

Microbiome and metabolome features in inflammatory bowel disease via multi-omics integration analyses across cohorts

Lijun Ning^{1,*}, Yi-Lu Zhou^{1,*}, Han Sun^{2,*}, Youwei Zhang^{3,*}, Chaoqin Shen^{4,*}, Zhenhua Wang¹, Baoqin Xuan¹, Ying Zhao¹, Yanru Ma¹, Yuqing Yan¹, Tianying Tong¹, Xiaowen Huang¹, Muni Hu¹, Xiaoqiang Zhu¹, Jinmei Ding¹, Yue Zhang¹, Zhe Cui⁵, Jing-Yuan Fang¹, Haoyan Chen¹, Jie Hong¹

¹State Key Laboratory for Oncogenes and Related Genes; Key Laboratory of Gastroenterology & Hepatology, Ministry of Health; Division of Gastroenterology and Hepatology; Shanghai Cancer Institute; Shanghai Institute of Digestive Disease; Renji Hospital, Shanghai Jiao Tong University School of Medicine. 145 Middle Shandong Road, Shanghai 200001, China.

²Department of Gastroenterology, Xuzhou Central Hospital, Clinical School of Xuzhou Medical University, Xuzhou, China.

³Department of Medical Oncology, Xuzhou Central Hospital, Clinical School of Xuzhou Medical University, Xuzhou, China.

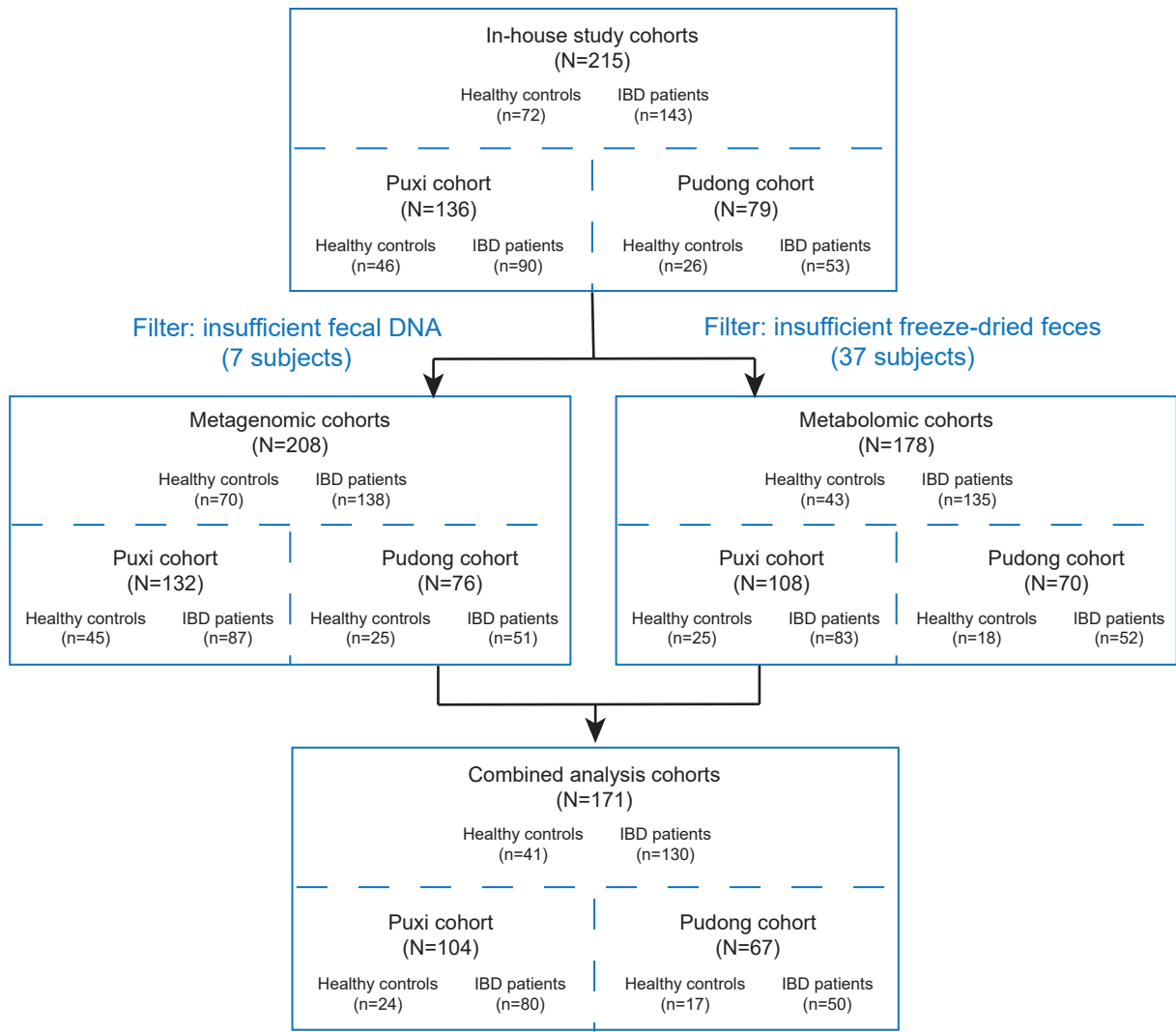
⁴Department of Gastroenterology and Hepatology, Zhongshan Hospital, Fudan University, Shanghai, P.R. China.

⁵Department of Gastrointestinal Surgery, Renji Hospital, Shanghai Jiao Tong University School of Medicine. 145 Middle Shandong Road, Shanghai 200001, China.

