which are *natural* to the systems under study. Since we are working with "small" systems, the SI *meter*, second, kilogram, and coulomb are of little use to us. Instead we will work in a system of units in which we define the mass of the electron, m_e , to be the scale by which we measure all other masses. This obviously means the numerical value of the electron mass becomes unity, $m_e = 1$. In the same way, we will use Planck's constant, \hbar , as the scale by which we measure angular momentum and action, the electron charge, e, will be our scale for electrical charge, and finally Coulomb's constant, k_e , will be our scale of electric permittivity.

The usual way to state this is to set $\hbar=e=m_e=k_e=1$, and the system of units derived from these four definitions is called Hartree atomic units. We can think of this as the *natural* system of units for the Hydrogen atom system. To better see why this is the case, let us combine these four quantities in such a way as to produce a length.

In terms of the four fundamental dimenions of physics: Length(L), time(T), mass(M), and charge(C), the units of \hbar , m_e , e, and k_e are $[\hbar] = \mathrm{ML^2T^{-1}}$, $[m_e] = \mathrm{M}$, $[e] = \mathrm{C}$, and $[k_e] = \mathrm{ML^3C^{-2}T^{-2}}$, respectively. Combining arbitrary powers of these four constants gives

$$[\lambda(a, b, c, d)] = [k_e^a \hbar^b m_e^c e^d] = (M^a L^{3a} C^{-2a} T^{-2a}) (M^b L^{2b} T^{-b}) (M^c) (C^d)$$

= $L^{2a+3b} T^{-a-2b} M^{a+b+c} C^{-2b+d}$. (A.1)

There is exactly one way to realize a length from these exponents, i.e. solving the four equations 2a + 3b = 1, -a - 2b = 0, a + b + c = 0, and -2b + d = 0: a = -1, b = 2, c = -1, and d = -2. This means that the natural length scale of our problem is simply (up to a numerical constant)

$$L_{\text{scale}} = a_0 = k_e^{-1} \hbar^2 m_e^{-1} e^{-2} = \frac{\hbar^2}{k_e m_e e^2} = \frac{4\pi \varepsilon_0 \hbar^2}{m_e e^2},$$
(A.2)

which re recognize as simply the Bohr radius.

We can go through this same exercise to find a natural *time* scale for our system. There is a unique way to combine the exponents a, b, c, and d in order to realize a time, namely a=-2, b=3, c=-1, d=-4, or

$$T_{\text{scale}} = k_e^{-2} \hbar^3 m_e^{-1} e^{-4} = \frac{\hbar^3}{k_e^2 m_e e^4} = \frac{\hbar a_0}{k_e e^2}.$$
 (A.3)

This is the revolution time of an electron in the lowest lying hydrogen state in the Bohr model (apart from a factor of 2π).

From a_0 and T_{scale} we can find the natural energy scale,

$$E_{\text{scale}} = m_e \frac{a_0^2}{a_0^2 \left(\frac{\hbar}{k_e e^2}\right)^2} = \frac{m_e k_e^2 e^4}{\hbar^2} \equiv E_h, \tag{A.4}$$

which we will call a Hartree.

Finally, before we go on we may use the expression for the *fine structure constant* to find the numerical value of c in this system. From

$$\alpha = \frac{k_e e^2}{\hbar c} \Rightarrow c = \frac{k_e e^2}{\hbar \alpha} = \frac{1}{\alpha} \simeq 137,$$
 (A.5)

after substituting $\hbar = e = k_e = 1$.

Appendix B

Basics of numerical integration

Riemann integral and Riemann integrable functions

Given a function f(x) and a closed finite subset of \mathbb{R} , [a,b] with a < b, a *Riemann sum* of f is defined as the sum of values attained on n sub-intervals of [a,b], i.e.

$$S_n = \sum_{i=1}^n (x_i - x_{i-1}) f_i.$$
(B.1)

The x_i s here define the partitionining into sub-intervals $[x_{i-1}, x_i]$ (i.e. $a = x_0 < x_1 < \cdots < x_{n-1} < x_n = b$), while $f_i \equiv f(\xi_i)$ with ξ_i some point in sub-interval i.

A sufficient condition for the *Riemann integral* to exist for the function f is that any such sum (any choice of x_i [for which $\max_i |x_i - x_{i-1}| \to 0$] and ξ_i) converge to the same value in the limit $n \to \infty$ [21]. In this case we say

$$\lim_{n \to \infty} S_n = S = \int_a^b f(x) \, \mathrm{d}x,\tag{B.2}$$

and that f is Riemann integrable.

