Annual Progression Review

Cecilia Maria Fabbri

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Contents

Chapter 1

Literature Review

Gravitational waves (GWs) are perturbations of spacetime generated by mass distributions with a non-vanishing second derivative of the quadrupole mass-moment. Binary systems of stellar objects are exemplary GW emitters and the more compact the object, the larger the wave amplitude, making the system more suitable for detection [1].

The LIGO-Virgo-KAGRA (LVK) collaboration uses a system of interferometers to detect gravitational waves [2–4]. The most recent complete catalogue they published is the third gravitational-wave transient catalogue (GWTC-3), which contains about a hundred signals generated by the coalescence of binaries of neutron stars (NSs) and stellar-mass black holes (BHs) [5].

When LVK detects an astrophysical signal, it analyzes the data to infer the properties of the event, such as the masses of the binary components, their spins, the distance from the observer and the sky localization. The statistical framework used for individual event analysis is Bayesian inference. As the number of detections is growing, population analyses become crucial, as they enable further constraints on the astrophysics of compact objects (COs) [5–8]. To this end, one uses Hierarchical Bayesian statistics [9, 10].

The models used have multi-dimensional parameters, resulting in probability distributions computationally prohibitive. Traditional approaches rely on stochastic sampling methods (e.g. Markov Chain Monte Carlo (MCMC) or Nested sampling) to infer probability distributions [10–13]. However powerful, this approach is computationally expensive, as probability distributions are evaluated iteratively million of times for each analysis. Evaluations require to generate a waveform on the fly, which substantially contributes to the overall computational cost. Machine learning approaches have the advantage of shifting most of the cost to the training stage, dramatically speeding up inference [14–16].

1.1 Bayesian statistics

Let us refer to the vector of binary parameters as θ. It consists of intrinsic parameters, such as the masses and spins, and extrinsic parameters, such as the redshift and binary orientation. The goal of the analysis is to infer the posterior distribution $p(\theta|d)$, which assigns to each point in the binary-parameter space the probability that binary the corresponding binary generated the observed data d. The observed data is the sum of the astrophysical signal, which is assumed to be deterministic and a function of binary-parameters, and a noise realization in the detector, which is assumed to be stochastic. To infer the posterior one needs a prior $\pi(\theta)$ and a likelihood $\mathcal{L}(d|\theta)$ [17]. The prior is the probability distribution that an event with parameters θ occurs in the Universe. A possible approach is to construct the prior based on theory or previous experiments. Nevertheless, the preferred approach is often conservative, using uninformative priors, such as priors with constant probability insiide the binary-parameters domain and zero outside. The likelihood is the probability in the data space, given parameters θ. To evaluate the likelihood one needs to generate waveforms for θ and a noise model [18, 19]. To construct the noise model one often assumes that noise is stationary and Gaussian. Bayes' theorem links the posterior to the prior and the likelihood:

$$p(\theta|d) = \frac{\pi(\theta) \times \mathcal{L}(d|\theta)}{p(d)}. \tag{1.1}$$

The term $p(d)$ is called evidence, and it is the probability of observing the data d under the assumed model. The evidence is defined as

$$p(d) = \int \mathrm{d}\theta \pi(\theta) \times \mathcal{L}(d|\theta). \tag{1.2}$$

The evidence acts as a normalization factor and does not affect the posterior shape. For this reason, it is typically not computed during inference, except when performing model comparison.

1.2 Hierarchical Bayesian statistics

The goal of population analysis is to infer how binary parameters are distributed at the population level. First, one parametrizes the distribution of binary parameters with the population parameters λ, which determine the shape of the distribution. Examples of such hyperparameters include the slope of the binary black hole (BBH) mass distribution, as well as the minimum and maximum mass of stellar-mass BHs. The prior on binary parameters is conditioned on the population parameters, and we refer to it as the population model $p_{\text{pop}}(\theta|\lambda)$. For the analysis, one also needs the prior on population parameters, called hyperprior, $\pi(\lambda)$.

The choice of the population model is crucial, and several approaches have been proposed to construct it. The state-of-the-art methods are parametric models, which rely on simple parametric forms motivated by qualitative astrophysical arguments [5, 9, 20]. Other approaches move toward more flexible models, referred to as semi-parametric or non-parametric models, where the hyperparameters are for instance spline knots and perturbations [21–23]. These models enable data-driven fits but their results are often more difficult to interpret physically. Astrophysical approaches often consist of comparing observed data with the output of simulations that synthesize binary populations [24–27].

In population analyses, it is necessary to take selection effects into account [28–30]. Since different events have different probabilities of being detected, the observed population is biased. An event is considered detectable if the data exceeds a given threshold. The detection probability for an event is defined as

$$p_{\rm det}(\theta) = \int_{d > treshold} \mathrm{d}d p(d|\theta). \tag{1.3}$$

Let us refer to the dataset of observed events as d and to individual events as d_i, with $i = 1, ..., N_{\rm obs}$, where $N_{\rm obs}$ is the number of observed events. The posterior for the astrophysical distribution, called the hyperposterior, is:

$$p(\lambda|d) = \frac{\pi(\lambda)}{p(d)} \prod_{i=1}^{N_{\rm obs}} \frac{\int \mathrm{d}\theta \mathcal{L}(d_i|\theta) p_{\rm pop}(\theta|\lambda)}{\int \mathrm{d}\theta p_{\rm pop}(\theta|\lambda) p_{\rm det}(\theta)}, \tag{1.4}$$

where $\mathcal{L}(d_i|\theta)$ is the likelihood of individual events as defined in Eq. 1.1. The term $p(d)$ is the hyperevidence, and it is the probability of the observed dataset under the assumed population model, i.e.:

$$p(d) = \int \mathrm{d}\lambda' \pi(\lambda') \prod_{i=1}^{N_{\rm obs}} \mathcal{L}(d_i|\lambda'). \tag{1.5}$$

Here, the likelihood respect to the hyperparameters $\mathcal{L}(d_i|\lambda')$ is related to the individual-event likelihood through

$$\mathcal{L}(d_i|\lambda') = \int \mathrm{d}\theta \mathcal{L}(d_i|\theta) p_{\rm pop}(\theta|\lambda). \tag{1.6}$$

The hyperevidence is often computed in population analysis to compare different population models and assess how well they describe the observed dataset.