****These authors contributed equally to this work and share first authorship.***

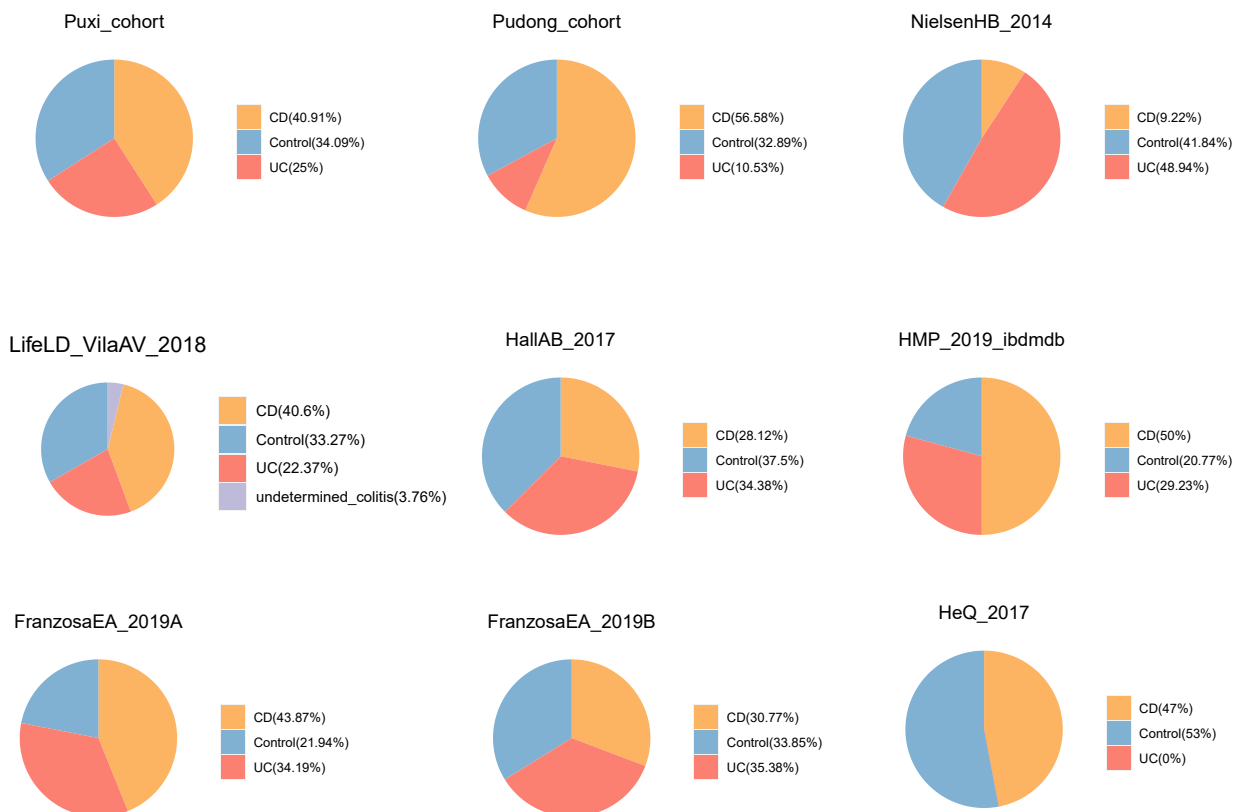
Supplementary Information

a



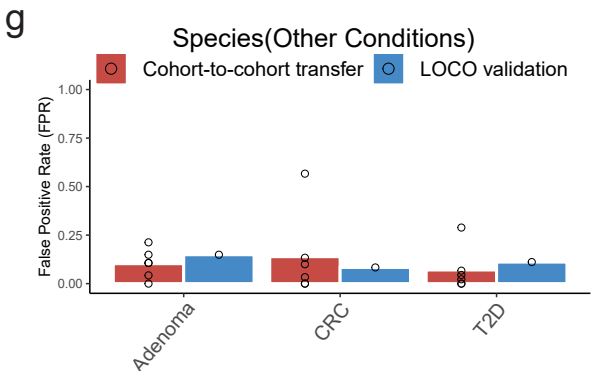
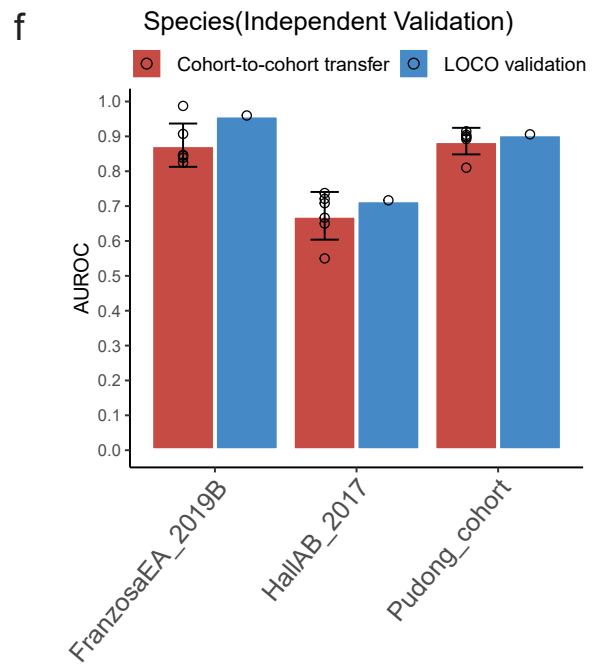
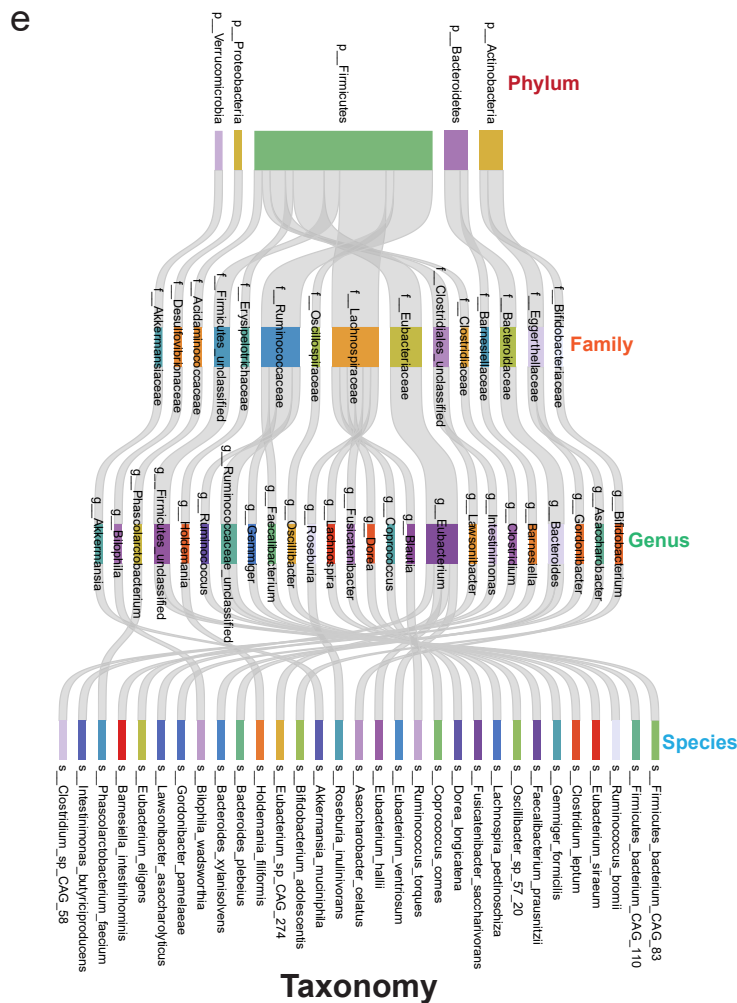
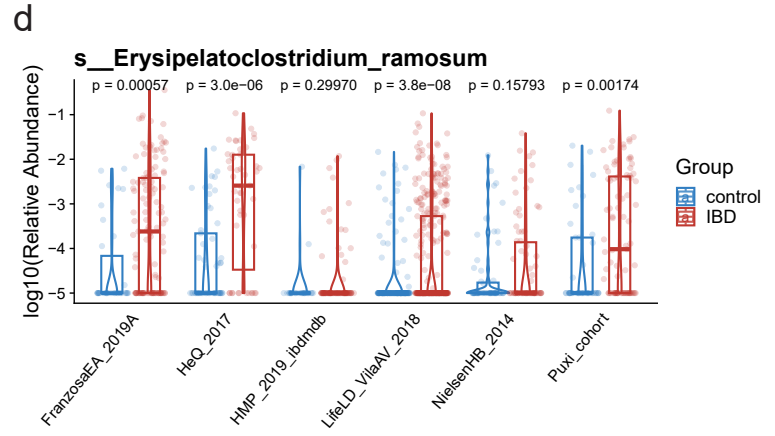
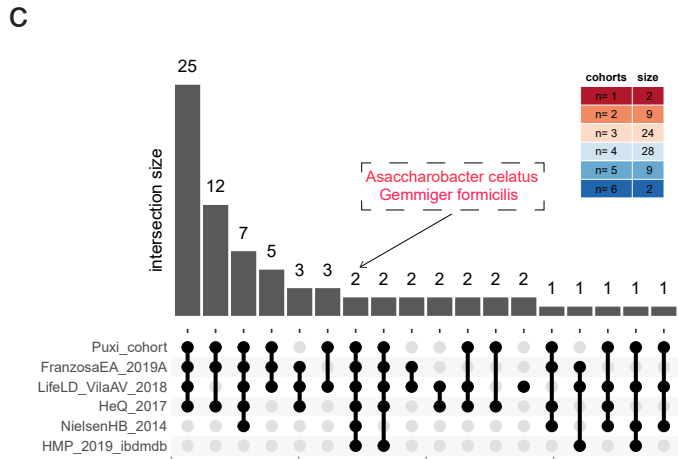
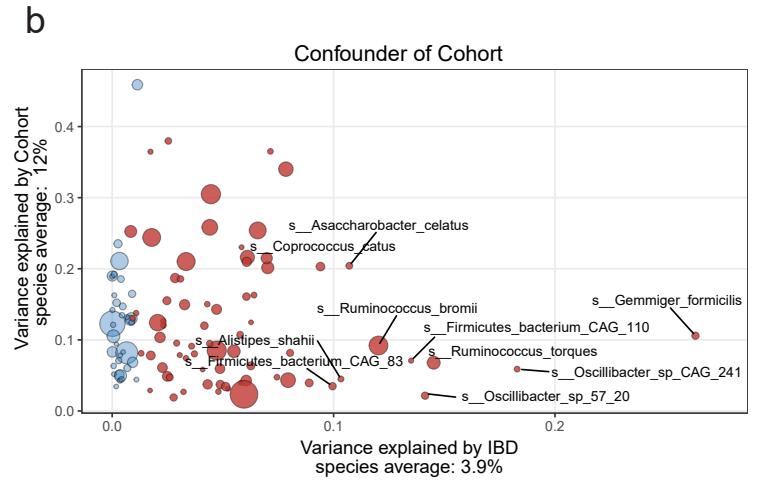
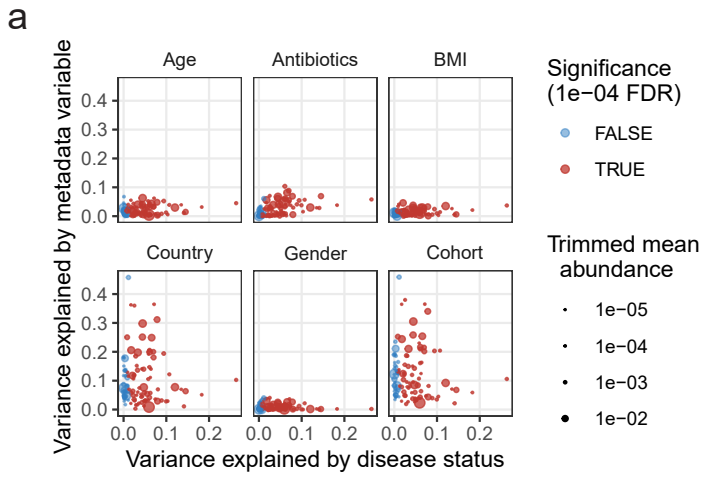
Only subjects, which contained both metagenomic and metabolomic data, were enrolled in the combined analysis.

