Abstract

Motivation: Recent developments in technology have enabled researchers to collect multiple OMICS datasets for the same individuals. The conventional approach for understanding the relationships between the collected datasets and the complex trait of interest would be through the analysis of each OMIC dataset separately from the rest, or to test for associations between the OMICS datasets. In this work we show that integrating multiple OMICS datasets together, instead of analysing them separately, improves our understanding of their in-between relationships as well as the predictive accuracy for the tested trait. Several approaches have been proposed for the integration of heterogeneous and high-dimensional (p \gg n) data, such as OMICS. The sparse variant of canonical correlation analysis (CCA) approach is a promising one that seeks to penalize the canonical variables for producing sparse latent variables while achieving maximal correlation between the datasets. Over the last years, a number of approaches for implementing sparse CCA (sCCA) have been proposed, where they differ on their objective functions, iterative algorithm for obtaining the sparse latent variables and make different assumptions about the original datasets.

Results: Through a comparative study we have explored the performance of the conventional CCA proposed by Parkhomenko et al., penalized matrix decomposition CCA proposed by Witten and Tibshirani and its extension proposed by Suo et al. The aforementioned methods were modified to allow for different penalty functions. Although sCCA is an unsupervised learning approach for understanding of the in-between relationships, we have twisted the problem as a supervised learning one and investigated how the computed latent variables can be used for predicting complex traits. The approaches were extended to allow for multiple (more than two) datasets where the trait was included as one of the input datasets. Both ways have shown improvement over conventional predictive models that include one or multiple datasets.

Availability and implementation: https://github.com/theorod93/sCCA.

Supplementary information: Supplementary data are available at Bioinformatics online.

1 Introduction

Nowadays, it is becoming a common practice to produce multiple OMICS (e.g. Transcriptomics, Metabolomics, Proteomics, etc.) datasets from the same individuals (Hasin et al., 2017; Hass et al., 2017; TCGA, 2012) leading to research questions involving the in-between relationships of the datasets as well as with the complex traits (responses). The datasets obtained through different mechanisms lead to different data distributions and variation patterns. The statistical challenge is how can these heterogeneous and high-dimensional datasets be analysed to understand their in-between relationships. A follow up question to address is how can these relationships be used for understanding the aetiology of complex traits.

Over the past years, a number of data integration approaches have been proposed for finding in-between dataset relationships (Li et al., 2018; Sathyanarayanan et al., 2019; Subramanian et al., 2020; Wu et al., 2019). These approaches can be split by their strategy: (A) Early: combining data from different sources into a single dataset on which the model is built; (B) Intermediate: combining data through inference of a joint model; and (C) Late: building models for each dataset separately and combining them to a unified model (Gligorjević and Pržulj, 2015). Huang et al. (2017) present a
review of available methods for data integration and argue the need for direct comparisons of these methods for aiding investigators choosing the best approach for the aims of their analysis. A number of data integration approaches have been proposed in the literature for clustering disease subtypes (Mariette and Villa-Vialaneix, 2018; Swanson et al., 2019), whereas only few approaches have been proposed for supervised learning, i.e. for predicting the disease outcome (Jiang et al., 2016; Zhao et al., 2015). Van Vliet et al. (2012) investigated early, intermediate and late integration approaches by applying nearest mean classifiers for predicting breast cancer outcome. Their findings suggest that multiple data types should be exploited through intermediate or late integration approaches for obtaining better predictions of disease outcome.

The focus of this paper is on canonical correlation analysis (CCA), an intermediate integrative approach proposed by Hotelling (1936). CCA and its variations have been applied in various disciplines, including personality assessment (Sherry and Henson, 2005), material science (Rickman et al., 2017), photogrammetry (Vestergaard and Nielsen, 2015), cardiology (Jia et al., 2019), brain imaging genetics (Du et al., 2018, 2019) and single-cell analysis (Buck et al., 2018).

In the case of integrating two datasets CCA produces two new sets of latent variables, called canonical (variate) pairs. Suppose that there are two datasets with measurements made on the same samples \(X_1 \in \mathbb{R}^{n \times p_1}\) and \(X_2 \in \mathbb{R}^{n \times p_2}\), assuming w.l.o.g. \(p_1 > p_2\). For every \(r\) th pair, where \(r = 1, \ldots, \min(p_1, p_2)\), CCA finds two canonical vectors, \(w^{(1)}_r\) and \(w^{(2)}_r\), such that \(\text{Cor}(X_1 w^{(1)}_r, X_2 w^{(2)}_r)\) is maximized based on the constraints described below. For the first pair, the only constraint to satisfy is \(\text{Var}(X_1 w^{(1)}_1) = \text{Var}(X_2 w^{(2)}_1) = 1\). In computing the \(r\)th canonical pair, the following three constraints need to be satisfied:

1. \(\text{Var}(X_1 w^{(1)}_r) = \text{Var}(X_2 w^{(2)}_r) = 1\).
2. \(\text{Cor}(X_1 w^{(1)}_r, X_2 w^{(2)}_r) = \text{Cor}(X_2 w^{(2)}_r, X_1 w^{(1)}_r) = 0\), \(\forall c = 1, \ldots, r - 1\).
3. \(\text{Cor}(X_1 w^{(1)}_r, X_1 w^{(1)}_c) = \text{Cor}(X_2 w^{(2)}_r, X_1 w^{(1)}_c) = 0\), \(\forall c = 1, \ldots, r - 1\).

