JUMP: replicability analysis of high-throughput experiments with applications to spatial transcriptomic studies

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Abstract

Motivation: Replicability is the cornerstone of scientific research. The current statistical method for high-dimensional replicability analysis either cannot control the false discovery rate (FDR) or is too conservative.

Results: We propose a statistical method, JUMP, for the high-dimensional replicability analysis of two studies. The input is a high dimensional paired sequence of p-values from two studies and the test statistic is the maximum of p-values of the pair. JUMP uses four states of the p-value pairs to indicate whether they are null or non-null. Conditional on the hidden states, JUMP computes the cumulative distribution function of the maximum of p-values for each state to conservatively approximate the probability of rejection under the composite null of replicability. JUMP estimates unknown parameters and uses a step-up procedure to control FDR. By incorporating different states of composite null, JUMP achieves a substantial power gain over existing methods while

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controlling the FDR. Analyzing two pairs of spatially resolved transcriptomic datasets, JUMP makes biological discoveries that otherwise cannot be obtained by using existing methods.

Availability: The proposed method is implemented in the R package JUMP available at `https://github.com/hongyuan-cao/JUMP`.

1 Introduction

Replicability is the cornerstone of modern scientific research, as it helps to build confidence in the validity and reliability of scientific findings. We study conceptual replicability, where consistent results are obtained from studies using different procedures and populations that target the same scientific questions. Replicability is related to but different from meta-analysis. Both approaches look at cross-experiment summaries. In a meta-analysis, the null hypothesis is that there is no effect in all studies. On the other hand, in replicability analysis, the alternative hypothesis is that the effects exist in all studies and the null hypothesis is a composite null, i.e., at least one study does not have an effect. Such differences make methods designed for meta-analysis, such as Fisher's method (Fisher, 1925), the Šidák method (Šidák, 1967), the Lancaster method (Lancaster, 1961) and the minimum of p-values not applicable for replicability analysis.

We focus on the replicability analysis of genomic data produced by high-throughput experiments (Li et al., 2011; Hung and Fithian, 2020; Bogomolov and Heller, 2022). In a high-throughput experiment, many candidates are evaluated for their association with a biological feature of interest, and those with significant associations are identified for further analysis. We aim to simultaneously identify replicable features from high-throughput experiments in multiple studies by analyzing them jointly. To analyze a single high-throughput experiment, an acute problem is the multiple comparison. A classic method for multiple comparisons is

the false discovery rate (FDR) control approach proposed in Benjamini and Hochberg (1995) (BH). The false discovery rate is defined as the expected value of the ratio of false rejections over total rejections. Suppose we have m hypotheses. The BH procedure works as follows. First, order p-values $p_{(1)} \leq \ldots \leq p_{(m)}$. Second, find the largest i_0 such that $p_{(i_0)} \leq \alpha i_0/m$. Third, reject hypotheses corresponding to $p_{(1)}, \ldots, p_{(i_0)}$. Under the assumption that p-values from the null are independent and follow standard uniform distribution, it is shown that FDR is controlled at level $\alpha\pi_0$, where π_0 is the proportion of null hypotheses. The BH procedure is robust under positive dependence among p-values under the null (Benjamini and Yekutieli, 2001).

When we have two studies, an *ad hoc* approach for replicability analysis is to first compute p-values for each study. Multiple comparison methods such as BH can be used to claim significance in each study. Replicable findings are those that are significant in both studies. This approach cannot control FDR (Bogomolov and Heller, 2013). As a toy example, suppose we have two studies and two features. The p-value of study 1 is 0 and study 2 follows a standard uniform distribution for the first feature and vice versa for the second feature. The probabilities of claiming feature 1 or feature 2 as replicable features are positive, as by chance alone, small p-values can appear from a standard uniform distribution. Neither of the two features is replicable and the FDR is 100% if there are any replicability claims. The partial conjunction approach in Benjamini et al. (2009) suggests applying a multiple testing procedure, such as BH, on the maximum of p-values across two studies. This provides effective FDR control yet the power is low.

To improve power, in this paper, we propose a joint super-uniform maximum p-value (JUMP) method that improves on the maximum of p-values for high-dimensional replicability analysis. The null hypothesis for replicability is composite and consists of three states. The vanilla version of the maximum of p-values does not incorporate different states of the null and has a cumulative distribution function far smaller than that of a standard uniform distribution,

causing power loss. We use four states for the p-value pairs indicating whether they are null or non-null (Chung et al., 2014). Conditional on the hidden states, we compute the cumulative distribution function of the maximum of p-values for each state separately. Combining with the proportion estimation for each state, we get a conservative approximation of the cumulative distribution function of the maximum of p-values under replicability null. To estimate the proportion of each state, we extend the proportion of null estimation in Storey et al. (2004) from the two-group model to a four-group model. We require p-values in each sequence to follow a standard uniform distribution under the null. This assumption is needed for the BH procedure and Storey et al. (2004)'s method of the proportion of null estimation. A step-up procedure is developed on the maximum of p-values to control FDR. By incorporating the composite null feature of replicability analysis, we achieve a substantial power gain. The computation is scalable with a computational cost similar to that of BH.