b



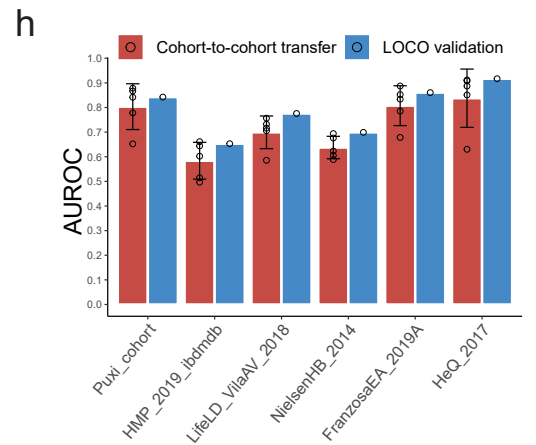
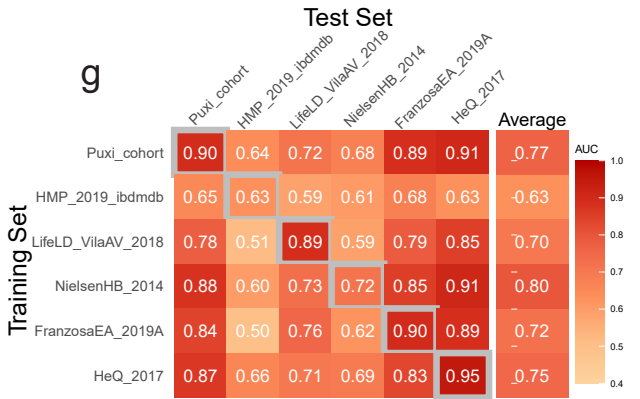
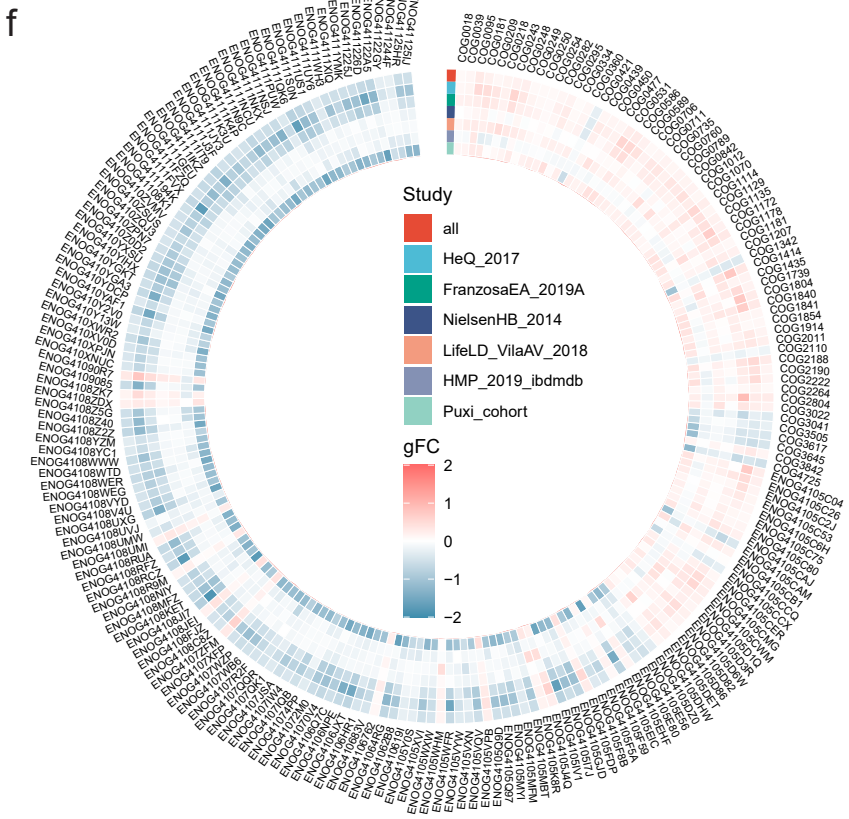
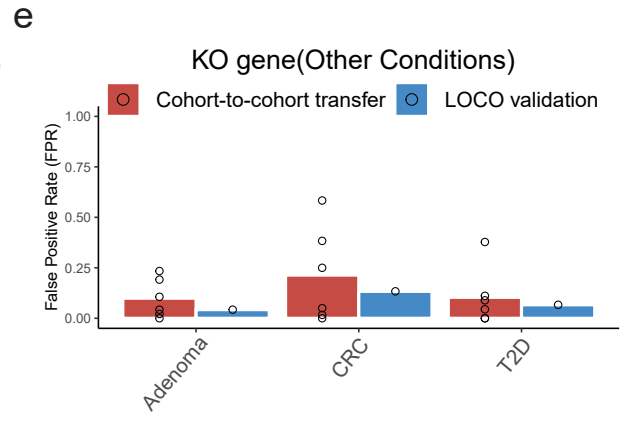
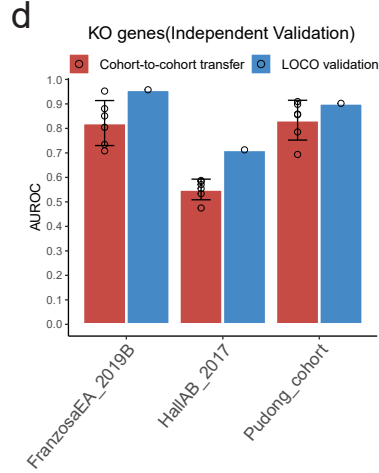
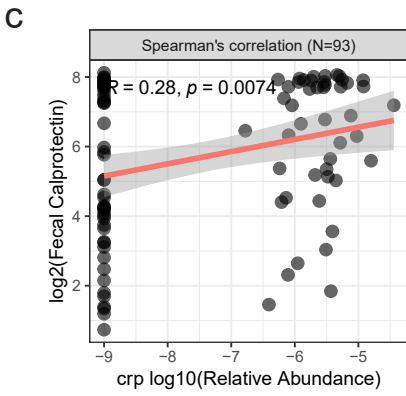
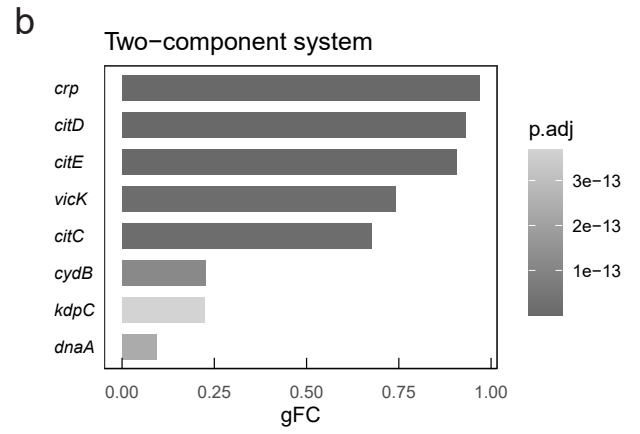
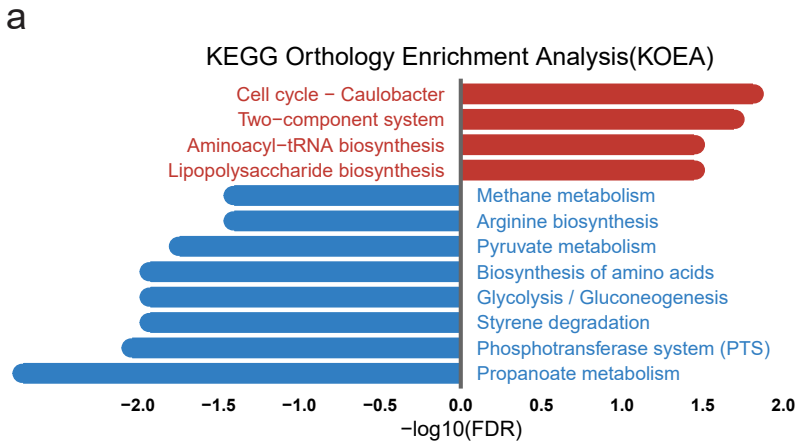
Supplementary Fig1. Workflow for cross-cohort integration analysis of fecal metagenomics and metabolomics in IBD

