

**Assessing the impact** of cell type deconvolution on differential gene expression analysis of COVID-19

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#### **Outline** •••

- 1. Introduction & Aims
- 2. **Aim 1:** Cell type deconvolution
- 3. **Aim 2:** Differential gene expression analysis and gene set enrichment analysis
- 4. **Aim 3:** Quantitative assessments of cell type model
- 5. Conclusion & Limitations

#### INTRODUCTION •••

- Mechanism of COVID yet to be fully elucidated
- Cell type information is hidden in bulk tissue sequencing



RESEARCH ARTICLE

# In vivo antiviral host transcriptional response to SARS-CoV-2 by viral load, sex, and age

Nicole A. P. Lieberman, Vikas Peddu, Hong Xie, Lasata Shrestha, Meei-Li Huang, Megan C. Mears, Maria N. Cajimat, Dennis A. Bente, Pei-Yong Shi, Francesca Bovier, Pavitra Roychoudhury, Keith R. Jerome, Anne Moscona, Matteo Porotto, Alexander L. Greninger

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- Sample size (n = 409):
  - 356 positive, 53 negative

We hypothesize that including cell type as a covariate will influence differential gene expression analysis results.



#### AIMS •••

#### AIM1

Perform cell type deconvolution to the dataset in Lieberman *et al.* paper.

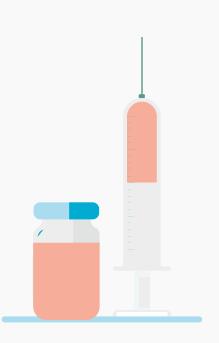
#### AIM2

Perform a DE analysis based on infection status and using sex, age and cell type as covariates.

#### AIM3

Evaluate the statistical importance of including cell type. Compare our GSEA with the Lieberman *et al.* paper.



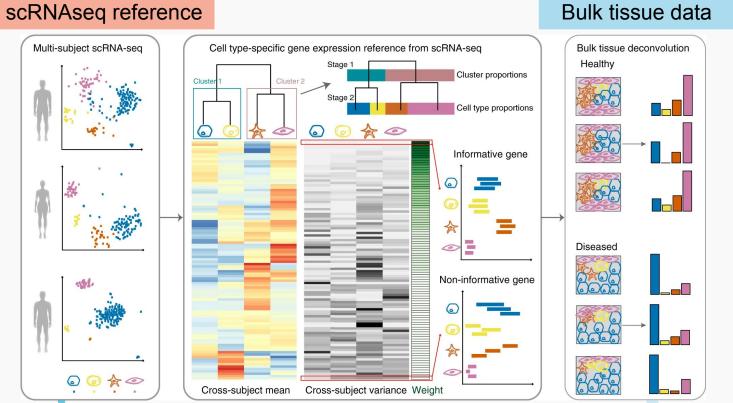


# **Aim 01**

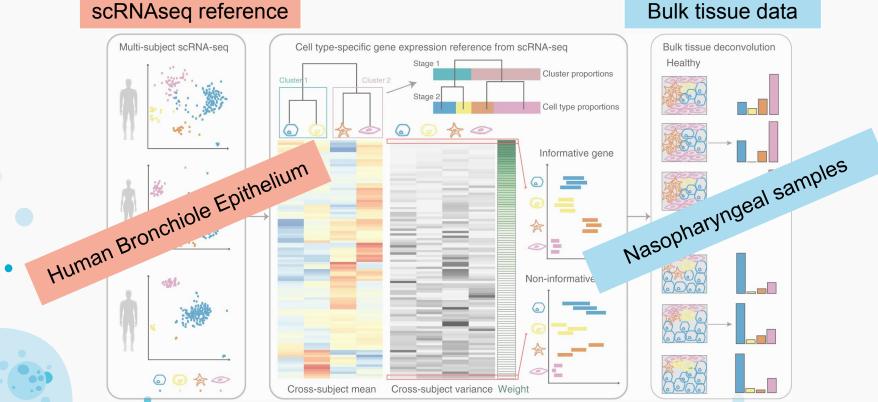
Cell type deconvolution



## Multi-subject Single-cell Deconvolution (MuSiC)



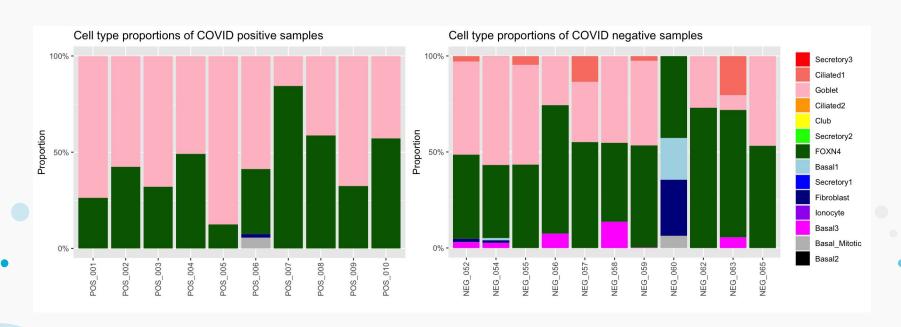
## Multi-subject Single-cell Deconvolution (MuSiC)