As proof of concept, we apply JUMP to the replicability analysis of spatial transcriptomic studies. Spatially resolved transcriptomics (SRT) links the transcriptomes to their cellular locations, providing a comprehensive understanding of gene expression profiles in the spatial context of biological systems (Kleino et al., 2022). An important first step toward characterizing the spatial transcriptomic landscape of complex tissues is identifying replicable spatially variable genes (SVGs), genes that are not homogeneous and have clustered signals in the 2-dimensional space for spatial transcriptomic data. For each study, we can apply existing SVG detection methods to get p-values (Edsgärd et al., 2018; Svensson et al., 2018; Sun et al., 2020; Zhu et al., 2021; Hu et al., 2021). The input to our method is a paired p-value sequence collected from different tissue sections: mouse olfactory bulb data measured with ST technology (Ståhl et al., 2016) and 10X Visium technology; mouse cerebellum data measured with Slide-seq technology (Rodriques et al., 2019) and Slide-seqV2 technology (Stickels et al., 2021). We show that at the same FDR level, JUMP identifies important replicable SVGs that would otherwise be missed by using existing methods.

2 Methods

2.1 Background and notations

Suppose we have m genes common to two studies. We are interested in identifying genes that display replicable expression patterns. The input of the replicability analysis is a pair of p-values from two studies $(p_{1i}, p_{2i}), i = 1, \ldots, m$. The null hypothesis for ith gene states that it does not show any replicable expression pattern. Let θ_{ji} denote underlying state of ith gene in study j $(j = 1, 2)$, where $\theta_{ji} = 1$ indicates ith gene is significant in study j and $\theta_{ji} = 0$ otherwise. A four-group model is assumed for the paired p-value sequence, i.e.,

$$
\begin{aligned}
&p_{1i} \mid \theta_{1i} \sim (1 - \theta_{1i}) f_0 + \theta_{1i} f_1, \\
&p_{2i} \mid \theta_{2i} \sim (1 - \theta_{2i}) f_0 + \theta_{2i} f_2, \quad i = 1, \ldots, m,
\end{aligned}
$$

where f_0 is the density function of p-values under the null, and f_1 and f_2 denote the non-null density functions of p-values from study 1 and study 2, respectively. Let $\tau_i = (\theta_{1i}, \theta_{2i}), i = 1, \ldots, m$ denote the joint hidden states across two studies. Then $\tau_i \in \{(0,0), (0,1), (1,0), (1,1)\}$ with $\mathbb{P}(\tau_i = (k,l)) = \xi_{kl}$ for $k, l \in \{0, 1\}$, and $\sum_{k,l} \xi_{kl} = 1$. Here ξ_{00}, ξ_{01}, ξ_{10} and ξ_{11} denote the probabilities of hidden states $(0,0), (0,1), (1,0)$ and $(1,1)$, respectively. Based on this four-group model, the replicability null hypothesis for ith gene can be defined as

$$
H_{i0} : \tau_i \in \{(0,0), (0,1), (1,0)\}, i = 1, \ldots, m,
$$

where the ith gene is replicable if it shows expression patterns in both study 1 and study 2. For simplicity, we denote the hidden state of H_{i0} as h_i, where $h_i = 0$ indicates H_{i0} is true and $h_i = 1$ otherwise. Hence $\mathbb{P}(h_i = 0) = \xi_{00} + \xi_{01} + \xi_{10}$ and $\mathbb{P}(h_i = 1) = \xi_{11}$.

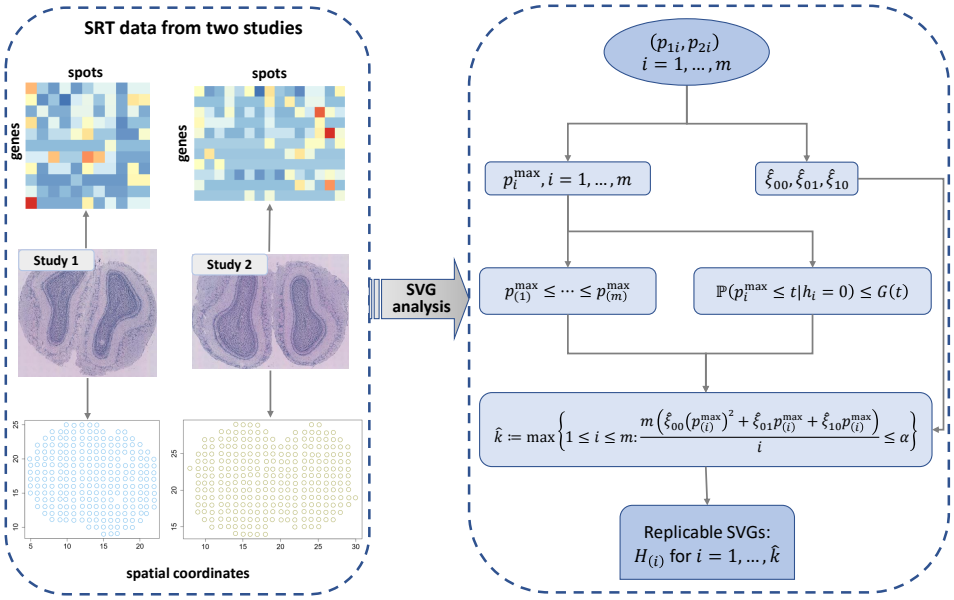

Figure 1: Schematic of JUMP for identifying replicable SVGs from two SRT studies

2.2 JUMP for replicability analysis

The schematic of JUMP for identifying replicable SVGs from two SRT studies is shown in Fig. 1. After obtaining paired p-values from two studies, we define the maximum p-values as

