A Sparse Gaussian Process Framework for Photometric Redshift Estimation

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ABSTRACT
Accurate photometric redshift are a lynchpin for many future experiments to pin down the cosmological model and for studies of galaxy evolution. In this study, a novel sparse regression framework for photometric redshift estimation is presented. Data from a simulated survey was used to train and test the proposed models. We show that approaches which include careful data preparation and model design offer a significant improvement in comparison with several competing machine learning algorithms. Standard implementation of most regression algorithms has as the objective the minimization of the sum of squared errors. For redshift inference, however, this induces a bias in the posterior mean of the output distribution, which can be problematic. In this paper we optimize to directly target minimizing \( \Delta z = (z_s - z_p) / (1 + z_s) \) and address the bias problem via a distribution-based weighting scheme, incorporated as part of the optimization objective. The results are compared with other machine learning algorithms in the field such as Artificial Neural Networks (ANN), Gaussian Processes (GPs) and sparse GPs. The proposed framework reaches a mean absolute \( \Delta z = 0.002(1 + z_s) \), with a maximum absolute error of 0.0432, over the redshift range of \( 0.2 \leq z_s \leq 2 \), a factor of three improvement over standard ANNs used in the literature. We also investigate how the relative size of the training affects the photometric redshift accuracy. We find that a training set of >30 per cent of total sample size, provides little additional constraint on the photometric redshifts, and note that our GP formalism strongly outperforms ANN in the sparse data regime.

Key words: methods: data analysis – galaxies: distances and redshifts

1 INTRODUCTION
The radial component of the position of a distant object is inferred from its cosmological redshift, induced by the expansion of the Universe; the light observed from a distant galaxy appears to us at longer wavelengths than in the rest frame of that galaxy. The most accurate determination of the exact redshift, \( z \), comes from directly observing the spectrum of an extragalactic source and measuring a consistent multiplicative shift, relative to the rest frame, of various emission (or absorption) features. The rest-frame wavelengths of these emission lines are known to a high degree of accuracy which can be conferred onto the measured spectroscopic redshifts, \( z_s \). However, the demand on telescope time to obtain spectra for every source in deep, wide surveys is prohibitively high, and only relatively small area spectroscopic campaigns can reach faint magnitudes (e.g. Lilly et al. 2009, Le Fèvre et al. 2013, 2015), or at the other extreme, relatively bright magnitudes over larger areas (e.g. Colless et al. 2003, Driver et al. 2011, Alam et al. 2015). This forces us towards the use of photometric observations to infer the redshift by other means. Rather than individual spectra, the emission from a distant galaxy is observed in several broad filters, facilitating the characterization of the spectral energy distribution (SED) of fainter sources, at the expense of fine spectral resolution.

Photometric redshift methods largely fall into two categories, based on either SED template fitting or machine learning. Template fitting software such as HYPERZ (Bolzonella, Miralles & Pelló 2000), ZEBRA (Feldmann et al. 2006), EAZY (Brammer, van Dokkum & Coppi 2008) and LE PHARE (Ilbert et al. 2006) rely on a library of SED templates for a variety of different types of galaxy, which (given the transmission curves for the photometric filters being used) can be redshifted to fit the photometry. This method can be refined in various ways, often with the use of simulated SEDs rather than only those observed at low redshift, composite SEDs, and through calibration using any available spectroscopic redshifts. Machine learning methods such as artificial neural networks (e.g.
ANnz (Firth, Lahav & Somerville 2003; Collister & Lahav 2004), nearest-neighbour (NN) (Ball et al. 2008), genetic algorithms (e.g. Hogan, Fairbairn & Seeburgh 2013) and self-organized maps (Geach 2012), to name but a few, rely on a significant fraction of sources in a photometric catalogue having spectroscopic redshifts. These ‘true’ redshifts are used to train the algorithm.

Both methods have their strengths and weaknesses, with the best performance often depending on the available data and the intended science goals. As such, future surveys may well depend on contributions from both in tandem, but there has been extensive work on comparing the current state of the art in public software using a variety of techniques (Hildebrandt et al. 2010; Abdalla et al. 2014). Artificial neural networks motivate the most commonly used machine learning software, however Gaussian Processes (e.g. Way et al. 2009) have not yet become well established in this area, despite comparison by Bonfield et al. (2010) suggesting that they may outperform the popular ANNz code, using the rms error as a metric.