A less strict, but still sufficient condition is to chose $\overline{f_i} = \max\{f(x) : x \in [x_{i-1}, x_i]\}$ and $\underline{f_i} = \min\{f(x) : x \in [x_{i-1}, x_i]\}$ and then only demand that the two sums converge to a common limit [22],

$$\lim_{n \to \infty} \overline{S_n} = \lim_{n \to \infty} \sum_{i=1}^n (x_i - x_{i-1}) \overline{f_i}$$

$$= \lim_{n \to \infty} \sum_{i=1}^n (x_i - x_{i-1}) \underline{f_i} = \lim_{n \to \infty} \underline{S_n}$$

$$= \int_a^b f(x) \, \mathrm{d}x.$$

Although easier than checking *every possible* Riemann sum, checking that the two upper and lower sums converge to a common limit is still a somewhat tedious

procedure for checking integrability. In fact it turns out that a sufficient condition on f is that it is continous and bounded on [a,b] [21]. The latter condition is not neccessary on a finite interval since all continous functions on a closed finite domain are bounded according to the extreme value theorem. However, if we extend the limits of integration to an infinite interval, for example $[0,\infty)$, then the boundedness of f is not guaranteed by the continuity we need to explicitly demand $|f(x)| < \infty$ for all $x \in [a,b]$.

It is easy to see that the converse is *not* true. Any Riemann integrable function is not automatically continous. Take for example the integral over [0,1] with the step function

$$f(x) = \begin{cases} 1 & \text{if} \quad x > 1/2 \\ 0 & \text{else} \end{cases}$$
 (B.3)

Even though the upper and lower Riemann sums both attain the value 1/2 in the limit $n \to \infty$ and the function is Riemann integrable, it demonstrably is not continous. A more careful analysis shows that a less strict but sufficient condition on f is that it be continous *almost everywhere* on [a,b] (i.e. continous on all of the interval, except possibly on a subset $C \subset [a,b]$ with measure zero) [23]. With this condition, the converse also holds.

Newton-Cotes quadrature

Since the Riemann integral is defined in terms of the limit of a sum, numerical approximations to it arise naturally from any scheme for choosing ξ_i and the partitioning. One of the simplest possible approximations is to take the midpoint value of each sub-interval to be ξ_i with a uniform mesh of equispaced x_i s. This constitutes the **midpoint rule** [21],

$$I \approx \sum_{i=1}^{n} f(x_{i-1} + \Delta x/2)(x_i - x_{i-1}) = \Delta x \sum_{i=1}^{n} f(x_{i-1} + \Delta x/2),$$
 (B.4)

where $\Delta x \equiv (x_i - x_{i-1})$ which is the same for all i.

Instead of the midpoint, we can use the *average* of the left and right endpoints of the subinterval as f_i . Geometrically, this means we are approximating the integral of each sub-interval by the integral over a right trapezoid with base points at $(x_{i-1}, 0)$ and $(x_i, 0)$ and upper point at the function values $(x_{i-1}, f(x_{i-1}))$ and $(x_i, f(x_i))$. The resulting approximation is known as the **trapezoidal rule** [11],

$$I \approx \sum_{i=1}^{n} \frac{f(x_{i-1}) + f(x_i)}{2} (x_i - x_{i-1}) = \Delta x \sum_{i=1}^{n} \frac{f(x_{i-1}) + f(x_i)}{2}.$$
 (B.5)

Yet another numerical scheme arises from replacing the integrand in each subinterval with an interpolating polynomial of degree two, which by construction coincides with f at the endpoints and the midpoint. This constitutes **Simpson's rule** [21],

$$I \approx \sum_{i=1}^{n} (x_i - x_{i-1}) \left(\frac{f(x_{i-1})}{6} + \frac{4f(x_{i-1})}{6} + \frac{4f(x_{i-1})}{6} + \frac{f(x_i)}{6} \right)$$

$$= \frac{\Delta x}{6} \sum_{i=1}^{n} \left(f(x_{i-1}) + 4f(x_{i-1}) + \Delta x/2 + f(x_i) \right).$$
(B.6)

All three approximations are examples of Newton-Cotes quadrature rules, which approximate the intergral by replacing the integrand by interpolating polynomials of order k on each of the n sub-intervals. We can build arbitrarily high order methods by constructing higher order interpolating polynomials within each interval. The interpolation procedure is described for example in [24]. We have just seen Newton-Cotes method for orders zero (midpoint rule, zero order polynomial [constant]), one (trapezoidal rule, linear polynomial), and two (Simpson's rule, quadratic polynomial). The next few commonly used methods are the third order *Simpson's 3/8 rule* and the fourth order *Boole's rule*.