Population analyses are typically carried out in two steps. First, individual events are analyzed using Bayesian statistics. Then, one uses the resulting individual-event posteriors and the assumed population model to infer the hyperposterior in Eq. 1.4.

1.3 Simulation based inference

Simulation-based inference (SBI) is a deep learning technique for approximating probability distributions using simulated data [31–34]. I am working with the DINGO code, which applies SBI to model posteriors of gravitational-wave data [15, 16, 35, 36]. To simulate data, we need to draw samples from the prior and the likelihood. Unlike to traditional methods, SBI does not require explicit evaluation of the likelihood. In principle, more complex models that lack an analytical expression can be used. For instance, one can relax the assumptions of stationary and gaussian noise, or use waveforms generated from simulations [37, 38].

Normalizing flows are often used in SBI to approximate complex distributions. A normalizing flow is a mapping from a simple $\pi(u)$ to an approximation of the posterior $q_\phi(\theta|d)$, where ϕ are the parameters of the mapping. The mapping $f_\phi(u)$ must be invertible and with a simple Jacobian determinant, so that:

$$q_\phi(\theta|d) = \pi(f_\phi^{-1}(\theta)) \left| \det J_{f_\phi}^{-1} \right|. \tag{1.7}$$

To evaluate $q_\phi(\theta|d)$ one uses Eq. 1.7. Drawing samples from $q_\phi(\theta|d)$ is equivalent to drawing $u \sim \pi(u)$ and transforming $\theta = f_\phi(u)$. One often chooses the base distribution $\pi(u)$ to be a multivariate standard normal. In the case of DINGO, the flow f_ϕ is a sequence of transforms $f_\phi^{(i)}$, such that

$$f_\phi^i(u) = \begin{cases} u_i & \text{if } i \leq d/2 \\ c_i(u_i; u_{1:d/2}, d) & \text{if } i > d/2 \end{cases}. \tag{1.8}$$

Half of the latent variables u remain unchanged, while the other half are transformed. At each $f_\phi^{(i)}$ the indices are permuted. The transformation used is the neural spline coupling transform c_i, whose parameters depend on the unchanged u_i and on data strain d.

During training, the neural network learns the mapping by optimizing the parameters ϕ to minimize a loss function. In these problems, the loss functions is typically based on the Kullback-Leibler divergence, defined as:

$$D_{\mathrm{KL}}(p||q_\phi) = \int \mathrm{d}\theta p(\theta|d) \log \frac{p(\theta|d)}{q_\phi(\theta|d)}, \tag{1.9}$$

which vanishes as the approximant becomes closer to the true posterior. Since the approximant should not depend on the individual data, we define the loss function as the expectation value over $p(d)$ of $D_{\mathrm{KL}}(p||q_\phi)$:

$$L = \int \mathrm{d}d p(d) \int \mathrm{d}\theta p(\theta|d) \log \frac{p(\theta|d)}{q_\phi(\theta|d)}. \tag{1.10}$$

Using Bayes Theorem one obtains:

$$L \simeq -\int \mathrm{d}\theta \pi(\theta) \int \mathrm{d}d p(d|\theta) \log q_\phi(\theta|d), \tag{1.11}$$

where the posterior at the numerator of the logarithm can be omitted since the minimization over ϕ does not depend on the true posterior. Simulating events is equivalent to drawing N events from the prior, $\theta_i \sim \pi(\theta)$, and data from the likelihood $d_i \sim p(d|\theta_i)$, with $i = 1, ..., N$. The loss is then given by

$$L = -\frac{1}{N} \sum_i \log q_\phi(\theta|d), \tag{1.12}$$

where Monte Carlo (MC) sums are used to approximate the integrals [39].

DINGO architecture uses an embedding network to compress data strains before passing them to the flow [16]. We train the embedding jointly with the flow. During training the network learns how to compress the data, i.e. it identifies the most important features.

Chapter 2

Completed Work

Transfer learning is a set of techniques in machine learning used to transfer knowledge from one neural network to another.

My first projects involves testing transfer learning with DINGO for individual-events analysis, following the multifidelity approach in Ref. [40]. The typical training dataset size required to obtain well-trained NNs in DINGO is of the order of 10^6 simulations. Let us consider two waveform models. A high-fidelity model is accurate but computational expensive, with prohibitive costs that limit the number of simulations to well below 10^6 (e.g. numerical relativity simulations). A low-fidelity model is less accurate and cheap, allowing us to easily simulate 10^6 data. Assuming that the flow architecture is the same in both cases, we fine-tune the high-fidelity network using the parameters optimized during the low-fidelity training run. The NN for the high-fidelity model achieves higher performances when pretrained, partially inheriting knowledge acquired during the low-fidelity training.

2.1 Diagnostics to check the performance of the neural network

There are several diagnostics to assess the quality of the posterior approximant.

The evolution of the loss function provides information on how training is progressing. When training a NN, the dataset is split into a training set and validation set. The training set is used to update the NN parameters in order to minimize the loss. The validation set is used to compute the loss after each update, allowing one to monitor the NN's performance on unseen data. A common sanity check consists in ensure that the validation and training losses decrease together during training. By the end of training, both losses should reach a plateau.

Importance sampling tests how closely $q_\phi(\theta|d)$ approximates $p(\theta|d)$ in multiple dimensions. During inference one draws samples θ_i from the approximant of the posterior $\theta_i \sim q_\phi(\theta|d)$. Each θ_i can be assigned a weight w_i:

$$w_i \propto \frac{\pi(\theta_i)p(d|\theta_i)}{q_\phi(\theta_i|d)}. \tag{2.1}$$

The variance of weights provides a measure of the sampling efficiency

$$\epsilon = \frac{\left(\sum_i w_i\right)^2}{n \sum_i w_i^2} \tag{2.2}$$

[36]. Smaller values of ϵ correspond to poorer posterior approximations.