In this paper, we introduce a novel sparse kernel regression model that greatly reduces the number of basis (kernel) functions required to model the data considered in this paper. This is achieved by allowing each kernel to have its own hyper-parameters, governing its shape. This is in contrast to the standard kernel-based model in which a set of global hyper-parameters are optimized (such as is typical in Gaussian Process (GP) methods). The complexity cost of such a kernel-based regression model is $O(n^3)$, where $n$ is the number of basis functions. This cubic time complexity arises from the cost of inverting a $n \times n$ covariance matrix. In a standard Gaussian Process model (Rasmussen & Williams 2006), seen as a kernel regression algorithm, we may regard the basis functions, as located at the $n$ points in the training set. This renders such an approach unusable for many large training data applications where scalability is a major concern. Much of the work done to make GPs more scalable is either to make the inverse computation faster or use a smaller representative training data sample or a set of “inducing points” to reduce the rank and ease the computation of the training data covariance matrix. Examples of the former include methods such as structuring the covariance matrix such that it is much easier to invert, using Toeplitz (Zhang, Leithead & Leith 2005) or Kronecker decomposition (Tsilekardis & Hero 2013), or inverse approximation as an optimization problem (Gibbs & MacKay 1997). To reduce the number of representative points, an $m \ll n$ subset of the training set can be selected which maximizes the accuracy or the numerical stability of the inversion (Foster et al. 2009). Alternatively, one may search for “pseudo” points not necessarily present in the training set to use as basis for the covariance matrix such that it maximizes the log marginal likelihood (Snelson & Ghahramani 2006).

The focus in this paper is on sparse GP modelling where we extend the sparse pseudo GP method using a smaller number of kernels. Moreover, a weighting scheme is modelled as an integral part of the process to remove, or introduce, any systematic bias to the model. The results are demonstrated on photometric redshift estimation for a Euclid-like survey (Laureijs et al. 2011). In particular, we use the weighting scheme to remove any distribution bias and introduce a linear bias to directly target the mission’s requirement.

The paper is organised as follows, a brief introduction to Gaussian Processes for regression is presented in Section 2 followed by an introduction to sparse GPs in Section 3. The proposed approach is described in Section 4 followed by an application to photometric redshift estimation in Section 5 where the details of the dataset are described. The experiments and results are discussed in section 6. Finally, we summarize and conclude in Section 7. The contributions of this paper are as follows:

(i) Increasing the modelling capability of sparse GPs via the use of more flexible kernels and fewer basis functions, thereby enhancing computational complexity without sacrificing accuracy.

(ii) Development of an efficient computational procedure to compute the gradients for both full covariance matrix and low rank approximations.

(iii) Incorporating a weighting scheme directly to the objective in order to counteract any undesired bias and/or to control the bias of the model.

(iv) A linear regression prior mean function is jointly optimized to enhance the model’s extrapolation performance.

(v) The proposed approach was applied to a simulated catalogue and achieved a mean $\Delta z = 0.002(1+z_i)$ exceeding the requirement for most future cosmology experiments based on photometric redshifts, and outperformed other machine learning algorithms such as ANnz and stableGP.

2 GAUSSIAN PROCESSES

In many modelling problems, we have little prior knowledge of the explicit functional form of the function that maps our observable variables into the variable of interest. Imposing, albeit sensible, parametric models, such as polynomials, makes a tacit bias. For this reason, much of modern function modelling is performed using non-parametric techniques. For regression, the most widely used approach is that of Gaussian Processes (Rasmussen & Williams 2006). A Gaussian Process is a supervised non-linear regression algorithm that makes few explicit parametric assumptions about the nature of the function fit. For this reason, Gaussian Processes are seen as lying within the class of Bayesian non-parametric models. The main underlying assumption in a GP is that the joint probability of the input variable $x$ and the output variable $y$ is a multivariate Gaussian with mean $\mu = [\mu_x \ \mu_y]^T$ and covariance $\Sigma = \begin{bmatrix} \Sigma_{xx} & \Sigma_{xy} \\ \Sigma_{yx} & \Sigma_{yy} \end{bmatrix}$, where $\Sigma_{xy} = (x - \mu_x)(y - \mu_y)^T$. The input variables $x$ is an $n$ by $d$ matrix, where $n$ is the number of data points and $d$ is the dimensionality of the input. Without loss of generality, the output variable $y$ is assumed to be a vector of length $n$ of target outputs but the same concept holds for multiple variable output. The joint distribution is hence:

\[
p(x, y) \sim \mathcal{N} \left( \begin{bmatrix} \mu_x \\ \mu_y \end{bmatrix} ; \begin{bmatrix} \Sigma_{xx} & \Sigma_{xy} \\ \Sigma_{yx} & \Sigma_{yy} \end{bmatrix} \right).
\]

The mean and covariance of the conditional probability $p(y|x)$ therefore is Gaussian distributed as follows:

\[
p(y|x) \sim \mathcal{N} \left( \mu, \Sigma_{yy} - \Sigma_{yx} \Sigma_{xx}^{-1} \Sigma_{yx} \right)
\]

\[
\mu = \mu_y + \Sigma_{yx} \Sigma_{xx}^{-1} (y - \mu_y),
\]

\[
\Sigma = \Sigma_{yy} - \Sigma_{yx} \Sigma_{xx}^{-1} \Sigma_{yx}.
\]

The calculation can be simplified by subtracting the mean of the input and the output variables and assuming a prior mean $\mu_x = \mu_y = 0$ and $\Sigma_{xy}$ redefined as $x y^T$. The mean and covariance of the conditional probability $p(y|x)$ can then be rewritten as:

\[
\mu = \Sigma_{yx} \Sigma_{xx}^{-1} y,
\]

\[
\Sigma = \Sigma_{yy} - \Sigma_{yx} \Sigma_{xx}^{-1} \Sigma_{yx}.
\]