$$p_i^{\max} = \max\{p_{1i}, p_{2i}\}, \quad i = 1, \ldots, m.$$

Under the assumption that f_0 follows the standard uniform distribution, we have

$$\begin{aligned}
&\mathbb{P}(p_i^{\max} \leq t | \tau_i = (0,0)) = t^2, \\
&\mathbb{P}(p_i^{\max} \leq t | \tau_i = (0,1)) \leq t, \\
&\mathbb{P}(p_i^{\max} \leq t | \tau_i = (1,0)) \leq t, \quad i = 1, \ldots, m,
\end{aligned}$$

where we use the assumption that conditional on the joint hidden states, two p-value sequences are independent.

Under the replicable null, $p_i^{\max}$ follows a two-group mixture model

$$p_i^{\max} \mid h_i \sim (1-h_i)g_0 + h_i g_1,$$

where g_0 and g_1 denote the density function of $p_i^{\max}$ under replicable null and non-null, respectively. For any $t \in (0,1)$, we compute the cumulative distribution function of $p_i^{\max}$ under replicable null as follows.

$$\begin{aligned}
&\mathbb{P}(p_i^{\max} \le t \mid h_i = 0) \\
=&\frac{\mathbb{P}(p_i^{\max} \le t, h_i = 0)}{\mathbb{P}(h_i = 0)} \\
=&\frac{\xi_{00}\mathbb{P}\left(p_i^{\max} \le t | \tau_i = (0,0)\right)}{\xi_{00}+\xi_{01}+\xi_{10}} + \frac{\xi_{01}\mathbb{P}\left(p_i^{\max} \le t | \tau_i = (0,1)\right)}{\xi_{00}+\xi_{01}+\xi_{10}} \\
&+ \frac{\xi_{10}\mathbb{P}\left(p_i^{\max} \le t | \tau_i = (1,0)\right)}{\xi_{00}+\xi_{01}+\xi_{10}} \\
\le&\frac{\xi_{00}t^2 + (\xi_{01}+\xi_{10})t}{\xi_{00}+\xi_{01}+\xi_{10}}
\end{aligned}$$

Denote

$$G(t) = \frac{\xi_{00}t^2 + (\xi_{01}+\xi_{10})t}{\xi_{00}+\xi_{01}+\xi_{10}}, \tag{1}$$

we have

$$G(t) - t = \frac{\xi_{00}}{\xi_{00}+\xi_{01}+\xi_{10}} t(t-1) \le 0.$$

Hence $\mathbb{P}(p_i^{\max} \le t \mid h_i = 0) \le t$, which means that $p_i^{\max}$ follows a super-uniform distribution under the replicability null. This verifies that the vanilla maximum p-value method has valid FDR control.

For $t \in (0,1)$, the number of rejections is $R(t) = \sum_{i=1}^m I\{p_i^{\max} \le t\}$, and the number of false rejections is bounded by $m(\xi_{00}+\xi_{01}+\xi_{10})G(t)$. At threshold t, we have a conservative

estimate of FDR by

$$\mathrm{FDR}^*(t) = \frac{m(\xi_{00} + \xi_{01} + \xi_{10})G(t)}{R(t) \vee 1}.$$

In the oracle case that we know ξ_{00}, ξ_{01} and ξ_{10}, at FDR level α, let

$$t_m = \sup\{t \in (0,1) : \mathrm{FDR}^*(t) \leq \alpha\}. \tag{2}$$

Reject H_i if $p_i^{\max} \leq t_m$.

2.3 Estimation of unknowns

As ξ_{00}, ξ_{01}, and ξ_{10} are unknown in practice, we provide their estimates in this section. Following Storey (2002) and Storey et al. (2004), in study j, the proportion of null hypotheses, $\pi_0^{(j)}$, can be estimated by

$$\hat{\pi}_0^{(j)}(\lambda_j) = \frac{\sum_{i=1}^m I\{p_{ji} \geq \lambda_j\}}{m(1-\lambda_j)}, j = 1, 2.$$

Similarly, we estimate ξ_{00} as

$$\hat{\xi}_{00}(\lambda_3) = \frac{\sum_{i=1}^m I\{p_{1i} \geq \lambda_3, p_{2i} \geq \lambda_3\}}{m(1-\lambda_3)^2},$$

where λ_1, λ_2 and λ_3 are tuning parameters. We use the smoothing method provided in Storey and Tibshirani (2003) to select tuning parameters. Please see Supplementary Notes A for more details. We have

$$\hat{\xi}_{01} = \hat{\pi}_0^{(1)} - \hat{\xi}_{00},$$
$$\hat{\xi}_{10} = \hat{\pi}_0^{(2)} - \hat{\xi}_{00}.$$

We estimate $\mathrm{FDR}^*(t)$ by

$$\widehat{\mathrm{FDR}}^*(t) = \frac{m(\hat{\xi}_{00}t^2 + \hat{\xi}_{01}t + \hat{\xi}_{10}t)}{R(t) \vee 1}.$$

The data-adaptive thresholding is

$$\hat{t}_m = \sup\{t \in (0,1) : \widehat{\mathrm{FDR}}^*(t) \leq \alpha\}. \tag{3}$$

We claim the replicability of ith gene if $p_i^{\max} \leq \hat{t}_m$.