Orthogonality among the canonical variate pairs must hold: that is, not just between the elements of each feature space, but also among all combinations of the canonical variates; except the ones in the same pair, for which the correlation must be maximized. Complete orthogonality is attained when these constraints are satisfied.

In other words, CCA finds linear combinations of \(X_1\) and \(X_2\) that maximize the correlations between the members of each canonical variate \(w^{(1)}_r X_1 + \cdots + w^{(1)}_p X_1 p;\) and \(w^{(2)}_r X_2 + \cdots + w^{(2)}_p X_2 p;\) by assuming that there exists some correlation between the datasets, we can look at their material science (Rickman et al., 2018). Their findings suggest that multiple data types should be exploited using different approaches, formulations and penalizations. Chu et al. (2013) implemented a trace formulation to the problem, Waaieenborg et al. (2008) applied Elastic-Net, while Fang et al. (2016) used a general fused lasso penalty to simultaneously penalize each individual canonical vector and the difference of every two canonical vectors. Other authors proposed methods based on sparse partial least squares. Lê Cao et al. (2009) assume symmetric relationships between the two datasets, Hardoon and Shawe-Taylor (2011) focus on obtaining a primal representation for the first dataset, while having a dual representation of the second, and the method proposed by Mai and Zhang (2019) that does not impose any sparsity on the covariance matrices.

In this paper, three sCCA methods that share similar characteristics in their formulation and optimizing criteria are discussed, investigated and extended. The first method, penalized matrix decomposition CCA (PMDCCA) proposed by Witten and Tibshirani (2009) obtains sparsity through \(l_1\) penalization, widely known as absolute shrinkage and selection operator (LASSO; Tibshirani, 1996). The bound form of the constraints is used in order to reach a converged solution by iteratively updating \(w^{(1)}_r\) and \(w^{(2)}_r\). One of the assumptions of the PMDCCA approach is that the two datasets are independent, i.e. the covariance matrix of each input dataset is assumed to be the identity matrix. The second method proposed by Suo et al. (2017) relaxes the assumption of independence by allowing dependent data to be analysed through proximal operators [for the rest of the article, we are referring to this method as RelPMDCCA (relaxed PMDCCA)]. Even though, the additional restrictions make RelPMDCCA practically more applicable, it is computationally more expensive than PMDCCA. The third sCCA method we investigated is conventional CCA (ConvCCA) proposed by Parkhomenko et al. (2009). Similarly to PMDCCA sparsity is obtained through \(l_1\) penalization. ConvCCA estimates the singular vector of \(X_1 X_2\) while iteratively applies the soft-thresholding operator. Chalise and Fridley (2012) extended ConvCCA to allow for other penalty functions and through a comparative study found the smoothly clipped absolute deviation (SCAD) penalty to produce the most accurate results. Motivated by this finding, in our work we have modified both ConvCCA and RelPMDCCA to be penalized through SCAD.

Section 2 starts with a description of the three sCCA approaches: PMDCCA, RelPMDCCA, ConvCCA, followed by a description of our proposed extension of ConvCCA and RelPMDCCA to allow for multiple input datasets. A comprehensive simulation study has been conducted for comparing the performance of the three methods and their extensions on integrating two and multiple datasets. To our knowledge, a comparison of the three sCCA methods has not been made elsewhere. The simulated datasets and scenarios considered are presented in Section 3.1.

We have further addressed the second important question; how can data integration be used for linking the multi-OMICS datasets with complex traits/responses? For addressing this question, we have looked the problem as both a supervised and an unsupervised one. For the supervised model, we have used the computed canonical pairs as input predictors in regression models for predicting the response. On the flip side, we have explored adding the response vector as an input matrix in the setting of multiple datasets integration. We have found both these approaches to have a better predictive accuracy than conventional machine learning methods that use either one or both of the input datasets. Section 4 presents the analysis of real datasets with the aim of predicting traits through sCCA.

2 Materials and methods

All sCCA methods share a common objective function, given by:

\[
\min_{w^{(1)}_r, w^{(2)}_r} - \text{Cor}(X_1 w^{(1)}_r, X_2 w^{(2)}_r) + p_{w^{(1)}}(w^{(1)}_r) + p_{w^{(2)}}(w^{(2)}_r). \tag{1}
\]

where \(p_{w^{(1)}}(w^{(1)}_r)\) and \(p_{w^{(2)}}(w^{(2)}_r)\) represent penalty functions on \(w^{(1)}_r\) and \(w^{(2)}_r\), respectively. It is a bi-convex optimization where, if \(w^{(1)}_r\) is fixed, then Equation (1) is strictly convex in \(w^{(2)}_r\) and vice versa. Hence, one can find a solution through an iterative algorithm.

In this section, the computation of the first canonical pair is presented. To derive additional pairs, we have extended an approach proposed by Suo et al. (2017), which is presented in Section 2.6.
2.1 Conventional CCA
Parkhomenko et al. (2009) proposed a solution of sCCA based on approximating the sample correlation matrix and applying $l_1$ penalization through the soft-thresholding operator proposed by Tibshirani (1996). An iterative procedure updates both canonical vectors, $w^{(1)}$ and $w^{(2)}$, at each iteration $k$. The procedure is illustrated in the following steps where one of the vectors (e.g. $w^{(1)}$) is updated while the second (e.g. $w^{(2)}$) is kept fixed:

1. Compute sample correlation matrix $K_{12} = \Sigma_{X_1X_2} / \sqrt{\Sigma_{X_1X_1}(\Sigma_{X_2X_2})}$.
2. $(w^{(1)})^{k+1} = K_{12}(w^{(2)})^k$.
3. Normalize $(w^{(1)})^{k+1} = \frac{(w^{(1)})^{k+1}}{||w^{(1)}||_1}$.
4. Apply soft-thresholding: $(w^{(1)})^{k+1} = S((w^{(1)})^{k+1} - \frac{1}{2} \tau_{w_1})$.
5. Normalize $(w^{(1)})^{k+1} = \frac{(w^{(1)})^{k+1}}{||w^{(1)}||_1}$.

where $S(a) = \{ x | x \geq 0 \} \frac{x}{\max(0, x)}$.