For the rest of this paper, the prior mean is assumed to be.
zero unless otherwise stated (this can readily be achieved without loss of generality). Thus far, the analysis has assumed that no noise (uncertainty) exists in the set of observed $y$ data. It is readily shown that assuming some noise $\epsilon \sim \mathcal{N}(0, \sigma^2_n)$ on the output variable $y$, yields the following updated mean and covariance (Rasmussen & Williams 2006):

$$
\begin{align*}
\mu &= \Sigma_{yx} (\Sigma_{xx} + I \sigma^2_n)^{-1} y, \\
\Sigma &= \Sigma_{yy} - \Sigma_{yx} (\Sigma_{xx} + I \sigma^2_n)^{-1} \Sigma_{xy} + \sigma^2_n.
\end{align*}
$$

(4)

For this definition of the covariance matrix $\Sigma$, the predictive mean is equivalent to a linear regression model, indeed, the same regression solution may be found by evaluating the (kernel) regression model that minimizes the sum of squared errors. For an in depth discussion on Gaussian processes for regression and its Bayesian interpretation, the reader is referred to (Rasmussen & Williams 2006). The specific use of Gaussian processes for timeseries modelling is discussed in (Roberts et al. 2013).

Since the solution is entirely defined in terms of inner products of the input space, one can utilize the so-called “kernel trick” to learn non-linear models by replacing the covariance matrix $\Sigma$ with a covariance function $K$, where $K_{x,y} = k(x_i, x_j)$.

The kernel function $k$ is defined such that the matrix $K$ will be a positive definite matrix. The kernel trick allows the computation of the covariance matrix of some high dimensional mapping of the input into a higher dimensional space without explicitly requiring the mapping of the data to that space. The choice of kernel is largely a modelling decision based on the definition of similarity for a given application. In this paper, the squared exponential kernel defined in Eq. (5) below is used, but the concepts introduced here apply to any other kernel function. We note that the basis functions’ internal dimensionality is that of the input space, thus they can be interpreted as function local to “pseudo points”. As we show later in this paper, the flexibility of the squared exponential kernel can be enhanced allowing us to learn more complex patterns using fewer basis functions.

$$
k(x_i, x_j) = \sigma^2 \exp \left(-\frac{1}{2\lambda^2} \|x_i - x_j\|^2 \right).
$$

(5)

The hyper-parameters of the squared exponential kernel $\sigma^2$ and $\lambda^2$ are referred to as the height (output, or variance) and characteristic length (input) scale respectively. Together with the noise variance $\sigma^2_n$, they define the set of hyper-parameters for the GP model. The optimal set of hyper-parameters are the set of values that maximizes the probability of the data given the model, which can be achieved by maximizing the log marginal likelihood defined in Eq. (6) below:

$$
\log p(y|x) = -\frac{1}{2} y^T (K + I \sigma^2_n)^{-1} y \\
- \frac{1}{2} \log |K + I \sigma^2_n| - \frac{n}{2} \log(2\pi).
$$

(6)

We search for the optimal set of hyper-parameters using gradient search optimization, hence we require the derivatives of the log marginal likelihood with respect to each hyper-parameter. In this paper, the L-BFGS algorithm was used to optimize the objective which uses a Quasi-Newton method to compute the search direction in each step by approximating the inverse of the Hessian matrix from the history of gradients in previous steps (Nocedal 1980; Schmid 2005).

### 3 SPARSE GAUSSIAN PROCESSES

Gaussian processes are often described as non-parametric regression models due to the lack of an explicit parametric form. GP regression can also be viewed as a feature transformation $x \in \mathbb{R}^d \rightarrow K \in \mathbb{R}^n$ parametrized by the data and the kernel function followed by linear regression, via optimization of the following objective:

$$
\min_w \frac{1}{2} (Kw - y)^T (Kw - y) + \frac{1}{2} \sigma^2_n w^T w.
$$

(7)

where $w$ are the set of coefficients for the linear regression model that maps the transformed features $K$ to the desired output $y$. The feature transformation $K$ evaluate how “similar” a datum is to every point in the training set, where the similarity measure is defined by the kernel function. If two points have a high kernel response via Eq. (5), this will result in very correlated features, adding extra computational cost for very little or no added information. Selecting a subset of the training set that maximizes the preserved information is a research question addressed in (Foster et al. 2009), whereas in (Snellson & Ghahramani 2006) the basis functions are treated as a search problem rather than a selection problem and their locations are treated as hyper-parameters which are optimized. These approaches result in a transformation $x \in \mathbb{R}^d \rightarrow K \in \mathbb{R}^m$, in which $m \ll n$ is the number of basis used. The transformation matrix $K$ will therefore be a rectangular $n \times m$ matrix and the solution for $w$ in Eq. (7) is calculated via standard linear algebra:

$$
w = (K^T K + I \sigma^2_n)^{-1} K^T y.
$$

(8)