This is equivalent to the following step-up procedure. First, order the maximum p-values $p_{(1)}^{\max} \leq \cdots \leq p_{(m)}^{\max}$. Second, find

$$\hat{k} := \max\left\{1 \leq i \leq m : \widehat{\mathrm{FDR}}^*\left(p_{(i)}^{\max}\right) \leq \alpha\right\}. \tag{4}$$

Reject $H_{(i)}$ for $i = 1, \ldots, \hat{k}$, where $H_{(i)}$ corresponds to $p_{(i)}^{\max}$.

The key to the power gain is to incorporate different states in the composite null. This is similar in spirit to plugging in the proportion of the null hypothesis with a single p-value sequence in Storey (2002).

3 Results

In this section, we evaluate the FDR control and power of JUMP via simulations and conduct data analysis to identify replicable SVGs from two pairs of SRT datasets measured with different technologies.

3.1 Simulation studies

We conducted extensive simulation studies to evaluate the performance of different methods. Power is defined as the expectation of true replicable discoveries over the total number of non-

null hypotheses. We compare JUMP with two other methods for replicability analysis, BH and MaxP. Here BH refers to the *ad hoc* method that applies the BH procedure (Benjamini and Hochberg, 1995) on each study and identifies genes significant in both studies as replicable signals. MaxP (Benjamini et al., 2009) directly applies the BH procedure (Benjamini and Hochberg, 1995) to the maximum p-values across two studies, $p_i^{\max}$.

In each simulation, states of genes in two studies, θ_{1i} and θ_{2i}, were generated from a multinomial distribution with probabilities, $\mathbb{P}(\theta_{1i} = k, \theta_{2i} = l) = \xi_{kl}, k, l \in \{0, 1\}$, for pre-specified $\xi_{00}, \xi_{01}, \xi_{10}$ and ξ_{11}. Denote $N(\mu, \sigma^2)$ as a normal distribution with mean μ and standard deviation σ. In simulation study 1, we independently generated summary statistic $X_{ji} \sim N(\mu_j, \sigma_j^2)$ for ith gene in study j ($j = 1, 2$), where $\mu_j = 0$ if $\theta_{ji} = 0$, and $\mu_j > 0$ if $\theta_{ji} = 1$. One-sided p-values for study j were obtained by $p_{ji} = 1 - \Phi(Z_{ji}), i = 1, \ldots, m$, where $Z_{ji} = X_{ji}/\sigma_j$ denotes the Z-statistic for the ith gene in study j and$\Phi(\cdot)$ denotes the cumulative distribution function of $N(0, 1)$. Fig. 2 presents the FDR control and power comparison of different methods under the setting of $m = 10,000, \xi_{11} = 0.05$ and $\xi_{01} = \xi_{10}$ over different values of ξ_{00}, μ_j and σ_j, where $j = 1, 2$. For a given value of ξ_{00}, corresponding ξ_{01} and ξ_{10} can be obtained by $\xi_{01} = \xi_{10} = (1 - \xi_{00} - \xi_{11})/2$. At a target FDR level of 0.05, we observe that MaxP and JUMP controlled the FDR at 0.05 across all settings. MaxP is overly conservative and JUMP showed substantial power gain. BH is not valid in practice since it failed to control the FDR in some settings (e.g., $\xi_{00} = 0.6$). In addition, for all methods, the power is increasing with increased signal noise ratio.

We also performed realistic simulations based on Replicate 9 and Replicate 12 of ST datasets measured in mouse olfactory bulb (Ståhl et al., 2016). Details of the data generation process and simulation results can be found in Supplementary Notes B, Fig. S2 and Fig. S3.