a. Recruitment and study design workflow for in-house IBD Renji cohorts. **b.** In this study, a total of 9 metagenomic cohorts from four different regions or countries were analyzed, including 1363 cases. These cohorts were divided into six discovery cohorts and three validation cohorts for further analysis and validation. Pie charts show the percentage composition of disease subtypes in different cohorts.



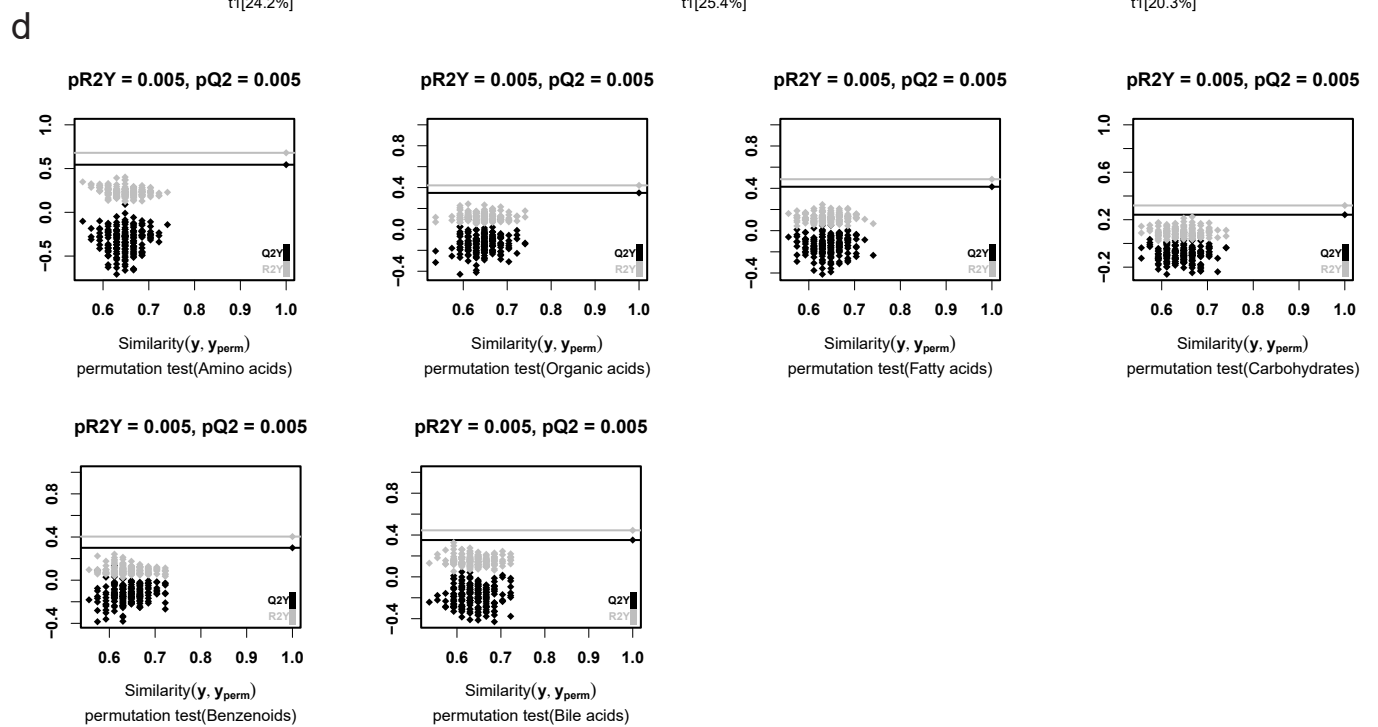
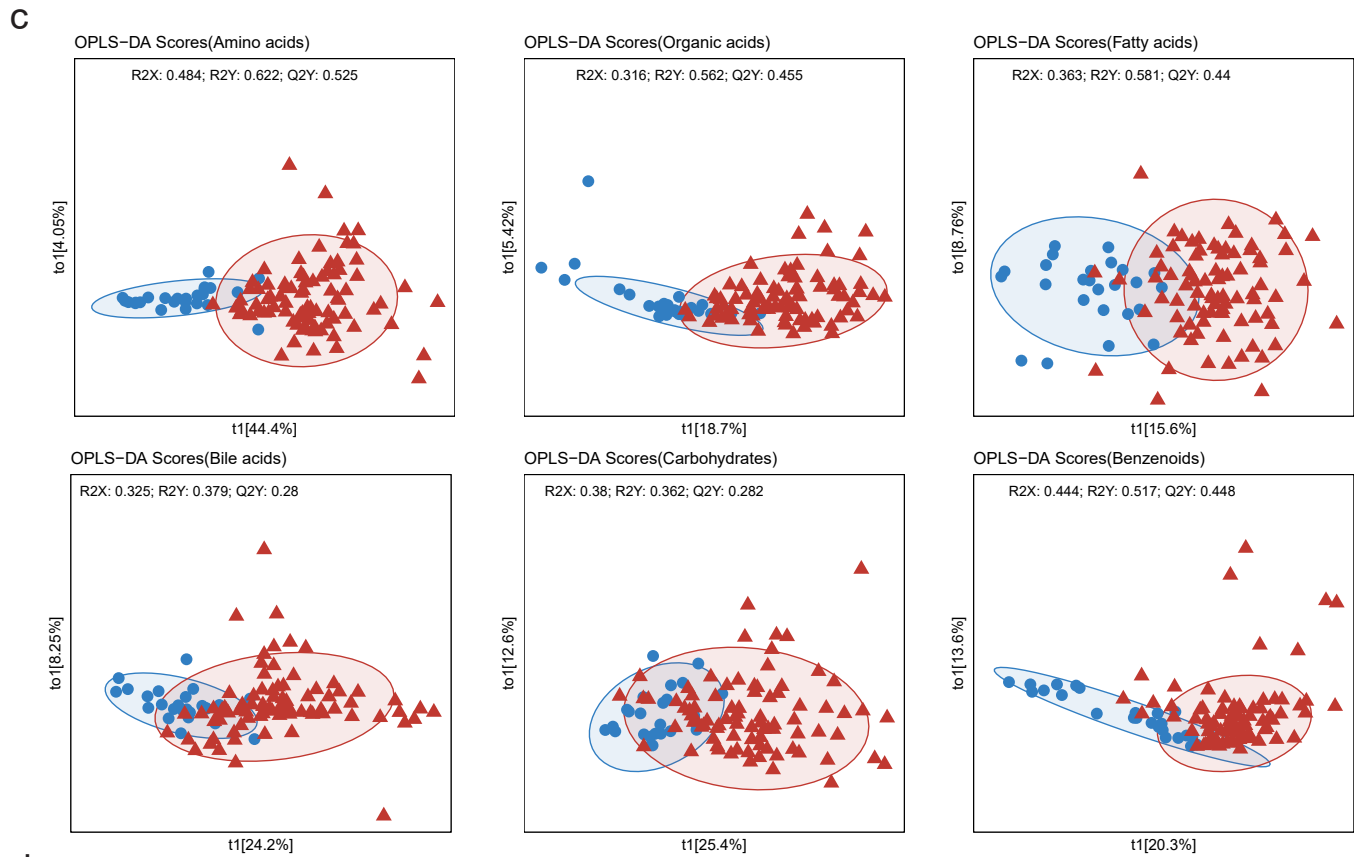
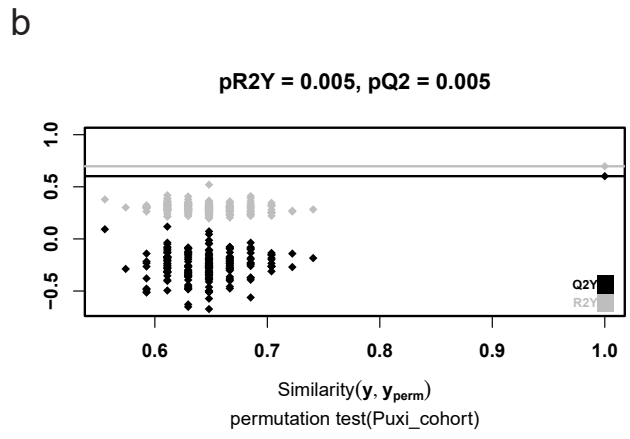
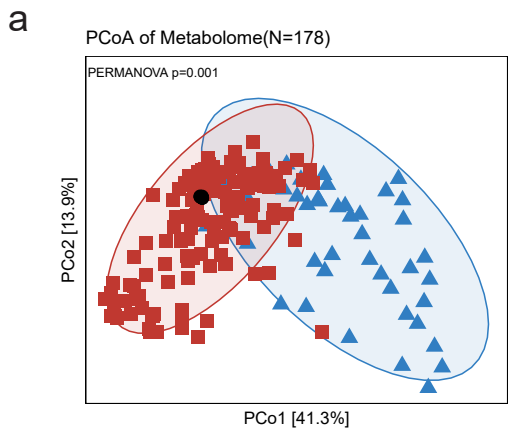
Supplementary Fig2. Identification of bacterial biomarkers at the species level for diagnosing IBD through cross-cohort demonstration of gut microbiota alterations in IBD patients