Even though these models improve upon the computational cost of a standard GP, very little is done to compensate for the reduction in modelling power caused by the “loss” of basis functions. The selection method is always bounded by the full GP’s accuracy, since the basis set is a subset of the full GP basis function set. On the other hand, the sparse GP’s ability to place the basis set freely across the input space does go some way to compensate for this reduction, as the kernels can be optimized to describe the distribution of the data. However, in both cases a global set of hyper-parameters is used for all basis functions, therefore limiting the algorithm’s local modelling capability. Moreover, the objective in Eq. (7), by definition, minimizes the sum of squared errors, therefore for any non-uniformly distributed output, the optimization routine will bias the model towards the mean of the output distribution and will seek to fit preferentially the region of space where there are more data. In the next section, a method is proposed which addresses the above issues by parametrizing each basis with bespoke hyper-parameters which account for variable density and/or patterns across the input space. This is particularly pertinent to determining photometric redshifts, where complete spectroscopic information may be restricted or biased to certain redshifts or galaxy types, depending on the target selection for spectroscopy of the training set. This allows the algorithm to learn more complex models with fewer basis functions. In addition, a weighting mechanism to remove any distribution bias from the model is directly incorporated into the objective.

### 4 PROPOSED APPROACH

In this paper, we extend the sparse GP approach by modelling each basis (kernel) with its own set of hyper-parameters. The kernel
function in Eq. (5) is hence redefined as follows:
\[ k(x_i, p_j) = \exp \left( -\frac{1}{2\lambda_j^2} \| x_i - p_j \|^2 \right), \]  
(9)
where \( P = \{ p_j \}_{j=1}^n \in \mathbb{R}^d \) are the set of basis coordinates and \( \lambda_j \) is the corresponding length scale for basis \( j \). The multivariate input is denoted as \( X = \{ x_i \}_{i=1}^n \in \mathbb{R}^d \). Throughout the rest of the paper, \( X_i,j \) denotes the \( i \)-th row of matrix \( X \), or \( x_i \) for short, whereas \( X_{*,j} \) denotes the \( j \)-th column and \( X_{i,j} \) refers to the element at row \( i \) and column \( j \) in matrix \( X \), and similarly for other matrices. Note that the hyperparameter \( \sigma \) has been dropped, as it interferes with the regularization objective.
This can be seen from the final prediction equation
\[ f(x_i, y) = \sum_{j=1}^n w_j \sigma_j \exp \left( -\| x_i - p_j \|^2 / 2\lambda_j^2 \right), \]
weights are always multiplied by their associated \( \sigma \). Therefore, the optimization process will always compensate for decreasing \( w_j^2 \) by increasing \( \sigma_j^2 \). Dropping the height variance ensures that the kernel functions do not grow beyond control and delegates learning the linear coefficients and regularization to the weights \( w_j \). The derivatives with respect to the length scale and position are provided in equations Eq. (10a) and Eq. (10b) respectively:
\[ \frac{\partial f(X, y, w)}{\partial \lambda_j} = E_{*,j} D_{*,j} \sigma_j^{-3}, \]  
(10a)
\[ \frac{\partial f(X, y, w)}{\partial p_j} = E_{*,j} \Delta_j \sigma_j^{-2}, \]  
(10b)
\[ \Delta_j = X - n p_j, \]  
(10c)
\[ D_{i,j} = \| x_i - p_j \|^2. \]  
(10d)
The symbol \( \circ \) denotes the Hadamard product, i.e. element-wise matrix multiplication and 1 denotes a column vector of length \( n \) with all elements set to 1. Finding the set of hyper-parameters that optimizes the solution, is in effect finding the set of radial basis defined by their positions \( p \) and radius \( \lambda \) that jointly describe the patterns across the input space. By parametrizing them differently, the model is more capable to accommodate different regions of the space more specifically. The kernel in Eq. (9) can be further extended to, not only model each basis with its own radius \( \lambda_j \), but also model each one with its own covariance defined by \( C_j \). This enables the basis to have any arbitrary shaped ellipses giving it more flexibility. The kernel in Eq. (9) can be extended as follows:
\[ k(x_i, p_j) = \exp \left( -\frac{1}{2} (x_i - p_j) C_j^{-1} (x_i - p_j)^T \right). \]  
(11)
To make the optimization process faster and simpler, we define the additional variables:
\[ C_j^{-1} = \Lambda_j \Lambda_j^T, \]  
(12a)
\[ V_j = \Delta_j \Lambda_j. \]  
(12b)
optimizing with respect to \( \Lambda_j \) directly ensures that the covariance matrix is positive definite and makes it faster from a computational perspective, as the kernel functions for all the points with respect to a particular basis can be computed more efficiently as below:
\[ k(X, p_j) = \exp \left( -\frac{1}{2} (V_j \circ V_j) \right). \]  
(13)
The exponent in Eq. (13) basically computes the sum of squares in each row of \( V_j \). This allows for a more efficient computation of the kernel functions for all the points in a single matrix operation.

Figure 1. Synthetic regression problem generated from a mixture of random Gaussian kernels.

Figure 2. Comparisons between different sparse GP approaches with 1 to 4 basis functions (top to bottom) using (a) a global length scale, (b) variable length scales and (c) variable covariances.