$t_{w_1}$ represents the tuning parameter for each dataset $X_j (j = 1, 2)$ and $(w^{(1)})^k$ is the value of $w^{(1)}$ at the $k$th iteration. To update $w^{(2)}$, the same procedure is followed with the difference of replacing the second step with $(w^{(2)})^{k+1} = K_{12}(w^{(1)})^{k+1}$.

2.2 Penalized matrix decomposition CCA
Witten and Tibshirani (2009) formulated the problem as:

$$\min_{w^{(1)}, w^{(2)}} - \text{Cor}(X_1w^{(1)}, X_2w^{(2)}) + \tau_{w_1}||w^{(1)}||_1 + \tau_{w_2}||w^{(2)}||_1,$$

subject to $||w^{(1)}||_2 \leq 1; ||w^{(2)}||_2 \leq 1$.

An iterative algorithm based on penalized matrix decomposition (PMD) is applied with the update formula:

$$w^{(l)} = S(X_1^T X_2 (w^{(l)}), \Delta_l) / ||X_1^T X_2 (w^{(l)}), \Delta_l||_2$$.

where $\Delta_l > 0$ is chosen such that $||w^{(l)}||_1 = 1$ holds, or $\Delta_l = 0$ if $||w^{(l)}||_1 \leq 1$, for $i = 1, 2, i \neq j$. Although the PMDCCA solution is different from the ConvCCA solution, both approaches assume that the features are independent within each dataset (i.e. $X_1^2 X_1 = I_{p_1}, i = 1, 2$).

2.3 Relaxed PMDCCA
Suo et al. (2017) proposed a solution that relaxes the independence assumption and applies penalization through proximal operators. Their formulation of the problem is similar to (2):

$$\min_{w^{(1)}, w^{(2)}} - \text{Cor}(X_1w^{(1)}, X_2w^{(2)}) + \tau_{w_1}||w^{(1)}||_1 + \tau_{w_2}||w^{(2)}||_1,$$

subject to $\text{Var}(X_1w^{(1)}) \leq 1; \text{Var}(X_2w^{(2)}) \leq 1$.

The solution to this optimization is obtained through linearized alternating direction method of multipliers (Boyd, 2010; Parikh and Boyd, 2014). The iterative updates on the canonical variate pairs are computed through proximal algorithms. Due to space limitations, to view the updates, we refer the readers to the original paper by Suo et al. (2017).

2.4 Implementing SCAD penalty
The SCAD (Fan and Li, 2001) penalty with tuning parameter $\tau$ applied on $w$ is given as follows:

$$p_{SCAD}(w) = \begin{cases} 
\frac{||w||_1^2}{2(a-1)} + \frac{2}{a} (\frac{1}{a} ||w||_1 + \frac{1}{2} \tau), & \text{if } ||w||_1 < \tau \\
\frac{2}{a} (\tau \frac{||w||_1}{\tau} + \frac{1}{2} \tau), & \text{if } \tau < ||w||_1 \leq a \tau \\
\frac{2}{a^2} ||w||_1^2, & \text{if } ||w||_1 > a \tau
\end{cases}$$

where $a$ is fixed and suggested by Fan and Li to be set as $a = 3.7$.

Motivated by the findings of Chalise and Fridley (2013), we have modified RelPMDCCA to perform penalization through SCAD.

Even though SCAD is a non-convex penalty function, Mazumder et al. (2011) argue that if the optimizing function is strictly convex, then penalization via SCAD is well-behaved and converges to a stationary point. In the objective functions of ConvCCA [Equation (1)] and RelPMDCCA [Equation (4)], $\tau_{w_1}||w^{(1)}||_1 + \tau_{w_2}||w^{(2)}||_1$ is replaced by $p_{SCAD}(w^{(1)}) + p_{SCAD}(w^{(2)})$.

As a result the iterative updates of the canonical vectors are different. In ConVCCA, the algorithm is adjusted accordingly by replacing the soft-thresholding operator in Step 4 with:

$$w^{(l)} = S((w^{(l)})^{k+1} - \frac{1}{2} \tau_{w_1}), \frac{||w^{(l)}||_1}{(a-1)||w^{(l)}||_1 + \frac{1}{2} \tau_{w_1}} + \frac{1}{a} \frac{1}{a} ||w^{(l)}||_1 + \frac{1}{2} \tau_{w_1}$$.

The updates of canonical vectors in RelPMDCCA with SCAD penalty are performed by:

$$\text{prox}_{p_{SCAD}}(w^{(l)}) = \{ (w^{(l)})^{k+1} - \frac{1}{2} \tau_{w_1}), \frac{||w^{(l)}||_1}{(a-1)||w^{(l)}||_1 + \frac{1}{2} \tau_{w_1}} + \frac{1}{a} \frac{1}{a} ||w^{(l)}||_1 + \frac{1}{2} \tau_{w_1}$$.