a. The analysis aimed to examine the relationship between the variance explained by disease status (IBD versus control) and various putative confounding factors for individual microbial species. The abundance of each microbial species is represented by the size of the corresponding dot on the graph. Among the species analyzed, 74 were found to be significantly different between IBD and control, and are highlighted in red. The analysis considered all available samples to calculate the variance explained by each confounding factor. **b.** Variance explained by disease status (IBD versus control) is plotted against variance explained by cohort effects for individual microbial species with dot size being proportional to abundance. **c.** UpSet plot showing the number of differential bacterial species in each cohort and shared by combinations of datasets. The number above each column represents the size of differential species. The connected dots represent the common differential species across connected cohorts. **d.** The combined boxplot displays the differential relative abundance of *Erysipelatoclostridium ramosum* between the control and IBD. The data is represented using interquartile ranges (IQRs), with the median shown as a black horizontal line, and the whiskers extending to the most extreme points within 1.5 times the IQR. Comparisons were performed using a two-sided Wilcoxon test, and the exact P values are shown. **e.** The Sankey diagram shows a taxonomic chart of 31 feature bacteria, with the majority of the aforementioned features belonging to the phylum Firmicutes. **f.** IBD classification accuracy for independent cohorts is indicated by the bar height for cohort-to-cohort transfer analysis (red) and LOCO (blue) models using species abundance profiles. The error bars indicate the mean \pm sd, n = 6. **g.** IBD classification specificity for non-IBD cohorts is indicated by the bar height for cohort-to-cohort transfer analysis (red) and LOCO (blue) models using species abundance profiles as assessed by the FPR.