The derivatives with respect to each \( \Lambda_j \) and \( p_j \) are shown in Eq. (14a) and Eq. (14b).
\[ \frac{\partial f(X, y, w)}{\partial \Lambda_j} = - \left( \Delta_j^T \circ \left( 1 / d \right) \right) V_j, \]  
(14a)
\[ \frac{\partial f(X, y, w)}{\partial p_j} = E_{*,j} V_j \Lambda_j^T. \]  
(14b)

We highlight the differences between the three approaches, using different numbers of basis functions, on a synthetic 2D regression example, as shown in Figures 1 and 2. We note the advantage of having basis functions with more flexible kernels. Moreover, setting up the problem in this manner allows the setting of matrix \( \Lambda_j \) to be of any size \( d \) by \( q \), where \( q < d \) which can be considered as a low rank approximation to \( C_j^{-1} \) without affecting the gradient calculations. In addition, the inverse of the covariance can be set to \( C_j^{-1} = \Lambda_j \Lambda_j^T + \text{diag}(\Lambda_j)^{-2} \) in the low rank approximation case to ensure that the final covariance can model a diagonal covariance. This is referred to as factor analysis distance (Rasmussen & Williams 2006, p. 107) but previously used to model a global covariance as opposed to variable covariance as is the case here.
4.1 Prior Mean Functions

In the absence of observations, all Bayesian models, Gaussian processes included, rely on their priors to provide function estimation. For the case of Gaussian processes this requires us to consider the prior over the function, especially the prior mean. For example, we may consider a mean function that is itself a simple linear regression from the independent to dependent variable. The parameters of this function are then inferred and the GP infers non-linear deviations. In the absence of data, e.g. in extrapolative regions, the GP will fall back to the linear regression prediction (Roberts et al. 2013). We can incorporate this directly into the optimization objective instead of having it as a separate preprocessing step by redefining \( K \) as a concatenation of the linear and non-linear features, or setting \( K = [K|X^1] \). Furthermore, the regularization matrix in Eq. (6) can be modified so that it penalises for learning high coefficients for the non-linear terms but no or little cost for learning linear terms by setting the corresponding elements in the diagonal of \( I \) to 0, or the last \( d + 1 \) elements. Therefore, as \( \sigma_n^2 \) goes to infinity, the model will get closer to a simple linear regression model.

4.2 Cost-Sensitive Learning

Thus far in the discussion, we make the tacit assumption that the objective of the inference process is to minimize the sum of squared errors between the model and target function values. Although this is a suitable objective for many applications, it is intrinsically biased by uneven distributions of training data in input and output, sacrificing accuracy in less represented regions of the space. Ideally we would like to train a model with distribution balanced data to avoid such bias. This however, is a luxury that we often do not have. For example, the lack of strong emission lines that are detectable with visible-wavelength spectrographs in the “redshift desert” at \( 1.2 < z < 1.8 \) means that this redshift range is often under-represented in spectroscopic samples. A common technique is to either over-sample or under-sample the data to achieve balance (Weiss, McCarthy & Zabar 2007). In under-sampling, samples are removed from highly represented regions to achieve balance, oversampling on the other hand duplicates under represented samples. Both approaches come with a cost; in the former good data are wasted and in the latter more computation is introduced due to the data size increase. In this paper, we perform cost-sensitive learning, which increases the intrinsic error function in under-represented regions. In regression tasks, such as we consider here, the output can be seen as a concatenation of the linear and non-linear features, or

\[
\text{min}_w \frac{1}{2} (Kw - y)^T W (Kw - y) + \frac{1}{2} \sigma_n^2 w^T w. \tag{15}
\]

The difference between the objectives in Eq. (7) and Eq. (15) is the introduction of the diagonal matrix \( W \), where each element \( W_{ii} \) is the corresponding cost for sample \( i \). The first term in Eq. (15) is a matrix form for a weighted sum of squares

\[
\sum_{i=1}^{n} W_{ii} (K_{ii} w - y_i)^2,
\]

where the solution can be found analytically as follows:

\[
w = \left( K^T W K + I \sigma_n^2 \right)^{-1} K^T W y. \tag{16}
\]

The only modification to the gradient calculation is to set the matrix

\[
E = W (Kw - y)^T \circ K.
\]

5 APPLICATION TO PHOTOMETRIC REDSHIFT ESTIMATION

Here, we specifically target the photometric bands and depths planned for Euclid. Euclid aims to provides imaging data in a broad \( RIZ \) band and the more standard near-infrared \( Y, J \) and \( H \) bands, while ground-based ancillary data are expected in the optical \( g, r \), \( i \) and \( z \) bands (Laureijs et al. 2011).

5.1 Dataset

We use a mock dataset from Jouvel et al. (2009), consisting of the \( g, r, i, z, RIZ, Y, J \) and \( H \) magnitudes (to 10\( \sigma \) depths of 24.6, 24.2, 24.4, 23.8, 25.0 for the former, and 5\( \sigma \) depth of 24.0 for each of the latter three near-infrared filters) for 156,904 simulated sources. We restrict ourselves to the redshift range of 0.2 \( \leq z_s \leq 2 \) to target the parameter space set out in Laureijs et al. 2011). We note that given that the main thrust of this paper is to describe a new
photometric method and compare to existing work, this redshift range suffices for our purposes; investigations beyond this redshift range will be the subject of a subsequent paper using real data. All sources with any missing measurement in any of their bands were removed prior to training. No additional limits on any of the bands were used, although some will be explicitly removed to test the extrapolation performance of the models. The distribution of the spectroscopic redshift is provided in Figure 3. For all experiments reported in this paper, we ignore the uncertainties on the photometry and treat them as known.