2.5 Multiple sCCA
In OMICS studies, it is common for a study to have more than two datasets (such as transcriptomics, genomics, proteomics and metabolomics) on the same patients. Incorporating all available data simultaneously through an integrative approach can reveal unknown relationships between the datasets. This section presents extensions of the three sCCA methods we have seen, for the integration of multiple (more than two) datasets simultaneously.

Suppose we have $M$ separate datasets denoted by $X_1, \ldots, X_M$, where $X_m \in \mathbb{R}^{n \times p_m}, \forall m = \{1, \ldots, M\}$. The problem of Equation (1) is then generalized as:

$$\min_{w^{(1)}, \ldots, w^{(M)}} \sum_{i < j} - \text{Cor}(X_iw^{(i)}, X_jw^{(j)}) + \sum_{m=1}^M \rho_{w_m}(w_m)$$

As sCCA is bi-convex, multiple sCCA is multi-convex, i.e. if $w^{(i)}, \forall i \neq i$ are fixed, then the problem is convex in $w^{(i)}$. Instead of producing maximal correlated canonical variate pairs (M-tuple), multiple sCCA produces canonical variate list (M-tuple), e.g. for $i = 1, \ldots, p_1, p_1, \ldots, p_2$, the $r$th canonical variate list would be $(X_1w^{(1)}_r, \ldots, X_Mw^{(M)}_r)$. Each $X_mw^{(m)}_r$ is taken such that, it is maximally correlated with the rest of the latent features $\sum_{i \neq m} X_iw^{(i)}_r$.

In multiple ConVCCA, we propose to update $w^{(i)}$ iteratively, by keeping $w^{(j)}, \forall j \neq i$ and computing $K_{ii}$, $\forall j \neq i$. On the $k$th
iteration, $w^{(l)}$ is updated by $(w^{(l)})^{k+1} = w^{(l)} - \sum_{j\neq l} K_{ij} (w^{(i)})^k$ (Algorithm 1 in Supplementary Material).

Witten and Tibshirani (2009) proposed an extension to their solution, by assuming that $X_i'X_m = \delta_{im}$, $\forall m = \{1, \ldots, M\}$. To update $w^{(i)}$, the canonical vectors $w^{(i)}/C20 \neq 0$ are kept fixed. Multiple PMDCCA can then be performed by minimizing $\mathbb{V}(w^{(i)}) = \sum_{i\neq j} \|X_i w^{(i)}\|^2$, $\forall i = \{1, \ldots, M\}$, with constraint functions $\|w^{(i)}\|^2 \leq 1$.

We have extended RetPMDCCA for multiple datasets by following the approach of PMDCCA. The constraint functions $\mathbb{V}(X_i w^{(m)}) \leq 1$, $\forall m = \{1, \ldots, M\}$ and the proximal operators remain the same. If $w^{(i)}$ is a fixed vector, we can update $w^{(1)}$, by replacing $-w^{(1)} X_i' X_j w^{(2)}$ in Equation (4) with $-w^{(1)} X_i' \sum_{j\neq i} X_j w^{(i)}$.

The tuning parameters in sCCA and multiple sCCA are selected as the ones producing maximal correlation through cross-validation. A detailed description of the procedure is presented in the Supplementary Material.

In this work, we have explored the performance of the methods in predicting the response of interest when the response is included as one of the datasets being integrated.

### 2.6 Computing the additional canonical vectors

We have only addressed the computation of the first canonical variate pair so far but this might not be adequate for capturing the variability of the datasets and of their relationships. Similarly to PCA as the number of computed principal components is increased the total amount of variability explained is increased. By computing the additional canonical vectors of CCA additional constraints must be satisfied as illustrated below.

Suo et al. (2017) compute the remaining canonical vectors by adding the second constraint to the optimization. Let $W_1 = (w^{(1)}, \ldots, w^{(r-1)})$ and $W_2 = (w^{(r+1)}, \ldots, w^{(2)})$ define the r - 1 canonical vectors which were computed. The rth canonical vector of $w^{(i)}$ is found through the optimization problem:

$$\min_{w^{(i)}} - w^{(i)} X_i' X_j w^{(2)} + p_{w^{(i)}} (w^{(1)}) + 1 (w^{(1)} : \|X_i w^{(1)}\|^2 \leq 1)$$

subject to $w^{(i)} X_i' X_i w^{(i)} = 0$ (9)

where $p_{w^{(1)}}$ and $p_{w^{(2)}}$ represent the penalty functions on $w^{(1)}$ and $w^{(2)}$ with parameters $\alpha_1$ and $\alpha_2$, respectively. This solution would successfully result in producing latent features that are uncorrelated within the new datasets of canonical vectors, although the correlation is not restricted between the two new datasets.

In an attempt to include the additional constraint to the optimization problem, we propose the following extension to Equation (9):

$$\min_{w^{(i)}} - w^{(i)} X_i' X_j w^{(2)} + p_{w^{(i)}} (w^{(1)}) + 1 (w^{(1)} : \|X_i w^{(1)}\|^2 \leq 1)$$

subject to $X_i' w^{(i)} = z_i; T_i' T_i z = 0_{n-1}; T_i' T_i z = 0_{n-1}$ (10)

The solution to this optimization problem is obtained by letting $\hat{X} = [W_1' X_i, Y]$ and $\hat{Y} = [W_1' X_j, X_j]$. The rth canonical vector is then computed by applying an sCCA method on $\hat{X}$ and $\hat{Y}$ to obtain $w^{(r+1)}$, $j = 1, 2$, respectively. The exact algorithm in computing the additional canonical vectors is presented in Algorithm 2 in Supplementary Material.