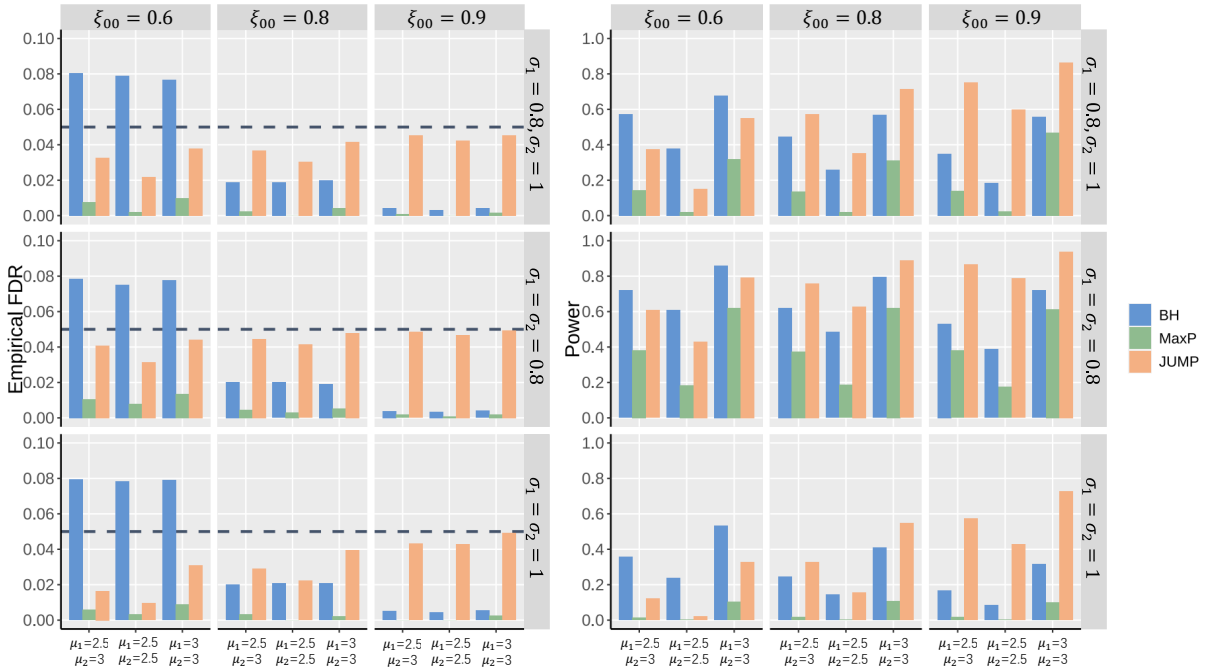

Figure 2: FDR control and power comparison of different methods in simulation study 1. $m = 10,000, \xi_{11} = 0.05$ and $\xi_{01} = \xi_{10}$. Each column corresponds to different ξ_{00}. Each row corresponds to different standard deviations. In each panel, the empirical FDR for different methods was calculated over 100 replications at a target FDR level of 0.05 (horizontal dashed line in the plots) for different non-null settings (left: $\mu_1 = 2.5, \mu_2 = 3$; middle: $\mu_1 = \mu_2 = 2.5$; right: $\mu_1 = \mu_2 = 3$).

3.2 Analysis of mouse olfactory bulb data

We first analyzed the SRT data from mouse olfactory bulb measured with ST technology (Ståhl et al., 2016) and 10X Visium technology. Ståhl et al. (2016) published 12 replicates of the mouse olfactory bulb ST datasets on the Spatial Research Website (`https://www.spatialresearch.org/`). We used Replicate 9 for our analysis, which includes $15,284$ genes on 237 spots. The 10X Visium dataset was downloaded from the 10X Visium spatial gene expression repository (`https://www.10xgenomics.com/resources/datasets`) and contains $32,285$ genes on $1,185$ spots. We filtered out genes that are expressed in less than 10% spatial spots and selected spots with at least ten total read counts, resulting in $9,547$ genes on 236 spots for the ST dataset and $10,680$ genes on $1,185$ spots for the 10X Visium dataset,

respectively. We separately analyzed the two datasets using SPARK (Sun et al., 2020) to produce p-values. Paired p-values of $8,547$ genes common to both studies is the input to the replicability analysis. As can be seen in Fig. 3a, JUMP has higher power than the other two methods. At the FDR level of 0.05, MaxP identified 618 replicable SVGs, which were all detected by BH and JUMP. JUMP identified 807 replicable SVGs, including 637 of the 638 SVGs detected by BH. This is consistent with the simulation results that MaxP is overly conservative and JUMP has higher power.

We clustered the 807 replicable SVGs identified by JUMP into three groups using the hierarchical agglomerative clustering algorithm implemented in the R package *amap* (v0.8-18) and summarized the spatial expression patterns based on the expression level of the genes in corresponding groups. In both studies, the summarized patterns were consistent with three main cell layers in mouse olfactory bulb. In Fig. 3b and Fig. S4a, Pattern I corresponds to the glomerular layer, Pattern II corresponds to the mitral layer and Pattern III corresponds to the granular layer. Spatial expression patterns of three representative SVGs (*Kctd12*, *Plcxd2*, *Ctxn1*) identified by JUMP are presented in Fig. 3c, which correspond to Pattern I-III, respectively and are consistent with the *in situ* hybridization images obtained from the Allen Brain Atlas. For comparison, we also randomly selected 30 genes from the 189 additional findings of JUMP compared to the overlaps of three methods and showed their spatial expression patterns in Supplementary Fig. S5a, b. Moreover, we calculated Moran's I statistic (Moran, 1950) of the 189 replicable SVGs additionally identified by JUMP and compared it with that using all $8,547$ genes to show the autocorrelations of the additional findings by JUMP (Fig. 3d).

To further compare and validate the replicable SVGs identified by different methods, we downloaded two published gene sets from the Harmonizome database (Rouillard et al., 2016) consisting of genes related to mouse olfactory bulb as a reference (Fig. 3e). The first gene set was summarized based on three layers (glomerular, mitral, and granular) of the main