We preprocess the data using Principle Component Analysis (PCA; Jolliffe [1986]) to de-correlate the features prior to learning. De-correlation accelerates the convergence rate of the optimization routine especially when using a logistic-type kernel machines such as Neural Networks (LeCun et al. 1998). To understand this, we consider a simple linear regression example where we would like to solve for $w$ in $A w = b$, the solution for this is $w = (A^T A)^{-1} A^T b$. Note that if $A$ is de-correlated $A^T A = I$, therefore learning $w_i$ depends only on the $i$-th column of $A$ and it is independent from learning $w_j$, where $i \neq j$. In an optimization approach, the convergence rate is a function of the condition number of the $A^T A$ matrix, which is minimized in the case of de-correlated data. This represents a quadratic error surface which helps accelerate the search. This is particularly important in the application addressed in this paper as the magnitude measured in each filter are strongly correlated with each other. An example of applying a simple coordinate-descent to optimize a linear regression model was applied to the toy dataset and the results are shown in Figure 4.

### 6 EXPERIMENTS AND RESULTS

Five algorithms are considered to model the data: Artificial Neural Networks (ANNz; Collister & Lahav 2004), a GP with low rank approximation (stableGP), a sparse GP with global length scale (GP-GL), a GP with variable length scale (GP-VL) and a GP with variable covariances (GP-VC). For ANNz, a single layer network is used, and to satisfy the input format for the code, the data were not de-correlated and the uncertainties on photometry for each band were used as part of the training input. For stableGP, we use the SRVP method proposed in Foster et al. (2009). In subsequent tests, the variable $m$ refers to the number of hidden units in ANNz, the rank in stableGP, and the number of basis functions in GP-GL, GP-VL and GP-VC. The data were split at random into 80 per cent for training, 10 per cent for validation and 10 per cent for testing. We note that we investigate the accuracy for various training set sizes in Section 6.2. The validation set was used for model selection and all the results here are reported on the test set. The following performance measures on the test set are reported for each experiment:

- $\Delta z = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (z_i - \bar{z})^2}$
- $\Delta z_{norm} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left( \frac{z_i - \bar{z}}{1 + \bar{z}} \right)^2}$

in which $\Delta z$ is the standard Root Mean Squared Error (RMSE) and $\Delta z_{norm}$ is a normalized version that weights low redshift objects more aggressively than higher redshift objects.

#### 6.1 Modelling Performance

In the first test, all models were trained using a fixed $m = 10$ to cross-compare the performance of the methods using the same number of basis functions. The number of basis functions was set deliberately low to highlight the sparse-limit modelling capabilities of each algorithm, as for large values of $m$ the performance gap between the algorithms naturally diminishes. The standard sum of squares objective was used, without cost-sensitive training or a prior mean function to keep the comparison as simple as possible. The $z_s$ versus $z_p$ density scatter plots are shown in Figure 5 and their performance scores are reported in Table 1. We find that we obtain a $\sim 75$ per cent improvement for the RMSE on $\Delta z_{norm}$ compared to our implementation of the widely-used ANNz.

| Algorithm | $\Delta z$ | $\Delta z_{norm}$ |
|-----------|------------|------------------|
| ANNz      | 0.0387     | 0.0241           |
| stableGP  | 0.2708     | 0.1559           |
| GP-GL     | 0.0802     | 0.0500           |
| GP-VL     | 0.0636     | 0.0402           |
| GP-VC     | 0.0234     | 0.0137           |
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Figure 5. Density scatter plots of the true $z$ vs the predicted $z_p$ for (a) ANNz, (b) stableGP, (c) GP-GL, (d) GP-VL and (e) GP-VC using $m = 10$ basis functions.

Figure 6. Density scatter plots of the true $z$ versus the predicted $z_p$ after training the GP-VC model with samples with $RIZ < 23$ (top) and $RIZ < 22$ (bottom) using $m = 10$ basis functions with (a) zero mean, (b) linear regression, (c) joint linear and non-linear optimization and (d) ANNz for comparison.

Table 2. The $\Delta z$ for the GP-VC model when trained using $m = 10$ basis functions with different prior mean functions and $RIZ$ splits. The results for ANNz are shown for comparison.
trained with a small sample size as in the show that the “Joint” method consistently outperformed the other. The results are reported in Table 2 and the den-
sity scatter plots are shown for comparison in Figure 6. Our results
also demonstrates the effectiveness of the algorithms in the sce-
ario where the brightest sources dominate the training set, as may
be true in practice. The results are reported in Table 2 and the den-
sity scatter plots are shown for comparison in Figure 6. Our results
show that the “Joint” method consistently outperformed the other
methods in extrapolation as well as in interpolation especially when
trained with a small sample size as in the RIZ < 22 case. More-
over, upon examining the density scatter plots in Figure 6 it has
fewer systematic and catastrophic errors than the other methods
with a factor of ~ 2 improvement over ANNz where the training
data are limited in magnitude/flux-density.