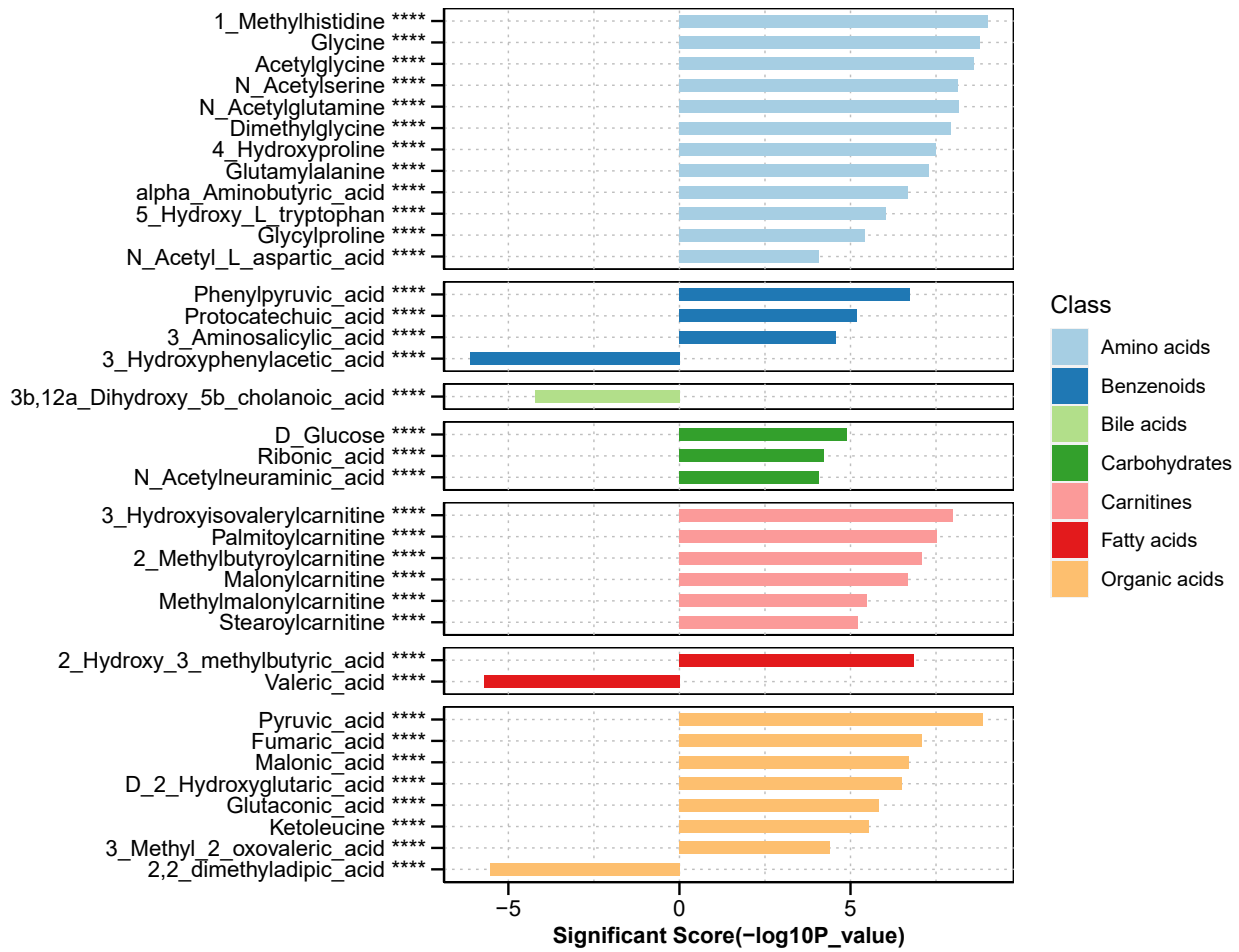


Supplementary Fig3. Identification of IBD diagnostic markers by demonstrating variations of Kyoto Encyclopedia of Genes and Genomes (KEGG) orthology (KO) across different IBD cohorts

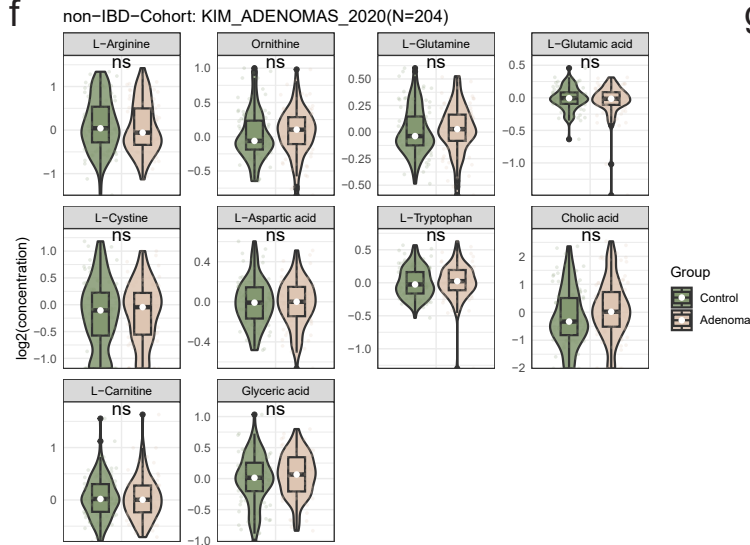
a. The differential bar chart shows the results of KEGG Orthology Enrichment Analysis (KOEa). The red bars represent pathways enriched in IBD, while the blue bars represent pathways enriched in the control group (FDR < 0.05, calculated using a two-sided Wilcoxon test with FDR-corrected P values). **b.** The generalized fold change (gFC) and p-value of the 8 KO genes enriched in the Two-Component System pathway (two-sided Wilcoxon test with FDR-corrected P values). **c.** Correlation analysis between the *crp* gene and fecal calprotectin protein (Spearman's correlation, FranzosaEA_2019A cohort, n=93). **d.** IBD classification accuracy for independent cohorts is indicated by the bar height for cohort-to-cohort transfer analysis (red) and LOCO (blue) models using KO genes abundance profiles. The error bars indicate the mean \pm sd, n = 6. **e.** IBD classification specificity for non-IBD cohorts is indicated by the bar height for cohort-to-cohort transfer analysis (red) and LOCO (blue) models using KO genes abundance profiles as assessed by the FPR. **f.** The circular complex heatmap displays the 209 most significant EggNOG genes ($P < 1 \times 10^{-12}$), as calculated using a two-sided Wilcoxon test with FDR-corrected P values in the cross-cohort analysis. The heatmap shows the gFC values of these 209 EggNOG genes, with red indicating enriched and blue indicating depleted in IBD. **g.** IBD classification accuracy resulting from 10-fold cross-validation within each cohort (gray boxes along the diagonal) and cohort-to-cohort model transfer (external validations off-diagonal) as measured by the AUROC for classifiers trained on the EggNOG genes abundance profiles. The last column depicts the average AUROC across the external validations. **h.** Classification accuracy, as evaluated by AUROC on a hold-out cohort, improves if functional data (EggNOG genes) from all other cohorts are combined for training (LOCO validation) relative to models trained on data from a single cohort. The error bars indicate the mean \pm sd, n = 5.