Witten and Tibshirani (2009) proposed to update the cross-product matrix $Y = X_i' X_j$ after the computation of each canonical pair, by $Y^{(m+1)} = Y^{(m)} - W^{(1)} (Y^{(2)} w^{(2)})^T$, where $w^{(1)}$ and $w^{(2)}$ are the rth canonical vectors. The authors of ConvCCA proposed to take the residual of $K$ by removing the effects of the first canonical vectors and repeat the algorithm in order to obtain the additional canonical pairs.
better how the methods work, and determine the likelihood of obtaining a high correlation by chance.

We assessed the performance of the sCCA methods for integrating multiple datasets by generating three datasets through three scenarios as shown in Table 1.

The sCCA methods in both simulation studies were evaluated by measuring: (i) the canonical correlation; (ii) the correct identification of sparsity in the data, by computing accuracy, precision and recall of the true non-zero elements of the estimated canonical vectors; and (iii) the loss between true and estimated canonical vectors. A detailed description of the evaluation measures is presented in the Supplementary Material.

An additional simulation study was conducted to evaluate orthogonality. Two datasets were generated, with each of the following scenarios used in all three data-generating models: (i) \( n = 500, p_1 = 100, p_2 = 200, p_1^{(cc)} = 20, p_2^{(cc)} = 40 \), (ii) \( n = 50, p_1 = 100, p_2 = 200, p_1^{(cc)} = 20, p_2^{(cc)} = 40 \), and (iii) \( n = 150, p_1 = 100, p_2 = 200, p_1^{(cc)} = 20, p_2^{(cc)} = 40 \).

### 3.1.2 Simulation outcomes

#### 3.1.2.1 Integrating two datasets

In the conducted simulation study, the performance of sCCA methods was assessed on the three data-generating models and six scenarios shown in Table 1. The results are based on the first canonical pair. Figure 1a depicts the resulting ROC curves and their area under the curve (AUC) values, averaged over all data-generating models and scenarios. ConvCCA with SCAD had the best performance in identifying correctly the sparseness and the non-zero elements of canonical vectors, as it produced the highest AUC. RelPMDCCA with SCAD obtained the lowest AUC value, which shows that the optimal choice of penalty function depends on the sCCA method.

### Table 1. Data characteristics and simulation scenarios used to evaluate the three sCCA methods for integrating two or three datasets

| Scenarios          | Data characteristics                  |
|--------------------|---------------------------------------|
| **Integrating two datasets** | **n = 100, 1000, 10000, \( p_1 = 80 \), \( p_2 = 60 \), \( p_1^{(cc)} = 5 \), \( p_2^{(cc)} = 15 \)** |
| 1                  | \( n = 40, \ p_1 = 80, \ p_2 = 60, \ p_1^{(cc)} = 5, \ p_2^{(cc)} = 15 \) |
| 2                  | \( n = 150, \ p_1 = 80, \ p_2 = 60, \ p_1^{(cc)} = 5, \ p_2^{(cc)} = 15 \) |
| 3                  | \( n = 40, \ p_1 = 200, \ p_2 = 60, \ p_1^{(cc)} = 5, \ p_2^{(cc)} = 15 \) |
| 4                  | \( n = 40, \ p_1 = 80, \ p_2 = 200, \ p_1^{(cc)} = 5, \ p_2^{(cc)} = 15 \) |
| 5                  | \( n = 40, \ p_1 = 80, \ p_2 = 60, \ p_1^{(cc)} = 50, \ p_2^{(cc)} = 15 \) |
| 6                  | \( n = 40, \ p_1 = 80, \ p_2 = 60, \ p_1^{(cc)} = 5, \ p_2^{(cc)} = 50 \) |
| **Integrating three datasets** | **n = 40, \ p_1 = 80, \ p_2 = 60, \ p_1^{(cc)} = 5, \ p_2^{(cc)} = 15 \)** |
| 1                  | \( n = 40, \ p_1 = 80, \ p_2 = 60, \ p_1^{(cc)} = 15, \ p_2^{(cc)} = 10, \ p_3^{(cc)} = 5 \) |
| 2                  | \( n = 40, \ p_1 = 200, \ p_2 = 60, \ p_1^{(cc)} = 15, \ p_2^{(cc)} = 10, \ p_3^{(cc)} = 5 \) |
| 3                  | \( n = 150, \ p_1 = 80, \ p_2 = 60, \ p_1^{(cc)} = 15, \ p_2^{(cc)} = 10, \ p_3^{(cc)} = 5 \) |

Note: \( n \) represents the number of samples, while \( p_i^{(cc)} \) and \( p_i \) represent the cross-correlated and total number of features, respectively, in dataset \( i \), for \( i = 1, 2 \).
the second dataset (and latent features $X_2w^{(2)}$) obtained slightly reduced sensitivity, the sCCA methods performed in a similar fashion as with the first dataset.

RelPMDCCA produced the highest loss between the true and estimated canonical vectors (Fig. 1b), but it also provided the highest canonical correlation (Fig. 1c). Its overall averaged correlation is close to 1, while for the other two methods, it is closer to 0.9.

Figure 1d shows the performance of the first canonical vector ($X_1w^{(1)}$) averaged over all data-generating models. As expected, by increasing the number of samples in a case where $n > p$ (Scenario 2), the AUC values on all sCCA increased, with RelPMDCCA showing the largest improvement. However, a decrease in the performance of the AUC values on all sCCA increased, with RelPMDCCA showing the performance on some of them. That might be due to the fact that sCCA methods (total number of elements), the methods fail to correctly identify zero elements of a canonical vector are at least half of its length (as with the first dataset).