6.2 Prior Mean

We also test the extrapolation performance of the GP-VC model using
different prior means, namely a zero mean, a linear regression
mean and a joint optimization approach which learns the linear and
non-linear features simultaneously by regularizing the non-linear
features more aggressively than linear features and compare them
with ANNz. To test this more effectively, the models were trained
using sources, with RIZ < 23 (26,367 objects from the training set) and tested on the unseen samples with RIZ < 23, RIZ ≥ 23,
and the entire test set. A similar test was also conducted using a
split of RIZ < 22 (10,629 objects from the training set). This
also demonstrates the effectiveness of the algorithms in the scen-
ario where the brightest sources dominate the training set, as may
be true in practice. The results are reported in Table 2 and the den-
sity scatter plots are shown for comparison in Figure 6. Our results
show that the “Joint” method consistently outperformed the other
methods in extrapolation as well as in interpolation especially when
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over, upon examining the density scatter plots in Figure 6 it has
fewer systematic and catastrophic errors than the other methods
with a factor of ~ 2 improvement over ANNz where the training
data are limited in magnitude/flux-density.

6.3 Cost-Sensitive Learning

We now perform a comparison between the cost-sensitive learning and
the normal sum of squares for the GP-VC model. Two different
weight configurations are tested, the first is to assign an error cost
to each sample equal to 1 / (1 + z)² (Normalized), and the second
experiment is to weight each sample according to the frequency
of their true redshift to ensure balanced learning (Balanced). Two
additional measures are reported, the maximum Δz and the max-
umum Δz_{norm}. The samples were grouped into bins of uniformly
spaced intervals of 0.05, the box plots are for the “Normal”, “Bal-
anced” and “Normalized” are shown in Figure 7. The figures show
that the cost-sensitive learning is more consistent across the red-
shift range as opposed to the normal sum of squares, especially in the
high redshift regions where there is less data. The confidence
intervals are also considerably smaller for the “Balanced” case.
The “Normalized” training on the other hand resulted in a system-
atic bias, as expected, towards the lower part of the redshift range.
The performance comparison for the “Normal”, “Balanced” and
“Normalized” training are summarized in Table 3. Balanced train-
ing showed a better generalization performance, as it outperformed
the normal sum of squares objective on the test set and has lower
maximum errors, although the differences are generally small.

6.4 Size of the training set

Table 3. Performance measures of training the GP-VC model using m = 10 basis functions and different weighting schemes.

| Percentage | Δz | ∆z_{norm} | Δz_{norm} |
|------------|----|-----------|-----------|
| Normal     | 0.0234 | 0.2813 | 0.0137 | 0.1567 |
| Balanced   | 0.0230 | 0.2388 | 0.0141 | 0.1440 |
| Normalized | 0.0234 | 0.3234 | 0.0131 | 0.1548 |

6.5 Size of the basis set

The model was trained using various percentages from 5% to 80% and the Δz as well as the Δz_{norm} are reported for each percentage split in the plot shown in Figure 7. The figures show that the cost-sensitive learning is more consistent across the redshift range as opposed to the normal sum of squares, especially in the high redshift regions where there is less data. The confidence intervals are also considerably smaller for the “Balanced” case. The “Normalized” training on the other hand resulted in a systematic bias, as expected, towards the lower part of the redshift range. The performance comparison for the “Normal”, “Balanced” and “Normalized” training are summarized in Table 3. Balanced training showed a better generalization performance, as it outperformed the normal sum of squares objective on the test set and has lower maximum errors, although the differences are generally small.

Until now, we have limited the number of basis function to 10, except for the last section to test the generalization performance of GP-VC. In practice, the only limitation on the number of basis used for training the GP is computing resources. In this section we
Table 4. The time complexity of each approach.

| Method   | Time Complexity |
|----------|-----------------|
| ANN      | $O(nmd)$        |
| stable GP| $O(nm^2)$       |
| GP-GL    | $O(nm^2 + nmd)$ |
| GP-VL    | $O(nm^2 + nmd)$ |
| GP-VC    | $O(nm^2 + nmd)$ |

investigate how the accuracy of the photometric redshifts depends on the number of basis functions.

We cross-compare all of the models by varying the number of basis functions $m$ from 5 to 200 by an increment of 5 to study the relationship between accuracy, complexity and speed. $\Delta z$ as a function of $m$ is shown in Figure 9a the y-axis is shown on a log scale for the purpose of visualisation. The stableGP showed the worst performance across the board, especially when the number of basis was low, while GP-VC on the other hand consistently outperformed the rest and most significantly when trained with a few number of basis. ANNz outperformed GP-GL and GP-VL, but it did not scale well with complexity as it started to over fit after $m = 45$. All the models were trained using a sum of squares objective with no cost-sensitive learning or prior mean function in this experiment.