Gaussian quadrature

Note that so far we have assumed the sub-intervals to all be the same size. If we drop this requirement, we can construct more advanced rules which exploit some convenient properties of orthogonal polynomials. Gaussian quadrature rules are a set of schema for numerical intergration in which we extract a *weight function* from the integrand

$$\int_{a}^{b} f(x) dx = \int_{a}^{b} W(x)g(x) dx \approx \sum_{i=1}^{n} w_{i}g(x_{i}).$$
 (B.7)

The weight function is associated with a set of orthogonal polynomials, and the integration points x_i are chosen as the zeros of the polynomial of degree n-1. Note carefully that $w_i \neq W(x_i)$. The weights w_i can in general be expressed as [25]

$$w_i = \left(\frac{a_n}{a_{n-1}}\right) \frac{\int_a^b W(x) p_{n-1}(x)^2 dx}{p'_n(x_i) p_{n-1}(x_i)}$$
(B.8)

where $p_n(x)$ is the orthogonal polynomial of degree n and a_n is the coefficient of the x^n term in $p_n(x)$. In some cases, the weight function is present in the original integral and the extraction constitutes a strict simplification of the function. For example, with Chebyshev polynomials¹ the weight function takes the form W(x) =

$$(1-x^2)\frac{\partial^2 y(x)}{\partial x^2} - x\frac{\partial y(x)}{\partial x} + n^2 y(x) = 0,$$
(B.9)

¹The Chebyshev polynomials are solutions to the differential equation

 $1/\sqrt{1-x^2}$, so trying to apply Gauss-Chebyshev quadrature to the integrand $(x^{10}+x+2)/\sqrt{1-x^2}$ would yield simply $g(x)=x^{10}+x+2$ and we would just have to evaluate g_i according to the zeroes of the nth Chebyshev polynomial. Each class of polynomials is associated with a specific interval of integration. For Chebyshev, this is [-1,1]. So using our previous example, we note that with only 3! integration points (exclamation point for emphasis and factorial function) we integrate exactly

$$I \equiv \int_{-1}^{1} \underbrace{\frac{x^{10} + x + 2}{\sqrt{1 - x^{2}}}}_{\equiv f(x)} dx = \sum_{i=1}^{6} w_{i} \underbrace{(x^{10} + x + 2)}_{g(x)} = \frac{575\pi}{256}.$$
 (B.11)

In general, if g(x) is a polynomial of degree 2n-1 for a weight function associated with some class of orthogonal polynomials, then the gaussian quadrature rule associated with the same class of polynomials will integrate the original f(x) (recall that g(x) = f(x)/W(x)) exactly with only n integration points [11].

Multiple integrals

Both of the aforementioned rules are straight forward to extend to higher dimensional integrals. For the Newton-Cotes rules, we can simply apply the rule again to the sum resulting from the application of the rule, i.e.

$$I_{2D} = \int_{a}^{b} \int_{a}^{b} f(x, y) dx dy \approx \int_{a}^{b} \sum_{i=1}^{n} \Delta x f(\xi_{i}, y) dy$$
$$\approx \sum_{i=1}^{n} \sum_{j=1}^{n} \Delta x \Delta y f(\xi_{i}, \zeta_{j}). \tag{B.12}$$

Since function evaluations on the endpoints of sub-intervals (sub-areas to be precise) coincide with the endpoints of the neighbouring sub-intervals, a number of points may be evaluated multiple times and thus have a higher *weight* in the final sum. For example, the 1D trapezoidal rule carries weights

$$1/2$$
 1 1 1 ... 1 1 1 $1/2$, (B.13)

with n a non-negative integer. In general, the solution can be written as [26]

$$T_n(x) = \sum_{k=0}^{\lfloor 1/2 \rfloor} \binom{n}{2k} (x^2 - 1) x^{n-2k}.$$
 (B.10)