Canonical correlation (Fig. 1c). Its overall averaged correlation is remained constant as presented in Table 1.

As sample size increases, the correlations obtained by all methods are decreasing (Table 2). Even though the datasets were simulation. On Scenarios 3 and 4, where the total number of features is increased while the non-zero elements are not, sCCA methods performed as well as on the baseline scenario.

After averaging over the scenarios, the methods’ performance on each data-generating model is shown in Figure 1e. The methods’ performance seems to be overall influenced by the choice of data-generating model. In the case of single-latent variable model, ConvCCA clearly produced the least errors, while in the simple model, PMDCCA produced the highest AUC values. In the covariance-based model, all sCCA methods performed equally well in estimating correctly non-zero elements of the canonical vectors. Methods on Toeplitz model produced higher AUC values than on Identity model, where Sparse model contained the most errors out of all data-generating models. Based on this observation, we can argue that the sparser the data, the less accurate the methods.

### 3.1.2.2 Null simulation model

To conclude our simulation study in integrating two datasets, we applied the three sCCA methods on two datasets, simulated to have low canonical correlation. Two datasets were generated by following the covariance-based model and setting the true correlation $\rho = 0.1$ on different sample sizes, $n = 100, 1000, 10000$. The rest of the simulation parameters remained constant as presented in Table 1.

As sample size increases, the correlations obtained by all methods are decreasing (Table 2). Even though the datasets were simulated to have low correlation, it is possible that a certain combination of their respective features could have high correlation by chance due to the small sample size. ConvCCA and RelPMDCCA captured this relationship and produced high canonical correlation on long-sampled simulations, while PMDCCA did a better job in avoiding it even with $n = 100$. PMDCCA produced the highest AUC on simulations with small sample size, while on $n = 10000$, RelPMDCCA captured the true non-zero features more accurately than PMDCCA and ConvCCA (Fig. 2).

### Table 2. Null simulation model

| Sample size | PMDCCA | ConvCCA | ConvCCA | RelPMDCCA | RelPMDCCA |
|-------------|--------|---------|---------|-----------|-----------|
| n = 100     | 0.53 (0.08) | 0.81 (0.05) | 0.80 (0.02) | 0.96 (0.05) | 0.98 (0.02) |
| n = 1000    | 0.22 (0.03) | 0.48 (0.02) | 0.48 (0.04) | 0.51 (0.01) | 0.50 (0.02) |
| n = 10000   | 0.12 (0.03) | 0.26 (0.05) | 0.24 (0.03) | 0.26 (0.04) | 0.26 (0.04) |

Note: Canonical correlations of PMDCCA, ConvCCA and RelPMDCCA averaged across 100 runs on the null scenarios.

### 3.1.2.3 Orthogonality and sparsity

A third simulation study was conducted, with the aim of evaluating orthogonality of the three sCCA methods. For each method, orthogonality was enforced differently. For RelPMDCCA the solution proposed in Section 2.6 was applied, while for ConvCCA and PMDCCA we applied the solutions proposed by Parkhomenko et al. (2009) and Witten and Tibshirani (2009), respectively.

The scenarios in this study are split into three cases, based on the data sparsity: (i) $n > p_2 > p_1$, (ii) $p_2 > n > p_1$ and (iii) $p_2 > p_1 > n$. Table 3 shows the classification of each case with one out of three classes: (A) Full (Orthogonality): all pairs were found to be orthogonal; (B) Partial: most, but not all pairs were found to be orthogonal; and (C) None: none, or limited pairs were found to be orthogonal. Different colours in Table 3 refer to the different simulation models: simple model, single-latent variable model, identity covariance-based model.

As summarized in Table 3, orthogonality is not always preserved, and that depends on the sCCA method, as well as on the data characteristics. The choice of data-generating model did not have a high impact in attaining orthogonality. All sCCA methods were penalized through $l_1$ during this simulation study.

In case (i), ConvCCA has attained full orthogonality on the first five canonical variate pairs, while PMDCCA and RelPMDCCA failed to do so (except between some pairs). In the other two cases, none of the canonical variates obtained from ConvCCA were orthogonal. PMDCCA preserved complete orthogonality in $p_2 > p_1 > n$ case and most when $p_2 > n > p_1$. Complete orthogonality was attained in both of those cases when RelPMDCCA was implemented. Parkhomenko et al. (2009) and Witten and Tibshirani (2009) only consider the first canonical pair in their examples and do not explicitly discuss the performance of their respective methods on additional canonical pairs.

Fig. 2. sCCA performance on Null scenario. ROC curves of the first canonical vector by all three sCCA on Null scenario with sample sizes $n = 100, 1000, 10000$.­
Table 3. Orthogonality of sCCA methods

| Methods – > | PMDCCA | ConvCCA | RelPMDCCA |
|-------------|--------|---------|-----------|
| n > p_2 > p_1 | None Orthogonality | Full Orthogonality | Partial |
| p_2 > n > p_1 | None | None | Full |
| p_2 > p_1 > n | Full | Full | None |

Note: The table shows whether the algorithms succeed in obtaining orthogonal pairs. None refers to not obtaining orthogonality at all; Full refers to obtaining orthogonality between all pairs; Partial for some, but not all. For each scenario, simulations via the simple simulation model, single-latent variable model and covariance-based model are represented by the first, second and third rows, respectively.