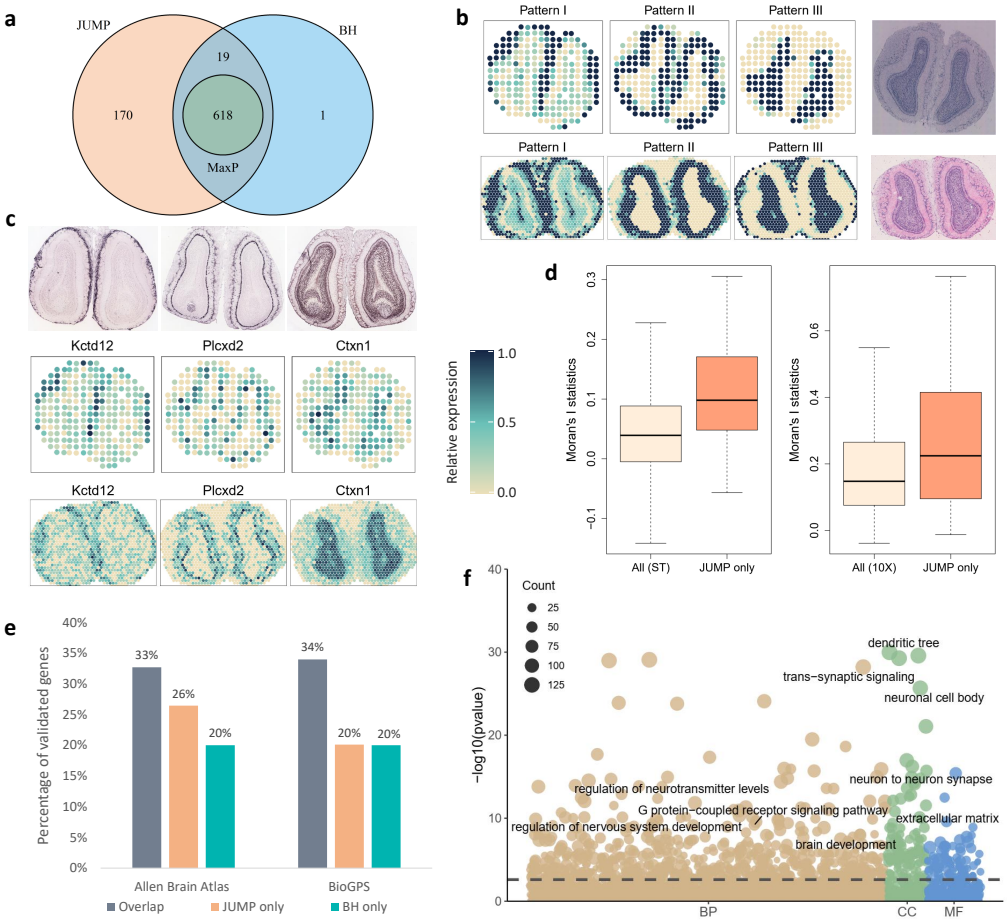

Figure 3: Analysis and validation results of the mouse olfactory bulb data measured with ST technology and 10X Visium technology. (a) Venn diagram shows the number of replicable SVGs identified by different methods at FDR level 0.05 and the intersection of discoveries. (b) Three distinct spatial expression patterns based on the 807 replicable SVGs identified by JUMP in the ST study (top) and 10X Visium study (bottom). Color represents relative expression levels (antique white: low; navy blue: high). The corresponding hematoxylin and eosin staining (HE) images for the two studies are shown in the right panel. (c) Spatial expression patterns of three representative genes identified by JUMP, corresponding to Pattern I-III, respectively. *In situ* hybridization images of corresponding genes obtained from the Allen Brain Atlas are shown in the top panel. (d) The box plot shows Moran's I statistic of the 189 replicable SVGs additionally identified by JUMP and that of all genes based on the ST study (left) and the 10X Visium study (right). (e) The bar chart displays the number of replicable SVGs additionally identified by JUMP and BH compared to that identified by all three methods. They were validated in two reference gene lists from the Harmonizome database: one from the Allen Brain Atlas dataset and the other from the BioGPS dataset. (f) The bubble plot shows the GO enrichment analysis result of JUMP. The horizontal dashed line represents the FDR level 0.01. The color of a bubble shows different GO term categories: BP (tan), CC (green), and MF (blue). The size of a bubble represents the counts of corresponding gene sets.

olfactory bulb from the Allen Brain Atlas adult mouse brain tissue gene expression profiles dataset (Sunkin et al., 2012), including $3,485$ genes with high or low expression in main olfactory bulb relative to other tissues. 33% of the 618 replicable SVGs that were identified by all three methods were validated. Among the 189 replicable SVGs additionally identified by JUMP, 26% were validated in the reference list, whereas only 4 of the 20 SVGs additionally identified by BH were in the same list. The second reference gene set includes $2,031$ genes differentially expressed in mouse olfactory bulb relative to other cell types and tissues from the BioGPS mouse cell type and tissue gene expression profiles dataset (Wu et al., 2013). In addition to the replicable SVGs identified by all three methods (34% validated), 38 of the 189 replicable SVGs only detected by JUMP were in the list, whereas 4 of the 20 replicable SVGs only detected by BH were validated in the same list. These results provide additional biological evidence for the improved power of JUMP.

Additionally, we performed Gene Ontology (GO) enrichment analysis on replicable SVGs identified by JUMP and BH (Fig. 3f). At the FDR level of 0.01, JUMP enriched 846 GO terms and BH enriched 764 GO terms (708 overlaps). Many of the 138 GO terms only identified by JUMP are related to nervous system development and olfactory bulb organization. For instance, transmission of nerve impulse (GO:0019226), neuronal action potential (GO:0019228), and forebrain neuron differentiation (GO:0021879) are closely related to the establishment of axodendritic and dendrodendritic synaptic contacts within the olfactory bulb (Belluzzi et al., 2003); GABA-ergic synapse (GO:0098982) plays a key role in the organization of olfactory bulb (Hanson et al., 2020); GO terms GO:0045744 and GO:0002029 are related to G protein-coupled receptor, which can be encoded by odorant receptor genes differentially expressed at conserved positions in the olfactory bulb (Katidou et al., 2018).