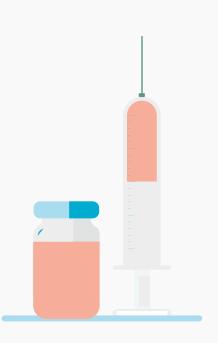
#### **Overview of variables**

Variables	Median or Count (range or %)
Age (years)	53 (2 - 89)
Gender (N females)	217 (53.06%)
Covid status (N positive)	356 (87.04%)
Cell type proportions (%)	Ciliated1: 0% (0-0.41%) Goblet: 55.98% (0-100%) FOXN4: 41.58% (0-100%) Basal1: 0% (0-25.72%) Fibroblast: 0% (0-29.38%) Basal3: 0% (0-29.16%)

## **COVID** status is associated with cell type



Cell types with low proportions in the overall dataset were dropped



# **Aim 02**

Differential gene expression



#### Workflow

Remove lowly expressed genes (<10 counts in total)

Remove samples with missing metadata information

Conduct an exploratory

⇒ analysis

Downstream analysis <

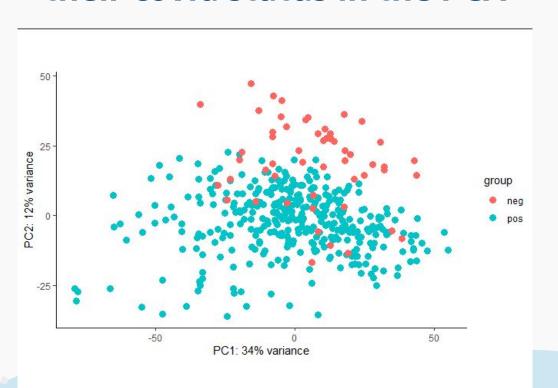
Visualize the results

\_\_\_\_ a

Perform the DE analysis with DESeq2



# Samples clustered based on their covid status in the PCA



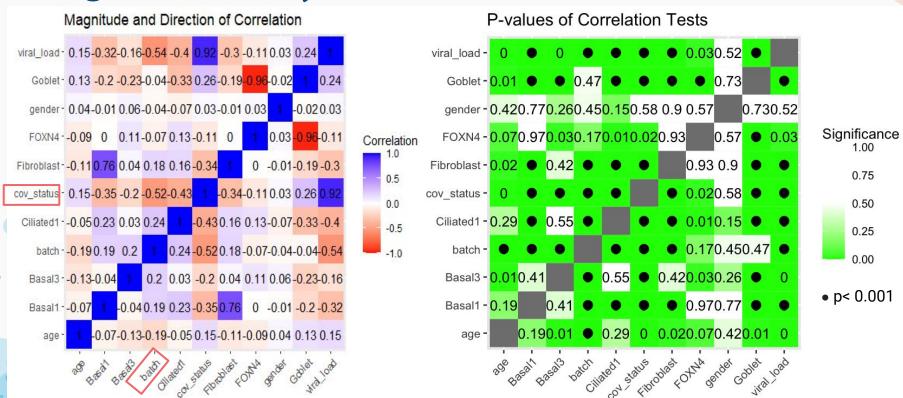


# **Model design**

age	gender	viral_load	cov_status	batch	Ciliated1	Goblet	FOXN4	Basal1	Fibroblast	Basal3
64	М	18.88	pos	1	0	0.7369542	0.2630458	0	0.0000000	0
30	F	21.18	pos	1	0	0.5761618	0.4238382	0	0.0000000	0
47	М	24.24	pos	1	0	0.6791802	0.3208198	0	0.0000000	0
67	F	18.91	pos	G	0	0.5092839	0.4907161	0	0.0000000	0
62	М	25.62	pos	Н	0	0.8761618	0.1238382	0	0.0000000	0
52	F	25.61	pos	Н	0	0.5874727	0.3380129	0	0.0198715	0