Table 4. A summary on the performance of sCCA methods based on both the simulation studies conducted and the analysis of real data

| Summary on the performance of sCCA methods | On two datasets | Multiple datasets |
|-------------------------------------------|----------------|------------------|
| ConvCCA | Great performance on simulation studies | Good performance on simulation studies, especially on single-latent model |
| PMDCCA | Low time complexity | Over-fitted cancerTypes data and performed well on nutriMouse |
| RelPMDCCA | Moderate to good performance on simulation studies | Over-fitted CancerTypes data and performed well on nutriMouse |
|          | High time complexity | Low time complexity |
|          | Avoided over-fitting and improved performance in both data studies | Avoided over-fitting and improved performance in both data studies |
|          | High time complexity | Low time complexity |

Note: It is an intuitive evaluation of the methods, split into having two datasets or multiple.

3.1.2.4 Integrating three datasets. A simulation study on multiple sCCA was performed by generating three datasets through the (i) simple model and (ii) single-latent variable model. The same evaluating measures as with the case with the two datasets were computed. Canonical correlation was evaluated by computing the average canonical correlation of each dataset with the rest.

Figure 3a presents the averaged (arithmetic) canonical correlation observed by each method. RelPMDCCA produced the highest, as it did in with the case of two datasets. PMDCCA produced the least correlated and least sparse solution, suggesting that it is not performing very well with multiple datasets where the objective of sCCA is to maximize the correlation between the datasets. Figure 3b shows the sparsity obtained by each method with RelPMDCCA providing the sparsest solution.

Overall, PMDCCA produces the highest AUC values. RelPMDCCA was superior only when the number of samples was increased (Scenario 3). RelPMDCCA and ConvCCA showed a decrease in their performance when the number of non-zero elements was increased, but PMDCCA was able to maintain its good performance.

3.2 Real datasets

3.2.1 NutriMouse

Martin et al. (2007) have performed a nutrigenomic study, with gene expression (X_1 \in \mathbb{R}^{p_1}) and lipid measurements (X_2 \in \mathbb{R}^{p_2}) on n = 40 mice, with p_1 = 120 genes and concentrations of p_2 = 21 lipids were measured. Two response variables are available: diet and genotype of mice. Diet is a five-level factor: coc, fish, lin, ref, sun and genotype is recorded as either Wild-type (WT), or Peroxisome Proliferator-Activated Receptor-α (PPARα). NutriMouse data are perfectly balanced in both responses, in which an equal number of samples is available for each class.

Through the analysis of the nutriMouse datasets we aimed to (i) evaluate which of three considered sCCA approaches performs better and (ii) determine whether data integration of datasets can improve prediction over conventional approaches that only analyse a single dataset. For addressing the second question, we have implemented the following off the shelf statistical machine learning approaches: (A) Principal Components Regression (PCR)—logistic model with first 10 principal components acting as predictors; (B) Sparse Regression (SpReg)—penalized (through LASSO and SCAD) logistic and multinomial models, when the response was diet and genotype, respectively; (C) k-Nearest Neighbours (kNN) for supervised classification; and (D) k-means for unsupervised clustering—acting as a benchmark in splitting the data by ignoring the labels. Since two datasets are available, these four methods were implemented on the following three cases of input data: (i) only X_1, (ii) only X_2 and (iii) X = (X_1, X_2) \in \mathbb{R}^{p_1+p_2}, where p_{total} = p_1 + p_2.

The aforementioned machine learning methods and the three sCCA approaches were applied on 100 bootstrap samples of the datasets,
taking separate training and test sets at each repetition, for assessing
the predictive accuracy of the methods. For the machine learning
methods applied, the version with the input dataset obtaining the
smallest error was compared with the sCCA approaches. In predict-
ing the genotype response using only $X_1$ (i.e. gene expression data)
was preferred, but both was chosen with diet acting as the response
(Supplementary Material).

Figure 4 shows the predictive accuracy of the methods on both
diet (Fig. 4a) and genotype (Fig. 4b). PCR and k-means were the
least accurate methods (Supplementary Material). In predicting
either response, sCCA methods outperformed the conventional
machine learning methods. Both the sCCA approaches and the
conventional machine learning approaches had very high accuracy
for predicting the genotype response whereas their accuracy was
lower for predicting the diet response. All the methods had an
accuracy between 0.7 and 0.86, except RelPMDCCA that had the
highest accuracy 0.92. The precision and recall measures showed
similar patterns with RelPMDCCA obtaining the highest values
for both measures against all other methods (Supplementary
Material).

**Multiple sCCA with response matrix.** We applied our proposed
extensions of the sCCA approaches for multiple datasets, where one
of the input datasets is the matrix of the two response vectors.

Figure 4c presents the canonical vectors of the first canonical
variate pair. The first column of plots shows the canonical vectors
obtained without considering a response matrix. On a two-setting
integration, the data are not separated well for neither response.
However, by including the response matrix, multiple sCCA methods
separated clearly the samples between WT and PPARa mice, as
shown in the second column of Figure 4c. A slight improvement in
their separation between diets was also observed. All multiple sCCA
methods performed equally well, although visually RelPMDCCA
indicates the clearest separation in terms of genotype.