2.2 From non-spinning to aligned-spins model

To test the multifidelity procedure, we use a non-spinning waveform as the low-fidelity model, while the high-fidelity model includes aligned spins. We use IMRPhenomXPHM as the approximant to generate waveforms is . For the low-fidelity model, we generate $\sim 10^6$ simulations. For the high-fidelity model, we generate multiple datasets of sizes $\sim 10^5$, $\sim 10^4$ and $\sim 10^3$. For the datasets of $\sim 10^6$ and $\sim 10^3$ simulations, we also perform additional training where we pretrain the embedding only. Results for pretraining only the embedding are preliminary. We plan to explore this approach further, as it could improve the flexibility of the high-fidelity model, allowing us to use pretraining while modifying the flow architecture.

Figure 2.1 shows the evolution of the validation and set loss functions during training. In the two cases with largest number of simulations ($\sim 10^6$ and $\sim 10^5$), pretraining both the embedding and the flow does not significantly affect the final loss plateau. The main advantage of pretraining is the reduced time to reach the plateau, resulting in lower computational costs. For limited simulation budgets ($\sim 10^4$ and $\sim 10^3$), pretraining reduces the loss to lower values than traditional training. Pretraining the embedding alone with $\sim 10^6$ simulations allows a slightly lower final loss compared to training from scratch. For $\sim 10^3$ simulations, this strategy improves results over traditional training but does not achieve the performance of pretraining both the embedding and the flow.

The cornerplot in Fig. 2.2 shows the analysis of an injection for different simulation budgets when pretraining both the flow and the embedding. The marginal posteriors are consistent across budgets. However, the marginal posterior for χ_1 deviates respect to the injected value, while the marginal posterior for χ_2 is close to the prior.

The sampling efficiencies for 1000 injections (Fig. 2.3) confirm that pretraining with $\sim 10^4$ and $\sim 10^3$ simulations improves performance. The histogram in Fig. 2.3 shows that even with pretraining, the $\sim 10^3$ simulation case has considerably lower efficiencies than the other cases, with most injections having $\epsilon < 1\%$. Contrarily to expectations, Fig. 2.3 shows no correlation between sampling efficiency and the higher spin magnitude.

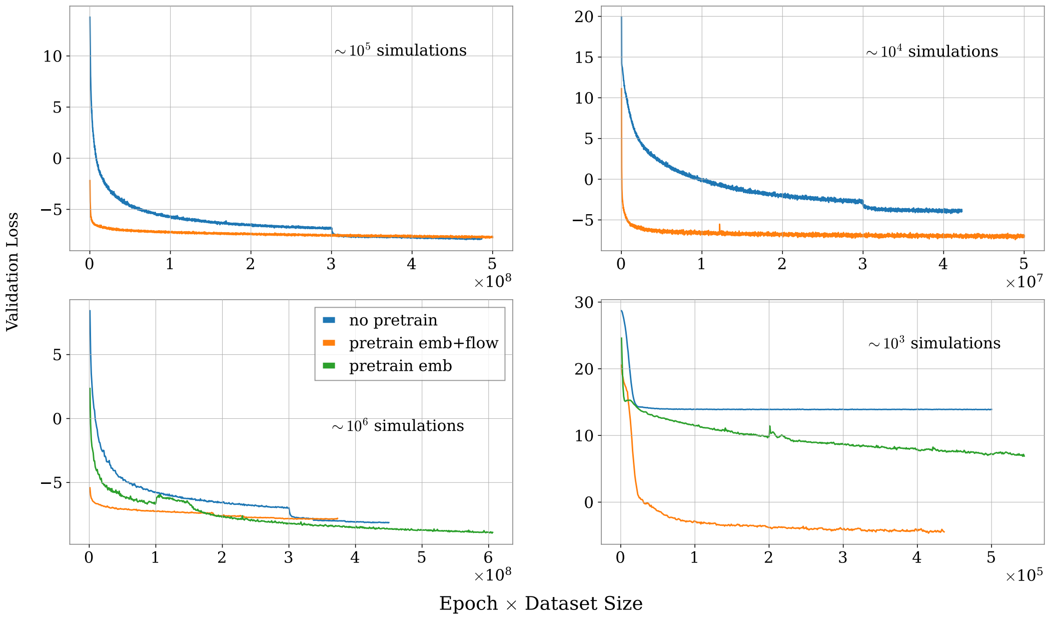

Figure 2.1: Evolution of the validation loss during training. The number of epochs corresponds to the number of times the full training set passes through the neural network. The top two panels show the losses for traditional training (blue) and pretraining both the embedding and the flow (orange) for $\sim 10^5$ (left) and $\sim 10^4$ (right) simulations. The bottom two panels show the validation losses for $\sim 10^6$ (left) and $\sim 10^3$ (right) simulations. In addition to the previous cases, results for pretraining the embedding only (green) are also shown.