## High collinearity between covid status and batch



All COVID+ samples were run on the same batches, all COVID- on other batches

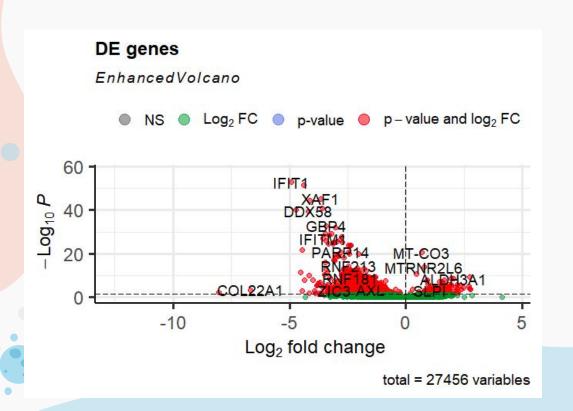
# Model design

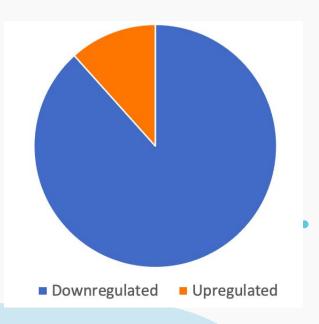
design = ~cov\_status + age + gender + Ciliated1 + Goblet + FOXN4 + Basal1 + Fibroblast + Basal3

age	gender	viral_load	cov_status	batch	Ciliated1	Goblet	FOXN4	Basal1	Fibroblast	Basal3
64	М	18.88	pos	1	0	0.7369542	0.2630458	0	0.0000000	C
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52	F	25.61	pos	н	0	0.5874727	0.3380129	0	0.0198715	(



### Most genes were downregulated





#### **Results**

ID	baseMean	log2FoldChange	IfcSE	stat	pvalue	padj
CSAG3	0.4478138	-29.930404	1.7745408	-16.86656	0	NA
IFIT1	449.0871812	-4.924876	0.3075396	-16.01380	0	0
OAS3	470.0654560	-4.394149	0.2784236	-15.78224	0	0
XAF1	324.4940444	-3.648678	0.2462750	-14.81546	0	0
IFI44L	351.9585267	-4.124200	0.2811023	-14.67153	0	0
OAS2	373.5151971	-3.601094	0.2560988	-14.06135	0	0
OR52W1	0.2509104	-29.966828	2.1357228	-14.03124	0	NA
IFIT2	567.2061236	-4.717428	0.3383309	-13.94324	0	0
DDX58	157.9347320	-4.202735	0.3035097	-13.84712	0	0
GBP4	162.3396890	-3.426630	0.2705122	-12.66719	0	0



## **Gene Set Enrichment Analysis**

- 1. Hypergeometric enrichment
  - MsigDB
- 2. Gene set enrichment analysis (GSEA)
  - MsigDB



#### **Broad Molecular Signatures Database (MSigDB) gene sets**

**a.** Hallmark: summarize and represent specific well-defined biological processes.

Total: 50

- b. Gene ontology [GO]
- Biological process: molecular-level activities performed by gene products. **Total:**

7481

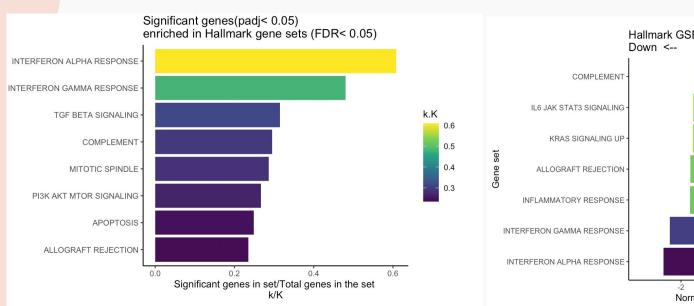
3. Disease enrichment analysis (GSEA)

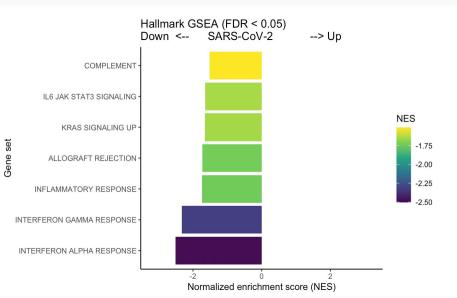
Cluster profiler

DOSE: used for DO(Disease Ontology)