3.3 Analysis of mouse cerebellum data

We next analyzed the SRT data from mouse cerebellum measured with Slide-seq technology (Rodriques et al., 2019) and Slide-seqV2 technology (Stickels et al., 2021). The two datasets were obtained from Broad Institute's single-cell repository (`https://singlecell.broadinstitute.org/single_cell`) with IDs SCP354 and SCP948, respectively. The Slide-seq dataset (file "Puck_180430_6") contains $18,671$ genes on $25,551$ beads. we filtered out beads with total counts less than 50. The Slide-seqV2 dataset contains $23,096$ genes on $39,496$ beads. We cropped regions of interest by filtering out beads with total counts less than 100. Mitochondrial genes and genes that are not expressed in any locations were filtered out from the two datasets, resulting in $17,481$ genes on $14,667$ beads for the Slide-seq data and $20,117$ genes on $11,626$ beads for the Slide-seqV2 data. After applying the SPARK-X method (Zhu et al., 2021) on the two datasets separately, we obtained two sequences of p-values and matched them by gene. We used the paired p-values for $16,519$ genes common to both studies as input for the replicability analysis of SVGs. At FDR level 0.05, MaxP identified 279 replicable SVGs, which were all identified by BH and JUMP. JUMP detected all BH findings (394) and identified 54 additional replicable SVGs.

We first examined the spatial expression patterns of the 448 replicable SVGs identified by JUMP by clustering them into three groups showing distinct spatial expression patterns (Fig. 4a). In both Slide-seq (left) and Slide-seqV2 (right) datasets, the 448 SVGs showed consistent patterns: Pattern I and Pattern III correspond to the purkinje cell layer and granular cell layer, respectively; and Pattern II corresponds to other cell layers. Three representative genes identified by JUMP (*Pcp2*, *Mbp*, and *Snap25*) exhibited corresponding spatial expression patterns, which were validated by *in situ* hybridization in the Allen Brain Atlas (Fig. 4b). Fig. S6a,b display spatial expression patterns of 24 genes randomly selected from the 169 replicable SVGs identified by JUMP in addition to genes identified by all three methods. As shown