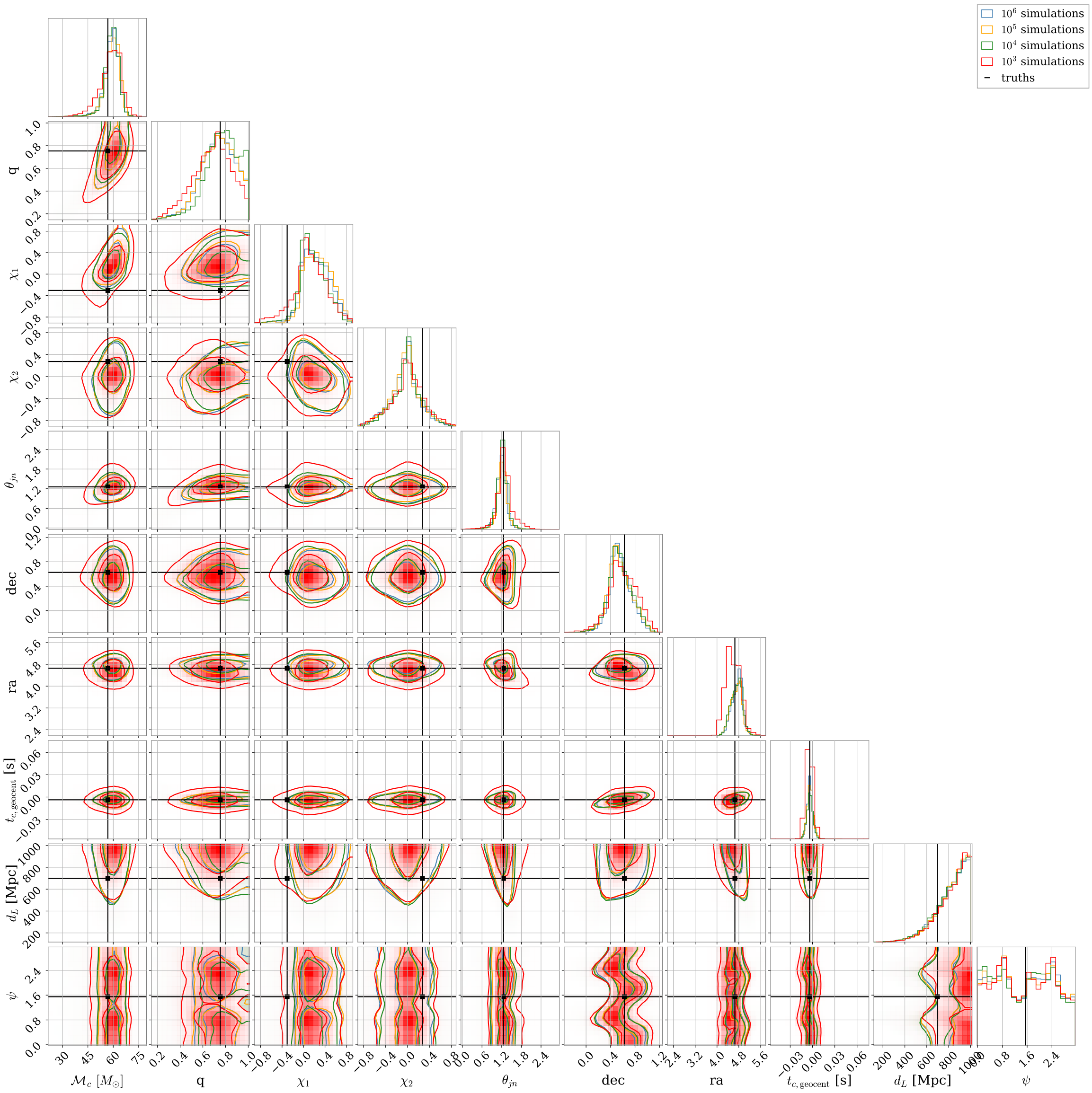

Figure 2.2: Cornerplots showing the one-dimensional (diagonal) and two-dimensional (off-diagonal) posteriors for binary parameters given an injected signal (black lines and markers). Results are obtained using DINGO with pretraining of both the embedding and the flow, with training datasets of order of magnitude $\sim 10^6$ (blue), $\sim 10^5$ (orange), $\sim 10^4$ (green), $\sim 10^3$ (red).