since

$$\frac{\Delta x}{2} \sum_{i=1}^{n} \left(f(x_{i-1} + f(x_i)) \right) = \frac{\Delta x}{2} \left[f(x_0) + 2 \sum_{i=1}^{n-1} \left(f(x_i) + f(x_{i+1}) \right) \right]$$

$$= \frac{\Delta x}{2} \left[f(x_0) + 2 \left(\sum_{i=1}^{n-1} f(x_i) \right) + f(x_n) \right]$$

$$= \frac{\Delta x}{2} \left[f(x_0) + 2 f(x_1) + 2 f(x_2) + \dots + 2 f(x_{n-2}) + 2 f(x_{n-1}) + f(x_n) \right].$$
(B.14)

In a similar way, the 2D trapezoidal rule has the weights

while the 2D Simpson's rule attains the weights (apart from a factor 1/6)

A similar scheme yields multi-dimensional Gaussian quadrature rules, where the total weights become products of the 1D weights.

Appendix C

Functionals and functional variations

Recall that a *function* is a mapping from some algebraic scalar field $\mathbb F$ to another (possibly different) field $\mathbb F'$, i.e. $g:\mathbb F\to\mathbb F'$. In physics, we are usually interested mainly in the cases where $\mathbb F$ and $\mathbb F'$ are the real or complex numbers, $\mathbb R$ or $\mathbb C$. An example is the complex exponential, $x\mapsto e^{ix}$, which takes complex values but the argument is real, so $g:\mathbb R\to\mathbb C$ in this case.

A *functional*, on the other hand, is a mapping from some function space, \mathcal{F} , to a scalar field \mathbb{F} , i.e. $f: \mathcal{F} \to F$. We will take the space of functions to be the underlying Hilbert space of our quantum mechanical system, \mathcal{H} , and the field to be the complex numbers, \mathbb{C} . The functional thus assigns to each $f \in \mathcal{H}$ a complex number.

As a familiar example of such a construction, let us consider the definite integral. For the moment, let us take the function space to be continuous real functions of a single real arguments in the range [0,1], C([0,1]). We call this *functional* I, such that $I:C([0,1]) \to \mathbb{R}$.

$$I[f] = \int_0^1 \mathrm{d}x f(x) \tag{C.1}$$

thus assigns a real number to any continous function on [0,1]. For example, $I[e^x] = e - 1 \approx 1.7183$ or $I[\sqrt{x}] = 2/3 \approx 0.6667$.

When working in a separable Hilbert space as we always do in quantum mechanics, we may always express any function $f \in \mathcal{H}$ in terms of some basis $\{chi_n\}_{n=1}^{\infty}$, (recall the Parseval relation from section ((QM math)))

$$|f\rangle = \left(\sum_{n=1}^{\infty} |\chi_n\rangle \langle \chi_n|\right) |f\rangle = \sum_{n=1}^{\infty} \underbrace{\langle \chi_n|f\rangle}_{c_n} |\chi_n\rangle = \sum_{n=1}^{\infty} c_n |\chi_n\rangle, \tag{C.2}$$

meaning we can think of a functional F[f] as a function of the vector of coefficients relative to the basis set, $\mathbf{c} = (c_1, c_2, \dots)$ [9].

C.0.1 Short mathematical interlude

Let B(X,Y) denote the set of all continous linear transformations from normed vector spaces X and Y (over the algebraic scalar field \mathbb{F}^1). For example we may consider $X = \mathbb{R}^n$ and $Y = \mathbb{R}^m$, i.e. the set of real vectors of length n and m, respectively. The set of continous linear transformations from X to Y, B(X,Y), thus consists of real valued matrices of dimensions $m \times n$, so we may write $B(\mathbb{R}^n, \mathbb{R}^m) = \mathbb{R}^{m \times n}$.

A *Banach space* is a normed vector space which is complete under the metric associated with the norm. Since any norm, $\|\cdot\|$ induces as metric by $d(\mathbf{x}, \mathbf{y}) = \|\mathbf{x} - \mathbf{y}\|$, and the inner product $\langle\cdot|\cdot\rangle$ induces a norm by $\|\cdot\| = \sqrt{\langle\cdot|\cdot\rangle}$ we can define a *Hilbert space* as a Banach space which is complete w.r.t. this specific metric [22, 23].