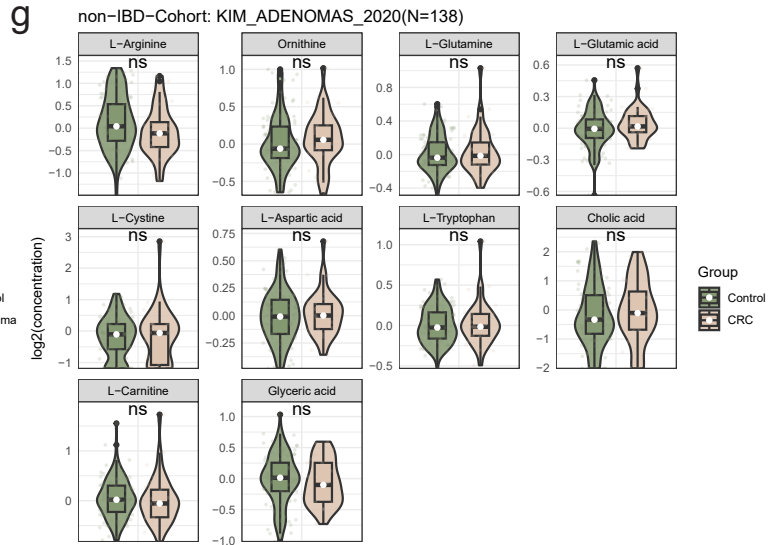
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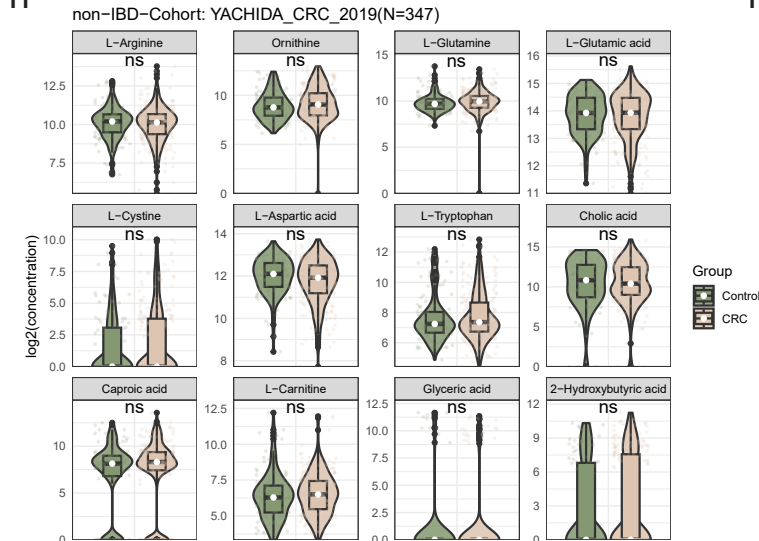
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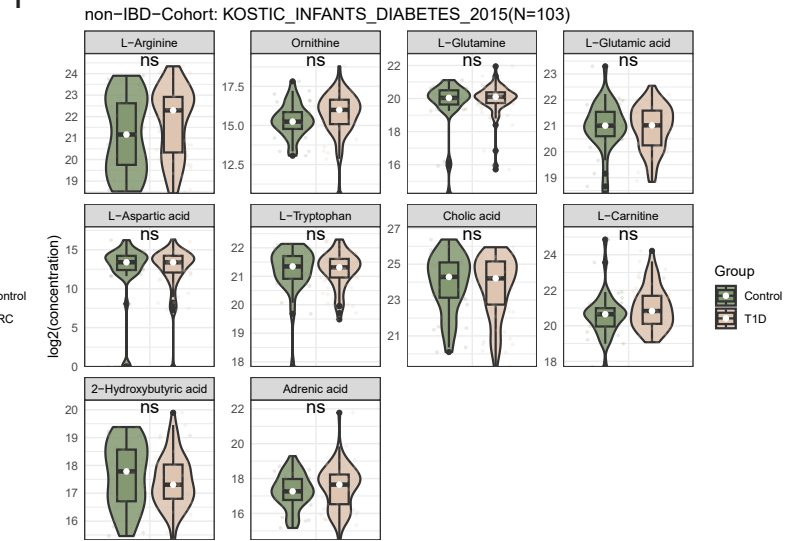
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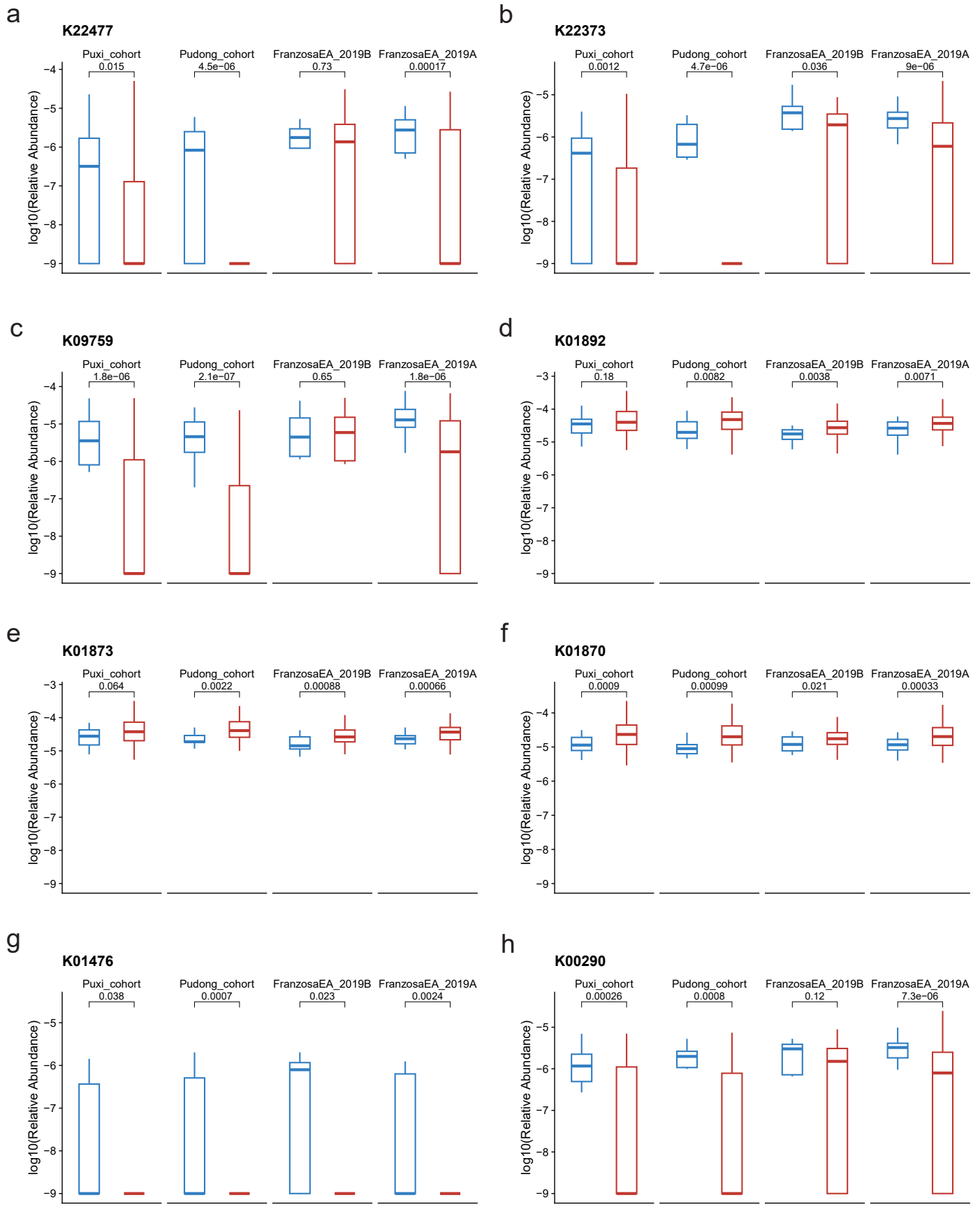


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Supplementary Fig4. Demonstration of Metabolomic Alterations across Different IBD Cohorts and Utilization of Signature Metabolites for IBD Diagnosis