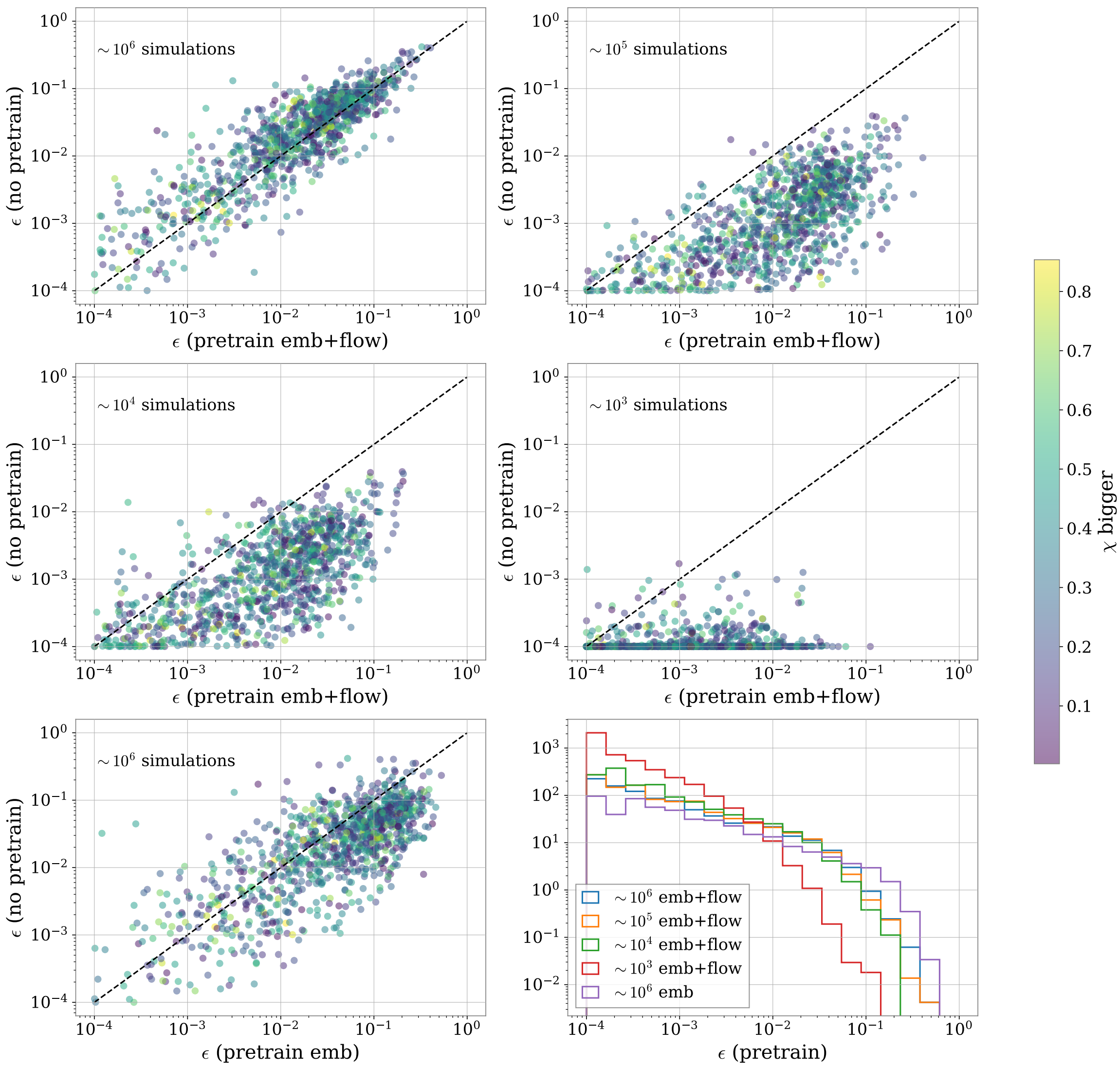

Figure 2.3: Scatter plots of sampling efficiecies for 10^3 injected signals, comparing pretraining (x axis) and no pretraining (y axis). The black dotted line corresponds to $y = x$; injections below the line have higher efficiency with pretraining. Markers are colored based on the higher-spin value. The top four plots show results when pretraining both the embedding and the flow for different simulation budgets, while the bottom-left plot shows results when pretraining the embedding only ($\sim 10^6$ simulations). The bottom-right panel displays histograms of the sampling efficiencies for pretraining cases.

Chapter 3

Work Plan

In the coming months I will continue working on the pretraining project, focusing on whether spin marginals are properly learned. With pretraining we can analyze events with numerical relativity waveform models, using, for instance, beyond general relativity (GR) models, or precessing and eccentric waveforms.

Some attempts are being to apply machine learning to populations [14, 41, 42]. One question we aim to address is whether SBI could solve the "growing pains" problem [43]. This issue arises because MC integrals have an intrinsic variance. In traditional methods likelihoods are estimated through MC integrals, which introduces an uncertainty that grows with the dataset size, and can bias future analyses. Another possible direction is to apply pretraining in population analyses, using population-synthesis codes to generate the dataset. This would allow us to perform inference directly on astrophysical processes, since population parameters would be the input parameters of the codes, e.g. the supernova kick strength, common-envelope efficiency, metallicity, and winds strength.

Chapter 4

Personal Development Plan

Below I attach the DNA form.

In the last months I deepened my knowledge on machine learning, particularly in SBI.

I have attended and passed two exams: one specifically on machine learning, and one on extreme astrophysics. These exams taught me about a variety of possible machine learning architectures, used in many fields also beyond astrophysics, as well as about astrophysical processes in galaxies.

I have also attended four conferences, three on general relativity (Nottingham, Birmingham and Glasgow, UK) and one on machine learning applied to gravitational-wave analyses (Providence, US). In Birmingham I gave a presentation, while in Glasgow and in Providence I presented a poster.

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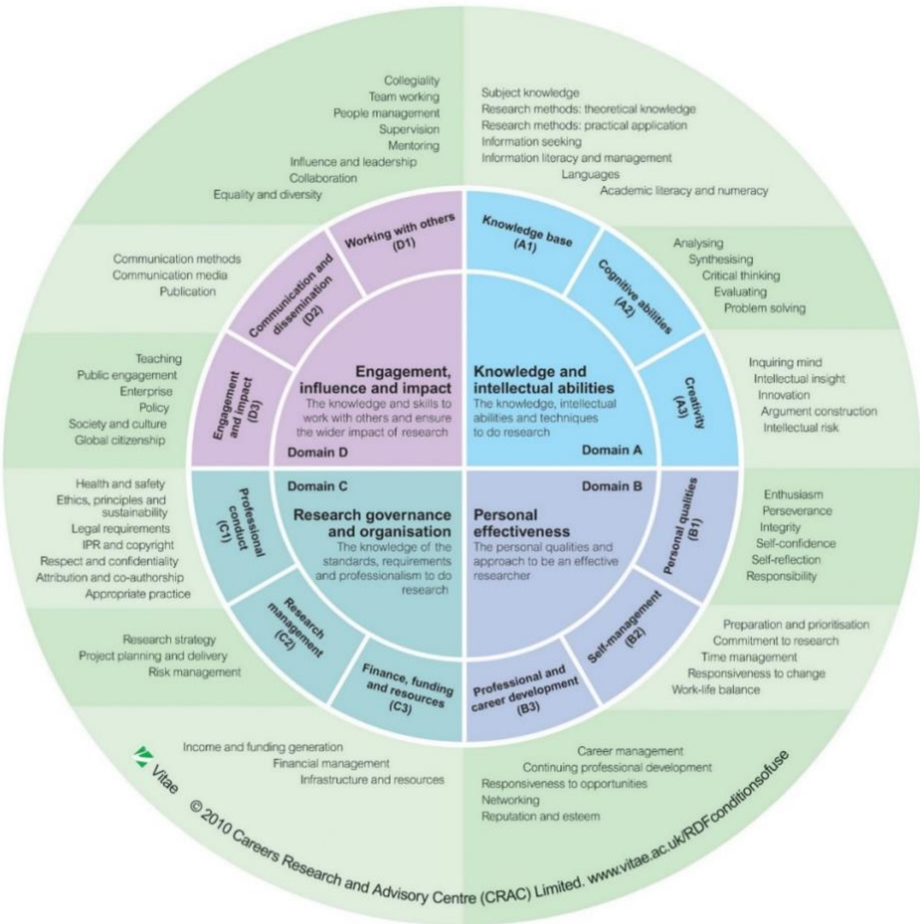
Faculty of Science
Development Needs Analysis Form

Successful and timely completion of your research degree will depend on developing a mixture of subject-specific skills, intellectual skills, such as critical thinking, and more generic skills, like communication and commercial awareness. Many of these skills will also be important in your future life, whatever career or life choices you make.

The Training & Development Needs Analysis form uses Vitae's Researcher Development Framework (RDF)[1] to help you think about your current skills, pinpoint gaps in your knowledge, and identify areas for future development. The RDF articulates the knowledge, behaviours and attitudes of researchers, from postgraduates to establish academic leaders and is endorsed by UK Research Councils and independent funders of research.