In Figure 10 we show $\Delta z$ and $\Delta z_{\text{norm}}$ for the GP-VC approach using an extended range of basis functions of 5, 10, 25, 50, 100, 200, 400, 800 and 1600 with cost-sensitive learning and joint mean optimization, using both the normalized weights and normal sum of squares. With the GP-VC we obtain $\Delta z_{\text{norm}} = 0.05$ with just $m = 5$ basis, and when using $m = 1600$ we obtain $\Delta z_{\text{norm}} = 0.002$ and a maximum normalized error $\Delta z_{\text{norm}} = 0.0492$. The time complexities for each algorithm are shown in Table 4 and the clock time in seconds, for a single iteration, are shown for various number of basis functions in Figure 9b. The time experiment was conducted on a machine with a 3.0 GHz Intel Core i7 processor using Matlab 2014a. We see from Figure 9b that all algorithms converged around $m = 50$ with a relatively small improvement for the time spent beyond this point. We note that although the training complexity costs require effort for large numbers of basis functions, once all parameters are inferred we enjoy effectively a linear basis model performance running over unseen (test) data. We therefore consider the performance for a realistic, yet large, number of functions.

We also generated photometric redshifts from a committee of five neural networks using a two-layer architecture, each layer with twice the number of hidden units as the number of filters as recommended in (Collister & Lahav 2004) and has become a standard for most ANNz users. The models were trained using the same training, validation and test sets. The results of the final GP-VC and ANNz models are summarized in Table 5 and the density scatter plots for the final models are shown in Figure 11 for comparison.

1 Note that even though stableGP has a lower theoretical time complexity compared to GP-VC, it is significantly slower. This has to do with the particular choice of implementation and the development environ-
Figure 10. A log-log plot reporting the $\Delta z$ and $\Delta z_{\text{norm}}$ after training GP-VC models with 5, 10, 25, 50, 100, 200, 400, 800 and 1600 with cost-sensitive learning and joint mean optimization. The results for the $\Delta z$ were optimized using normal sum of squares whereas the results for the $\Delta z_{\text{norm}}$ were optimized using normalized weights.

Table 5. Performance measures for the final ANNz model using a committee of 5 networks with 8:16:16:1 architectures and the final GP-VC model using $m = 1600$ basis functions with a jointly optimized linear mean function, balanced and normalized weights.

|        | $\Delta z$ | $\max (\Delta z)$ | $\Delta z_{\text{norm}}$ | $\max (\Delta z_{\text{norm}})$ |
|--------|------------|--------------------|---------------------------|----------------------------------|
| ANNz   | 0.0101     | 0.0983             | 0.0061                    | 0.0710                           |
| GP-VC  | 0.0035     | 0.0589             | 0.0020                    | 0.0432                           |

We find that the GP-VC algorithm provides a factor of $\sim 3$ improvement in the accuracy of $\Delta z$ and $\Delta z_{\text{norm}}$ over the commonly-used ANNz implementation.

7 CONCLUSION

In this paper a sparse Gaussian process framework was presented and applied to photometric redshift estimation. The framework was able to out perform Artificial Neural Networks, sparse GP parametrized by a set of global hyper-parameters and low rank approximation GP. The performance increase is attributed to the handling of distribution bias via a weighting scheme integrated as part of the optimization objective, parametrizing each basis function with bespoke covariances, and integrating the learning of the prior mean function to enhance the extrapolation performance of the model. The methods were applied to a simulated dataset and the proposed approach consistently outperformed the other models on all measures. We find that the model scales linearly in time with respect to the size of the data, and generalizes well even when presented with a limited training set. Results show that with only 30 per cent of the data, the model was able to reach accuracy close to that of using the full training set. Even when data were selectively removed based on $RIZ$ magnitudes, the model was able to show the best recovery performance compared to the other models. The cost-sensitive learning component of the framework regularizes the predictions to limit the effect caused by the biased distribution of the output and allows for direct optimization of the survey objective (e.g. $z_{\text{norm}} = |z_s - z_p|/(1 + z_s)$). The model consistently outperformed other approaches, including ANNz and stableGP, in all reported experiments. We also investigate how the size of the training set and the basis functions set affects the accuracy of the photometric redshift prediction. We show that for the simulated set of galaxies, based on the work of [Jouvel et al. (2005)] that we are able to obtain a photometric redshift accuracy $\Delta z_{\text{norm}} = 0.002$ and $\max (\Delta z_{\text{norm}}) = 0.0432$ using 1600 basis functions which is a factor of three improvement over the standard ANNz implementation.

In this work we have only considered simulated data, and as such the tests performed could be considered slightly idealized. However, the consistent strong performance of the GP-VC algorithm in outperforming the widely used ANNz algorithm is encouraging. In future work we will test the algorithm on a range of real data, and pursue investigations of how the algorithm performs over different redshift regimes and for different galaxy types as a further advantage of GPs over ANN is their natural ability to deliver variance predictions for the photometric redshifts.
ACKNOWLEDGMENTS

IAA acknowledges the support of King Abdulaziz City for Science and Technology. MJJ and SNL acknowledge support from the UK Space Agency.

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