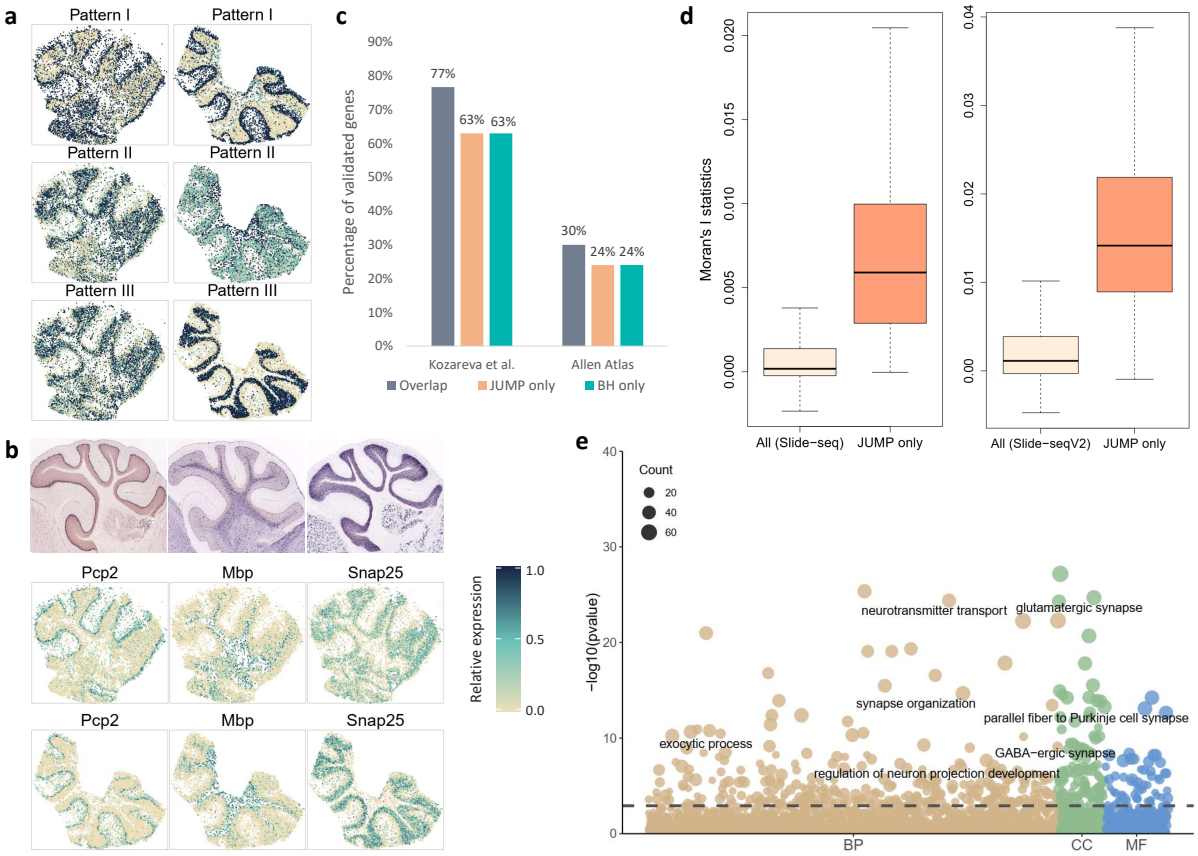

Figure 4: Analysis and validation results of the mouse cerebellum data measured with Slide-seq technology and Slide-seqV2 technology. (a) Three distinct spatial expression patterns based on the 448 replicable SVGs identified by JUMP in the Slide-seq study (left) and Slide-seqV2 study (right). Color represents relative expression levels (antique white: low; navy blue: high). (b) Spatial expression patterns of three representative genes identified by JUMP, corresponding to Pattern I-III, respectively. *In situ* hybridization images of corresponding genes obtained from the Allen Brain Atlas are shown in the top panel. (c) The bar chart displays the number of replicable SVGs additionally identified by JUMP and BH compared to that identified by all three methods. They were validated in two reference gene lists: one from Kozareva et al. (2021) and the other from the Allen Brain Atlas dataset summarized in the Harmonizome database. (d) The box plot shows Moran's I statistic of the 169 replicable SVGs additionally identified by JUMP and that of all genes based on the Slide-seq study (left) and the Slide-seqV2 study (right). (e) The bubble plot shows the GO enrichment analysis result of JUMP. The horizontal dashed line represents the FDR level 0.01. The color of a bubble shows different GO term categories: BP (tan), CC (green), and MF (blue). The size of a bubble represents the counts of corresponding gene sets.

in Fig. 4d, the additional spatial autocorrelations revealed by JUMP were further confirmed by Moran's I (Moran, 1950).

We provided two gene sets obtained from published literature to validate the results of different methods. First, we obtained a list of genes that are highly differentially expressed across all clusters in mouse cerebellar cortex from Kozareva et al. (2021). We further filtered out genes with absolute log fold change smaller than 0.05 and obtained $3,976$ genes for the validation. In addition to genes identified by all three methods (77% validated), 107 of the 169 replicable SVGs additionally identified by JUMP were in the list, whereas 73 of the 115 findings by BH were validated. Second, we downloaded three gene sets related to mouse cerebellum in the Allen Brain Atlas datasets (Sunkin et al., 2012) from the Harmonizome database (Rouillard et al., 2016) and summarized them to a list of $3,000$ genes that are differentially expressed in mouse cerebellum, cerebellar cortex, and cerebellar hemisphere. Among the 279 SVGs identified by all three methods, 30% were in this gene list. 39 of the 169 replicable SVGs additionally identified by JUMP were validated, whereas 28 of the 115 SVGs additionally identified by BH were in the same list.

Finally, we performed GO enrichment analysis on the replicable SVGs identified by different methods to evaluate the biological significance additionally identified by JUMP. At the FDR level of 0.01, JUMP enriched 452 GO terms and BH identified 418 GO terms (394 overlaps). Among the 58 GO terms only enriched by JUMP, many are closely related to the structural constitution and functional development of mouse cerebellum, such as GO terms of cerebellar cortex development (GO:0021695), cerebellum development (GO:0021549), central nervous system neuron development (GO0021954), dendritic transport (GO:0098935), and photoreceptor ribbon synapse (GO:0098684), among others.

4 Discussion

We present a new method, JUMP, for identifying replicable features from two high-throughput experiments. JUMP models the joint hidden states and calculates rejection probabilities under each state. This provides a better approximation to the probability of rejection under a composite replicability null hypothesis. Analysis of different SRT studies identifies important replicable SVGs that might otherwise be missed by existing methods. JUMP is simple to implement and computationally scalable to tens of thousands of genes (Supplementary Table S1 and S2). Moreover, JUMP does not require two SRT studies to have the same spatial alignment or the same tissue thickness. In practice, using alignments, rotations and normalizations may distort important biological information contained in the data. In addition, JUMP is flexible and can accommodate data from other modalities, such as scRNA-seq, ATAC-seq, and CITE-seq, among others.

One limitation of JUMP is that it only identifies replicable features from two high-throughput experiments. If we want to extend it to more than two studies, say n studies, we require a 2^n-group model for the data, and the composite null is composed of $(2^n - 1)$ hidden joint states whose proportions need to be estimated. We leave this for future research.

Data availability

The data underlying this article are publicly available in corresponding repositories. The mouse olfactory bulb ST dataset can be obtained with file 'MOB Replicate 9' in the Spatial Research Website at `https://www.spatialresearch.org/resources-published-datasets/doi-10-1126science-aaf2403/`. The mouse olfactory bulb 10X Visium dataset is available in the 10X Visium spatial gene expression repository at `https://www.10xgenomics.com/resources/datasets/adult-mouse-olfactory-bulb-1-standard-1`. The mouse cerebel-

lum Slide-seq dataset and Slide-seqV2 dataset are provided in the Broad Institute's single-cell repository at `https://singlecell.broadinstitute.org/single_cell/` under IDs SCP354 (file 'Puck_180430_6') and SCP948, respectively.

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Competing interests

The authors declare that they have no competing interests.

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