There are four sections to this form, based on the four RDF domains illustrated below. Use these four sections within the form to outline your goals for this year in each area. It is important to recognise that you cannot and that you are not expected to work on all of your identified training needs within a 12 month period, but at the same time you do not want to leave everything until the last year. Once you have identified your training needs you will need to prioritise after discussion with your supervisor(s). See the **Appendix** for questions related to each domain.



[1] For the full version, go to: https://www.vitae.ac.uk/vitae-publications/rdf-related/researcher-development-framework-rdf-vitae.pdf. If you want to focus on a specific area, go to: https://www.vitae.ac.uk/researchers-professional-development/about-the-vitae-researcher-development-framework/lenses-on-the-vitae-researcher-development-framework

Domain A: Knowledge and Intellectual Abilities

The knowledge, intellectual abilities, and techniques to do research.
(A1: Knowledge base. A2: Cognitive abilities. A3: Creativity)

Use the questions in the **Appendix** to help guide you.

- How would you assess your existing level of expertise in areas A1, A2, and A3?

A1 Knowledge base
I believe my background knowledge is sufficient for the research I am starting in Nottingham, although I need to deepen the technical skills required, especially those regarding machine learning. I have solid experience in gravitational waves and data analysis for populations. I will have access to the necessary information through papers, conferences, workshops, and library books, and I know how to assess whether a source is reliable. To keep the record of my research findings I will daily back-up my notes and codes in file-hosting services. I still do not feel confident in producing written research material and communicating the complex aspects of my research clearly and simply.

A2 Cognitive abilities
I believe I can take a critical approach to my research work and sometimes to that of others, if close to my own research field. I can recognise the important arguments and assumptions in research. I can find broad connections, but not specific ones, between my research field and other research areas or with the world outside. I can summarise the impact of my research more widely, stressing the key points. I think I am good at receiving constructive criticism but I am less apt at giving it. Doing research, I am deepening my problem-solving skills. My project is based on developing and/or applying new methods to anlyse data in differently from the traditional data anlyses in that field.

A3 Creative thinking
I find it difficult to ask difficult questions and go beyond the obvious arguments on research topics unless I have been working on those for some time. I am aware of the main trends in research that are very closely related to my field, but not when considering broader areas of research for astrophysics of gravitational waves. These trends strongly influence the projects I am involved in, as we aim to address some of the main problems in the state-of-the-art data analysis routine. I am not yet able to make connections between previously unrelated issues in my research field. I have not considered the idea of interdisciplinary collaboration for my research topic so far, although the machine-learning techniques that we are interested in can be applied across multiple fields. I think it is important to be rigorous in constructing arguments and producing evidence. To do this, in the past experience I used mathematical calculation as well as empirical tests on problems where the solution was known, starting from simple cases and later applying the techniques on real data. I belive that it is important to critically analyse the status quo of research and to take the risk of challenging it, whether one thinks it is necessary.

- Are there any areas that will require further training/development during your doctoral degree? (See the Researcher Academy's Training Hub for more information and the Faculty of Science Training Programme).

Technical skills on machine learning, and deeper knowledge of gravitational waves and astrophysics. Make connections between previously unrelated issues in my research field. I would like to develop my skills in scientific writing and presentations.

- Which training courses and development opportunities are you planning to engage with to address your training needs?

I will attend two modules (likely ML in Science and Extreme Astrophysics, offered by Physics and Astronomy) offered by the University of Nottingham.

Domain B: Personal Effectiveness
The personal qualities and approach to be an effective researcher.
(B1: Personal qualities. B2: Self-management. B3: Professional and Career development)

Use the questions in the **Appendix** to help guide you.

1. How would you assess your existing level of expertise in areas B1, B2, and B3?

B1 Personal qualities
I tend to stay motivated but I am not good at motivating others. I am part of a small research network connected to my Master's and PhD advisors, but I would like to expand my network further. I am perseverant, though sometimes I find it difficult to ask others for support to overcome obstacles. I prefer to produce fewer works with higher quality. I seek feedback on my work and I take action to improve. I take responsibility for my work.

B2 Self-management
To plan my projects, I often write down daily and weekly task lists. I tend to procrastinate on bureacratic tasks. I feel able to focus on research. I meet deadlines but I still need to improve my time management. To maintain an acceptable work-life balance, I do not work during weekends and I engage with some weekly activities (e.g. sports).

B3 Professional & Career development
I like to have flexibility in my long-term plans for the future. I like to meet new people but I am unsure how I feel about networking for career purposes. I reflect on the work that I do and I think about how I can improve it. When I consider a project, I always think about what I will learn by engaging in it. In this period of my life, I am not interested in how my skills can be applied to non-academic jobs.

2. Are there any areas that will require further training/development during your doctoral degree? (See the Researcher Academy's Training Hub for more information and the Faculty of Science Training Programme).

I would like to improve my networking skills. In the longer term, I would also like to improve my leadership skills (supervision of more junior students).

3. Which training courses and development opportunities are you planning to engage with to address your training needs?

I will consider taking "A scientist's guide to the art of networking" offered by the Researcher Academy.

Domain C: Research Governance and Organisation

The knowledge of the standards, requirements, and professionalism to do research.
(C1: Professional conduct. C2: Research management. C3: Finance, funding and resources)

Use the questions in the **Appendix** to help guide you.

1. How would you assess your existing level of expertise in areas C1, C2, and C3?

C1 Professional conduct

My research is theoretical and does not involve significant health and safety risks. I have an awareness of health and safety issues regarding myself and those around me. I consider ethical issues (in particular, dual use) related to my research. I have a basic understanding of data ownership rules as they apply to my own research. I recognise the contributions of others in my work.

C2 Research Management

I do not know the strategic research strands in my schools and which ones my research fits into. I plan and agree on goals with my supervisors. I will make a basic risk assessment of my project.

C3 Finance, funding & resources

I do not have an awareness of small grant opportunities available to me and I do not feel confident to write a funding application. I have not had the opportunity to learn the basic principles of financial management.

2. Are there any areas that will require further training/development during your doctoral degree? (See the Researcher Academy's Training Hub for more information and the Faculty of Science Training Programme).

Finance, funding & resources. It will be important to learn how to write fellowship applications by the end of my PhD.