The space of linear transformations from X to \mathbb{F} , with X being some normed vector space, is called the *dual space* of X, sometimes denoted X^* . We note that a linear transformation from X to \mathbb{F} is exactly a linear *functional*, and so functionals "live in the dual" of the vector space itself. It turns out that if X is normed, the dual is always a Banach space [27]. Since we are inherently working with Hilbert spaces in quantum mechanics, it is natural to ask: What can we say in general about the vector space of functionals on a Hilbert space \mathcal{H} ?

In the following, we take $f \in \mathcal{H}^*$ to be a linear functional on \mathcal{H} and $x \in \mathcal{H}$ to be a function in the Hilbert space itself. It can be shown that for any such x there exists a unique $y \in \mathcal{H}$ such that $f[x] = f_y[x] = \langle x|y \rangle$, where the functional $f_y[\cdot] \equiv \langle \cdot|y \rangle$ [27, 23]. This is known as the Riesz representation theorem or sometimes the Riesz-Fréchet theorem. Essentially, this means that we can associate the dual space of \mathcal{H} with the space itself since there is a correspondance between the functionals and the elements of the space itself. This is more succintly stated as Hilbert spaces are self-dual, and it is this property that justifies the use of Dirac bra-ket notation since we are guaranteed that any ket has a unique corresponding bra which is its Hermitian conjugate.

C.0.2 Functional differentials and derivatives

The differential of a functional F[f] is the part of the difference $F[f+\delta f]-F[f]$ that depends linearly on δf , where δf is an infinitesimal variation of the argument function f [28]. Since we need to account for the continous variation of F over the infinitesimal range $[f, f+\delta f]$ we take the integral

$$\delta F[f] = \int \frac{\delta F[f]}{\delta f(x)} \delta f(x) \, \mathrm{d}x, \tag{C.3}$$

where we have defined the functional derivative of F w.r.t. f at the point x as

$$F'[f] \equiv \frac{\delta F[f]}{\delta f(x)}.$$
 (C.4)

¹Meaning X and Y are closed under scalar multiplication with elements $c \in \mathbb{F}$.

If the underlying space is a Banach space, meaning the dual space is also a Banach space (c.f. section C.0.1), we can write the functional differential in a way that is familiar [29]:

$$\delta F[f] = \lim_{\varepsilon \to 0} \frac{F[f + \varepsilon \delta f(x)] - F[f]}{\varepsilon} = \int \frac{\delta F[f]}{\delta f(x)} \delta f(x) \, \mathrm{d}x. \tag{C.5}$$

In the following, assume g[f] is a functional of the function f. It turns out that the functional derivative behaves a lot like ordinary derivatives, [30]

$$\frac{\delta}{\delta f(x)} \Big(aF[f] + bG[f] \Big) = a \frac{\delta F[f]}{\delta f(x)} + b \frac{\delta G[f]}{\delta f(x)}$$
 (linearity)
$$\frac{\delta}{\delta f(x)} \Big(F[f] G[f] \Big) = G[f] \frac{\delta F[f]}{\delta f(x)} + F[f] \frac{\delta G[f]}{\delta f(x)}$$
 (product rule)
$$\frac{\delta}{\delta f(x)} \Big(F[g] \Big) = \int \frac{\delta F[g]}{\delta g(x')} \frac{\delta g(x')}{\delta f(x)} dx$$
 (chain rule)

We can also define higher-order functional derivaties, for example the equivalent of the ordinary double derivative

$$\frac{\delta^2 F[f]}{\delta f(x)\delta f(x')} = \frac{\delta}{\delta f(x)} \left(\frac{\delta F[f]}{\delta f(x')} \right). \tag{C.6}$$

We may use this to compute the Taylor expansion of a functional F[f] as

$$F[f + \Delta f] = F[f] + \sum_{n=1}^{\infty} \frac{1}{n!} \int \cdots \int \frac{\delta^{(n)} F[f]}{\delta f(x_1) \dots \delta f(x_n)} \Delta f(x_1) \Delta f(x_2) \dots \Delta f(x_n) dx_1 dx_2 \dots dx_n$$

$$F[f + \Delta f] = F[f] + \int \frac{\delta F[f]}{\delta f(x)} \Delta f(x) dx + \frac{1}{2} \int \int \frac{\delta^2 F[f]}{\delta f(x) \delta f(x')} \Delta f(x) \Delta f(x') dx dx' + \dots,$$
(C.7)

where $\Delta f(x)$ is a finite (not infinitesimal) variation in the function f(x) [28].

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