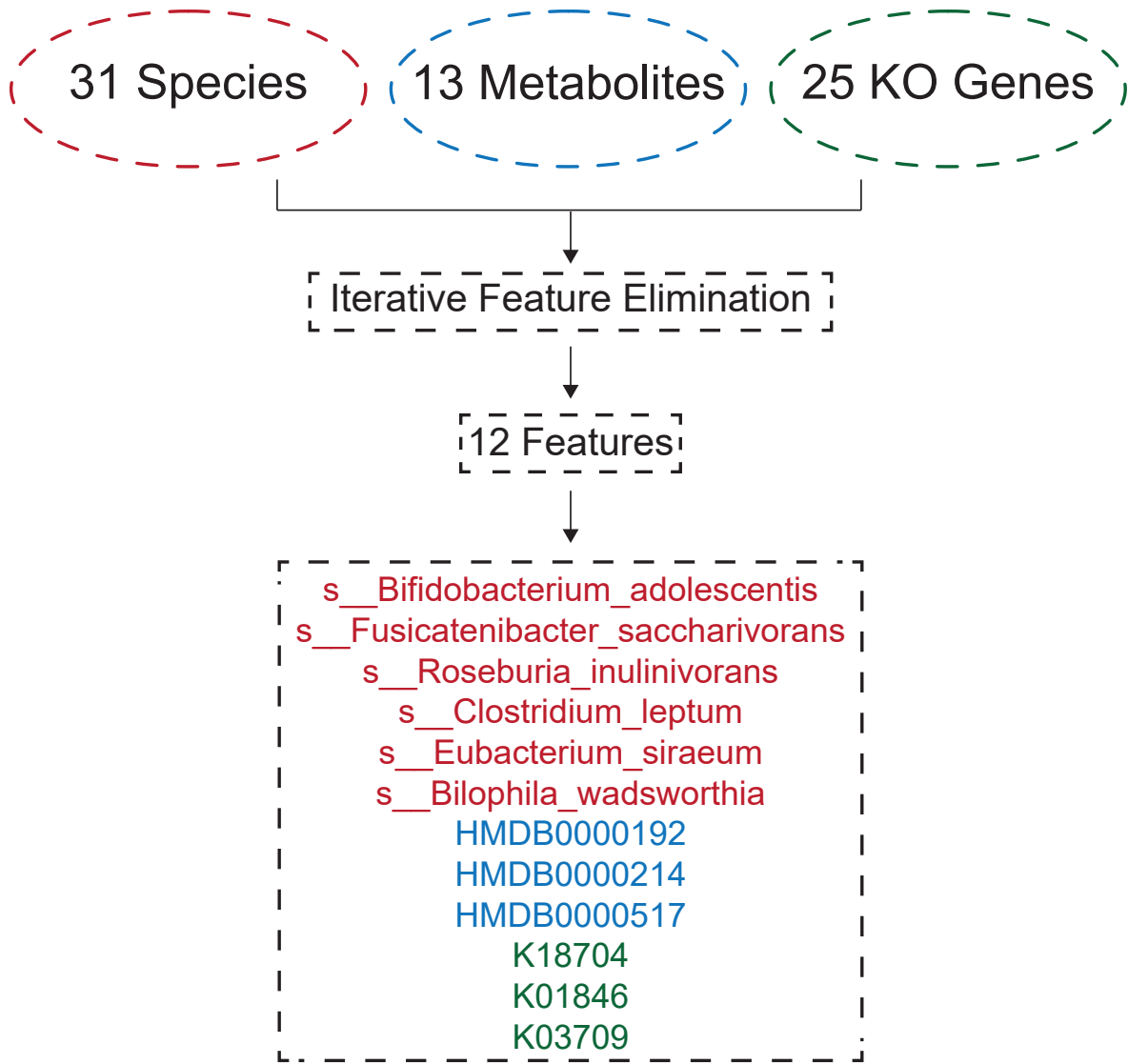
a. A principal coordinates analysis (PCoA) was performed on individuals from the Puxi cohort (n=108). The analysis showed significant differences in metabolites composition between QC, control and IBD ($P = 0.001$), as determined by PERMANOVA using Bray-Curtis distance with 999 permutations (two-sided test). **b.** The OPLS-DA model validation involves conducting a permutation test on the Puxi cohort (perml = 200, two-sided test, n=108), which is a nonparametric test. **c.** The OPLS-DA models illustrate the differences between different classified metabolites between control (n = 25) and IBD (n= 83). The full model's predictive performance is evaluated using the cumulative Q²Y metric: Q²Y ranges from 0 to 1, and the higher the Q²Y, the better the performance. **d.** The OPLS-DA model validation involves conducting a permutation test on the different classified metabolites between control (n = 25) and IBD (n= 83) on the Puxi cohort (perml = 200, two-sided test), which is a nonparametric test. **e.** The bar plot illustrates 36 unique identified differential fecal metabolites in the in-house dataset. Their significance scores calculated using a two-sided Wilcoxon test with FDR-corrected P values (denoted as ****p < 0.0001), positive values indicate enrichment in IBD, while negative values indicate enrichment in the control group. **f-i.** The violin plot illustrates the validation of disease specificity for our feature metabolites across four additional non-IBD metabolomics cohorts, which consist of one adenoma cohort, two CRC cohorts, and one T1D cohort. Their significance scores calculated using a two-sided Wilcoxon test with FDR-corrected P values (denoted as ns p > 0.05). Exact p values are provided in the Source data file.



Supplementary Fig5. Construction of a multi-omics biological association map of gut microbiota in IBD

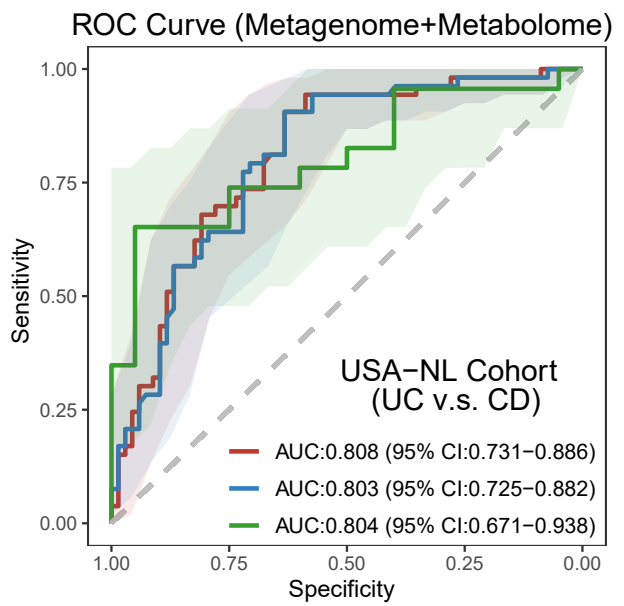
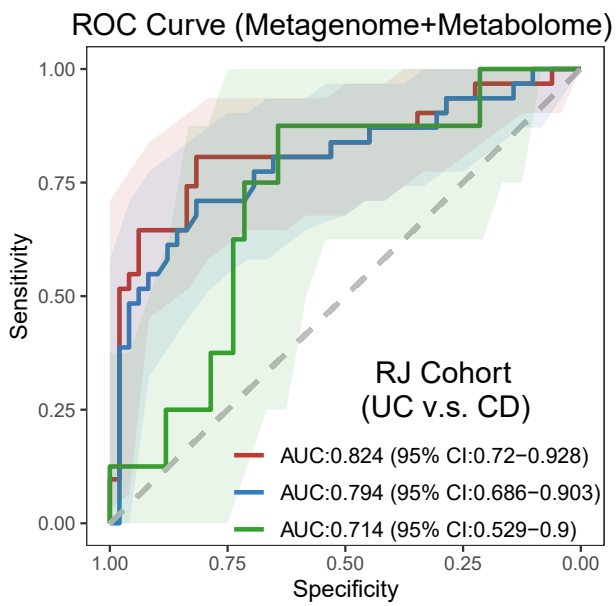
a-h. The box plots display the differences between control and IBD in four distinct cohorts for eight differential KO genes that are associated with metabolism and disease phenotypes. The data is represented using interquartile ranges (IQRs), with the median shown as a black horizontal line, and the whiskers extending to the most extreme points within 1.5 times the IQR. Comparisons were performed using a two-sided Wilcoxon test, and the exact P values are shown. (Puxi_cohort, control=24, IBD=80; Pudong_cohort, control=17, IBD=50; FranzosaEA_2019A, control=34, IBD=121; FranzosaEA_2019B, control=22, IBD=43)

a



b

c



— 10-Fold Cross-Validation — Leave-One-Out Cross-Validation — Independent Validation

Supplementary Fig6. Identification of multi-omics biomarkers for distinguishing subtypes of IBD

a. Flowchart for identifying 12 features to distinguish between UC and CD. **b-c.** We trained RF classifiers on multi-omics panel to identify IBD subtypes. Training/testing was carried out within the Puxi cohort cohort using 10-fold cross-validation (red) and leave one out cross-validation (LOOCV) (blue), in addition to models trained on the full Puxi cohort, and then tested (validated) on the independent validation (green) in Pudong cohort. Training/testing was carried out within the FranzosaEA_2019A cohort cohort using 10-fold cross-validation (red) and leave one out cross-validation (LOOCV) (blue), in addition to models trained on the full FranzosaEA_2019A cohort, and then tested (validated) on the independent validation (green) FranzosaEA_2019B cohort. Receiver operating characteristic (ROC) curves depict trade-offs between RF classifier true and false positive rates as classification stringency varies. Shaded areas represent the 95% confidence intervals of the corresponding ROC curves.