3. Which training courses and development opportunities are you planning to engage with to address your training needs?

I will take the course on Research Integrity. In my third year, I will take course "Preparing for research independence" or another course on applying for positions in academia or beyond academia, depending on my future plans.

Domain D: Engagement, influence and impact

The knowledge and skills to work with others and ensure the wider impact of research
(D1: Working with others. D2: Communication and dissemination. D3: Engagement and impact)

Use the questions in the **Appendix** to help guide you.

1. How would you assess your existing level of expertise in areas D1, D2, and D3?

D1 Working with others

I have done team working during my studies and extra-curricular activities. I believe that the key to achieve successful teamwork is communication (one should be clear on what they can and cannot do, or when something is not going smoothly). If I have the opportunity to be involved in undergraduate teaching or mentoring, I will work together to support the learning of others, clarifying things that are not clear and providing supporting material (e.g., references). I often do not engage in debates. I intend to bring my research to the wider community through conferences.

D2 Communication and dissemination

I do not have a web presence as a researcher. I understand most of the process behind getting a paper published. I intend to produce some publishable material this year. I only have a vague idea of potential journals for publication in my research area.

D3 Engagement and impact

I will be seeking an opportunity to teach undergraduates at this University. I intend to participate in research meetings. I have never taught before, and thus I am not aware of the strengths and weaknesses in my own teaching style and techniques. I will not seek out opportunities to understand the value of establishing relationships in small business or semi-commercial contexts. I have never analysed policies. I am not aware of my corporate and social responsibilities as a University of Nottingham researcher. I understand how my research fits in a national and global context.

2. Are there any areas that will require further training/development during your doctoral degree? (See the Researcher Academy's Training Hub for more information and the Faculty of Science Training Programme).

Knowledge about (i) the potential journals for publication in my research area, (ii) policies, (iii) my corporate and social responsibilities as a University of Nottingham researcher. Improve my web presence by making a personal website and curating my profile on Inspire and Google Scholar.

3. Which training courses and development opportunities are you planning to engage with to address your training needs?

I plan to address these training needs with my supervisors.

Appendix – Domain Descriptors & Questions

Domain A: Knowledge and Intellectual Abilities

The Knowledge, intellectual abilities, and techniques used in research.

A1 Knowledge base

- **Subject knowledge**: Have you got to grips with the key concepts underpinning your research? Are you aware of recent advances? Are you aware of where your research touches other disciplines/research areas? Do you know who is working in the same research area as you? Within the University? Within the country? Internationally?
- **Research Methods**: What research methodologies and techniques have you explored (if applicable)? How are they used within your own research area? Can you justify what methodologies you have chosen to use in your own research? Do you need to combine methods and techniques? How are hoping to do that? Is your work inter-disciplinary? If so, how?
- **Information seeking:** How do you carry out your research? What resources do you use on-line? In the library? Are there specialist resources that you will need to access? Do you know how to access them? What are their limitations? How do you assess and understand the reliability, reputation and relevance of sources?
- **Information literacy and management:** How do you keep a record of your research findings? (e.g. word document, spreadsheet, database) Do you back-up your files? Will you still know how to find a quote/piece of data/thought in 3 years time? Do you have a good understanding of issues surrounding copyright and IPR and how they relate to your thesis?
- **Languages:** Do you feel confident in your ability to produce excellent written language appropriate for research? Can you/Do you have the opportunity to change your language to communicate appropriately with academics, students, the public, potential funders, potential employers?
- **Academic literacy and numeracy:** Do you successfully write grammatically and syntactically correct text? Are you IT literate and digitally competent? Do you use virtual networks for research? Are you happy that you can present complex ideas with clarity? Can you/Do you have the opportunity to critique the work of your peers?

A2 Cognitive abilities

- **Analysing:** Do you take a critical, analytical approach to your own work and the work of others?
- **Synthesising:** Do you find it easy to see connections between sections of own information/data and previous studies? Do you recognise patterns and connections outside of your own discipline/research area? Do you think about connections and patterns across disciplines/research areas/agendas and beyond academia?
- **Critical thinking:** How good are you at following critical arguments (oral and textual) and talking about your own ideas? Can you spot problems and flaws in your own arguments and in the arguments of others? Can you recognise significant and important arguments and assumptions? Can you confidently apply your critical thinking skills?
- **Evaluating:** Can you easily summarise texts? Can you think/talk about the impact of your own research in its field and more widely? Do you consciously assess the quality, integrity and authenticity of primary and secondary research information/data? How good are you at giving and receiving constructive criticism?
- **Problem solving:** Can you pinpoint the basic themes in your own research? Can you use these to formulate basic research questions? Is your project challenging traditional thinking and if so how?

A3 Creative thinking

- **Inquiring mind:** Do you find it easy to ask difficult questions about your research topic? Do you see beyond the obvious arguments?
- **Intellectual insight:** Do you absorb new ideas readily? Are you aware of trends in research being undertaken in your particular field? How do they influence your research and the research area you choose to position yourself in?
- Shows initiative, and works independently: Do you make connections between previously unrelated issues in your research?
- **Innovation:** Have you considered the idea of interdisciplinary collaboration for your research topic? Are you actively seeking out different disciplinary perspectives?
- **Argument construction:** Are you rigorous in argument construction and production of evidence? How do you try to ensure you produce convincing arguments in your work?
- **Intellectual risk:** Will our thesis challenge the status quo within the discipline/research area. How do you feel about the risk implicit in this? Do you wish you could take more of a risk in your research? What prevents you?

Domain B: Personal Effectiveness

The personal qualities and approach to be an effective researcher.