**3.2.2 CancerTypes**

Due to the abundance of data in the Cancer Genome Atlas (TCGA)
database, a lot of researchers have applied various integrative algo-
rithms for cancer research (Lock et al., 2013; Parimbelli et al., 2018;
Poirion et al., 2018; Wang et al., 2014). Gene expression, miRNA
and methylation data from three separate cancer types were taken:
(i) breast, (ii) kidney and (iii) lung. For each patient, we also have in-
formation about their survival status. Thus, the goal of this analysis
was to assess whether (multiple) sCCA can improve conventional
classification methods in determining the cancer type, and survival
status.
The data consist of 65 patients with breast cancer, 82 with kidney cancer and 106 with lung cancer, from which 155 patients are controls. The data in this study cover 10,299 genes ($X_1$), 22,503 methylation sites ($X_2$) and 302 mi-RNA sequences ($X_3$). Data cleaning techniques such as removing features with low gene expression and variance were used, leaving us with a remaining of 2250 genes and 5164 methylation sites. Similarly to Section 4.1, k-NN, PCR and SpReg were applied, along with sCCA algorithms. After investigating the best combination, miRNA expression and methylation datasets were selected for integrating two datasets. Multiple sCCA was implemented on all three available datasets.

Figure 5a presents the accuracy, precision and recall of each method in predicting the patients' survival status. SpReg, ConvCCA and PMDCCA produced perfect recall, while their precision was recorded around 60%. Such finding suggests over-fitting as a single class is favoured. Thus, a solution providing good results while avoiding over-fitting would be preferable.

PCR and k-NN did not show any signs of over-fitting, but did not perform well (PCR had accuracy below 0.5 and k-NN had consistently low values on all three measures). RelPMDCCA did not over-fit the data and produced high measure values, especially with LASSO being the penalty function. Multiple RelPMDCCA produced the most accurate and precise solution out of all methods applied. Multiple PMDCCA and ConvCCA improved the results of their respective integration method on two datasets, as they avoided over-fitting, with precision and recall values being more balanced. Regardless of the response, same conclusions were reached, i.e. implementing multiple sCCA can avoid over-fitting.

Figure 5b presents the scatter-plots of the test set of the canonical vectors of the first canonical variate pair. In contrast with the nutriMouse study, visually there is no clear separation observed between cancer types or survival status of the patients. Since the objective of sCCA is to maximize canonical correlation, it is important to preserve it. The canonical vectors of the test set are computed by linearly combining the estimated canonical vectors (through training), with the original test datasets. RelPMDCCA produced the highest correlation in all three combinations of canonical vectors (Fig. 5b).

4 Discussion

The increasing number of biological, epidemiological and medical studies with multiple datasets on the same samples calls for data integration techniques that can deal with heterogeneity and high-dimensional datasets.

Over the years, a lot of methods for sCCA have been proposed that integrate high-dimensional data. In this study, we have focused on ConvCCA, PMDCCA and RelPMDCCA, as these methods penalize the same optimizing function [Equation (1)]. We modified RelPMDCCA to penalize canonical vectors through SCAD and we compared its performance against LASSO penalty. Further, we proposed an extension in computing the additional canonical pairs. The extension satisfies necessary conditions in enforcing orthogonality among them. Finally, we extended ConvCCA and RelPMDCCA for integrating more than two datasets instead of just two as their original version.

By collectively reducing the dimensions of the datasets, while obtaining maximal correlation between the datasets, sCCA methods were found to have better accuracy in predicting complex traits than other conventional machine learning methods. Through our proposed extensions of the ConvCCA and RelPMDCCA approaches for integrating more than two datasets and for incorporating the response matrix as one of the integrated datasets, we have showed that over-fitting can be avoided and higher predictive accuracy can be obtained.

Through the analysis of the two real datasets, we illustrated that the sCCA methods can improve our predictions of complex traits in both cases: (i) when a regression model is built with the new canonical matrices as input matrices and (ii) when the response matrix is one of the input matrices in the data integration. For both cases, the sCCA methods can improve the predictions of the response.

Table 4 summarises our conclusions on each of the three sCCA methods applied on two or multiple datasets. Even though both nutriMouse and cancerTypes datasets have small sample sizes, the latter has a large number of features, providing an indication of a true genomic-wide scale analysis. We found that RelPMDCCA obtained the best results, but it is also more computationally expensive than the other methods. We conclude that in cases where datasets with large number of features or samples, PMDCCA might be a
more appropriate method to consider due to its advantage regarding computational time. This observation calls for further optimizing RelPMDCCA in reducing its complexity and increasing its feasibility on large-scale analysis. The computation times of the methods are presented in the Supplementary Material.

Our simulation study findings are in agreement with Chalise and Fridley (2012) that showed that ConvCCA has better results with SCAD penalty rather than LASSO. When analysing two uncorrelated datasets both ConvCCA and RelPMDCCA had a greater likelihood of obtaining higher correlation compared to PMDCCA, when the number of samples is small. With larger sample sizes, all methods obtained smaller correlations. With no exception, RelPMDCCA provides the highest canonical correlation in all simulation studies and all real-data analyses performed in this paper.

To preserve orthogonality, the results of our simulation study suggest different methods based on data characteristics. If the data satisfy $n > p_1 > p_2$, then ConvCCA is a more sensible choice. In the other cases ($p_1 > n > p_2$ or $p_1 > p_2 > n$), ConvCCA failed to provide orthogonal canonical pairs, while PMDCCA and RelPMDCCA, attained orthogonality on synthetic data from all three data-generating models. We observed the performance of the sCCA methods to depend on the structure of the input data. For sparse datasets, we recommend the use of the RelPMDCCA approach as it is the one that performed better for such datasets.

Huang et al. (2017) argued the need for a comparison of data integration approaches. This paper has addressed this by evaluating the performance of the three sCCA approaches. We have further illustrated that integrating datasets through multiple sCCA could improve the prediction power, suggesting that researchers with access to two or more datasets should aim for an integrative analysis.

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