B1 Personal qualities

- **Enthusiasm:** Do you find it easy to stay motivated? How do you do it when the work is mundane? How do you enthuse others? Are you part of a research network yet?
- **Perseverance:** Do you consider yourself to be thorough? Do you use the support of others to help you overcome obstacles? Do you perform (produce high quality work/good presentations/excellent project work consistently? How do you achieve this?
- **Integrity:** Do you understand and can you demonstrate standards of good research practice
- **Self-confidence:** Do you recognise the skills that you do have and are you willing to show them? Do you know where the boundaries of your own knowledge, skills and expertise lie? Are you able to handle challenging questions with confidence? Do you give other people confidence? How do you manage to do that?
- **Self-reflection:** Do you take time to reflect on practice and experience? Do you seek out feedback on your work? Do you act on it?
- **Responsibility:** Do you take responsibility for own project? Do you take responsibility for your own well-being? Do you have the opportunity to take responsibility for others?
- **Alert to the needs for well-being of others:** How do you work with others in a way that makes you sensitive to their needs? E.g. If you have work-in-progress seminars how do you give feedback and criticism positively?

B2 Self-management

- **Preparation and prioritisation:** What experience do you have of project planning? Do you treat your PhD as a project? Do you write a task list and set milestones? Are you happy to adapt to the unexpected if necessary? Do you see gaps and opportunities in project plans? Can you/have you had the opportunity to juggle multiple projects/tasks.

- **Commitment to research:** Do you feel able to focus on your thesis? How do you evaluate and manage potential distractions?
- **Time management:** How do you manage your time? Do you meet deadlines? Are you in sufficient control of your work to react to unexpected opportunities/challenges?
- Responsiveness to change: Are you able to adapt your approach to a task when required to? How do you balance risk and opportunity? How do you know when to seek advice? How do you feel about change (and your ability to respond to it)?
- **Work-life balance:** What sources of support do you turn to avoid undue pressure? How do you manage stress and maintain an acceptable work-life balance? Do you notice stress in others and how do you provide support?

B3 Professional & Career development

- **Career management:** Do you feel in control of your own career progression? Do you have a career “plan”? And a “plan B”? Do you feel able to present your skills and abilities effectively in a job application? Have you thought about establishing a career network by making a list of relevant people you want to/need to make contact with? Do you pursue networking opportunities? Do you reflect on the work that you do and think about how you can improve it?
- **Continuing professional development:** Do you think about the transferability of your own experience and skills? Do you keep your own records of achievement and experience? Do you feel aware of your own potential in academic or non-academic job market? Do you have an understanding of the kind of skillset employers might be looking for in the type of job you would like? Does this understanding inform the skills you are developing now?
- **Responsiveness to opportunities:** Are you able to demonstrate/or are you working towards showing a broad range of experience (within and outside Academia). Are you aware of opportunities to research/work abroad? Have you considered/done a work placement? Do you recognises, create and confidently act on opportunities with the potential to develop your own career within or outside academia.
- **Networking:** Do you use personal and/or on-line networks/social media to get feedback, advice, critical appraisal of work? Do you engage with learned societies and public bodies?
- **Reputation and esteem:** How can you develop and maintain a good reputation? What are considered as esteem indicators?

Domain C: Research Governance and Organisation

The knowledge of standards, requirements, and professionalism to do research.

C1 Professional conduct

- **Health and safety:** Do you have an awareness of health & safety issues regarding yourself and those around you?
- **Ethics, principles and sustainability:** Have you considered any ethical issues related to your research?
- **Legal requirements:** Do you have a basic understanding of the legal requirements (if applicable) surrounding your research (e.g. Data Protection Act, Freedom of Information.)
- **IPR and copyright:** Do you have a basic understanding of data ownership rules as they apply to your own research?
- **Respect and confidentiality:** If applicable, are you aware, within your own research, of the rights of participants to confidentiality and anonymity.
- **Attribution and co-authorship:** Are you confident about the concept of attribution? Do you consistently recognise the contributions of others in your work (including proper referencing and footnotes)? Do you manage to footnote and reference consistently?

C2 Research Management

- **Research strategy:** Do you know the strategic research strands in your schools and which ones your research fits into? Do you have awareness of how UoN research organises and manages its research?
- **Project planning and delivery:** What planning methods and tools do you have knowledge or? Do you use them consistently? Do you plan and agree goals with your supervisor?
- **Risk management:** Do you make basic risk assessment of your project? Do you make contingency plans? Do you understand the risks of the virtual environment to your project?

C3 Finance, funding & resources

- **Income and funding generation:** Do you have an awareness of small grant opportunities available to you? Do you feel confident to write a funding application?
- **Financial management:** Have you had the opportunity to learn the basic principles of financial management?

Domain D: Engagement, influence and impact

The knowledge and skills to work with others and ensure the wider impact of research

D1 Working with others

- **Collegiality & Team working:** Do you have or make opportunities to work in a team regularly? How do you achieve successful team-working? Do you think about your own behaviour and notice how it influences the behaviour of others? Have you ever had to resolve conflict in a team? How did you do that? How do you encourage and support others?
- **People management:** How do you negotiate activities and deadlines with your supervisor (and line manager)? If you have the opportunity to lead others, how do you do that successfully?
- **Mentoring:** If you have the opportunity to be involved in undergraduate teaching or mentoring, how do you support the learning of others?
- **Influence and leadership:** Engages in debate and invites challenge. Are you involved in public engagement? How do you/do you intend to bring your research to the wider community?

D2 Communication and dissemination

- **Communication methods:** How do you share your ideas with fellow postgraduates? How do you choose to share your research with the wider community?
- **Communication media:** Do you have a web presence as a researcher? Can you confidently use e-resources?
- **Publication:** Do you understand the process behind getting a paper published? Have you yet or do you intend to produce some publishable material in print or electronic format this year? Do you have a clear idea of potential journals for publication in your research area?

D3 Engagement and impact

Teaching: Have you had the opportunity/will you be seeking out an opportunity to teach undergraduates at this University at other Universities locally? Do you (intend to) participate in research meetings (seminars, workshops, conferences, etc.)? Are you aware of the strengths/weaknesses in your own teaching style and techniques? Is there an opportunity for you to get involved in the assessment of undergraduate work?

Public engagement:

- **Enterprise:** Will you seek out opportunities to understand the value of establishing relationships in small business or semi-commercial contexts, such as production companies or museums?
- **Policy:** Do you analyse policies? Do you understand which policies are relevant to your research context?
- **Society and culture:** Are you aware of your corporate and social responsibilities as a University Of Nottingham researcher?
- **Global citizenship:** Do you understand how your research fits in a national and global context?

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