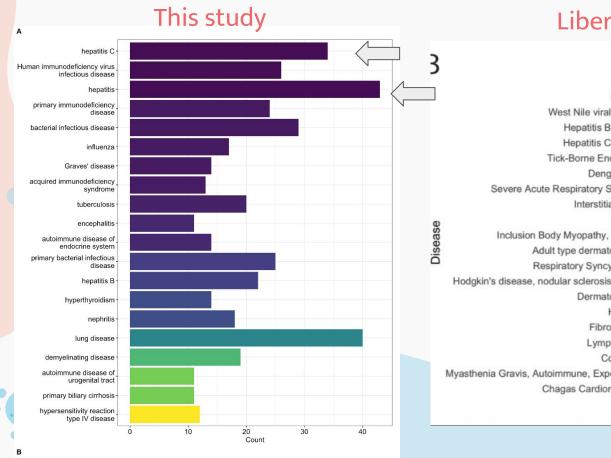
#### **Hallmark Gene Set Results**



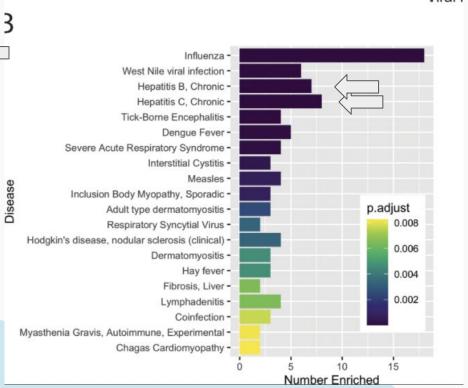


Enrichment of signature genes of Interferon Alpha, Interferon Gamma, and Inflammatory Responses

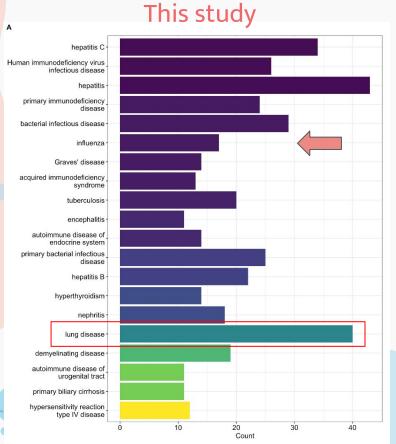
#### **Disease Enrichment Analysis**



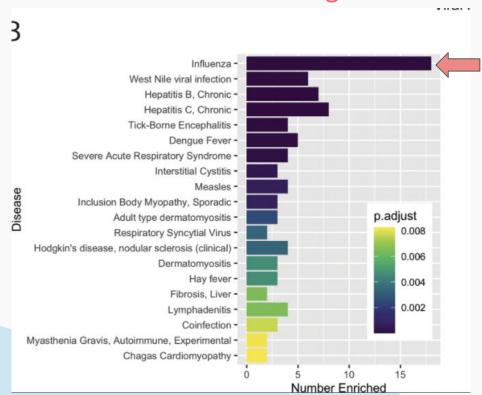
#### Liberman's findings



## A high degree of overlap with lung disease signature



#### Liberman's findings





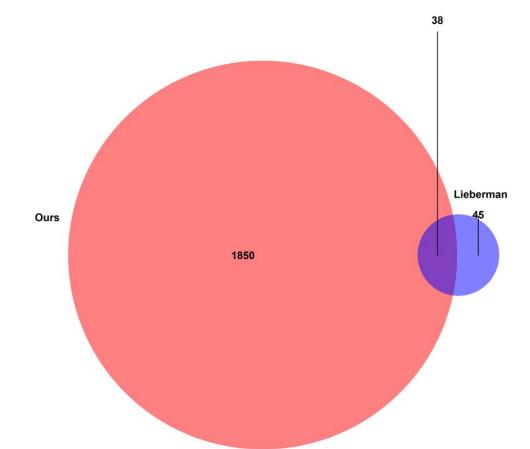
# **Aim 03**

**Quantitative comparison** 



- 1. How many DE genes overlap between ours and theirs?
- 2. How many of our DE genes were better explained by the cell type model?

# How many overlapping DE genes?





#### **Likelihood Ratio Test (LRT)**

Tests the following hypothesis

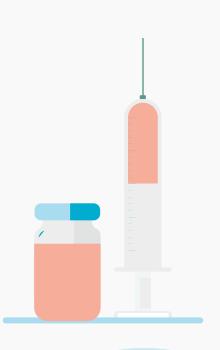
H0: covid status + age + gender (reduced model)

H1: covid status + age + gender + cell types (full model)

- Results
  - 7630 genes with significantly increased likelihood with full model
  - o This is 27.7899% of all gene

# How many of our DE genes were better explained by the cell type model?

- Results
  - Out of the 2960 our DE genes, we find 1888 with significantly increased likelihood with full model
  - This is 85.0636% of our findings
- Observation
  - Full model better characterizes significant DE genes



# Conclusion

Limitations and Final remarks





#### **Conclusion**

- Limitations
  - Large correlation between batch and Covid status, could not reproduce author's exact model
  - Reference data set is lower airways versus batch data set is upper airways
  - The experiment was not a balanced design (not possible to circumvent statistically)
- Final Remarks
  - Overall, cell type is a possible confounder associated with covid status and gene expression
  - Adding cell type corrects for possible confounding

#### References

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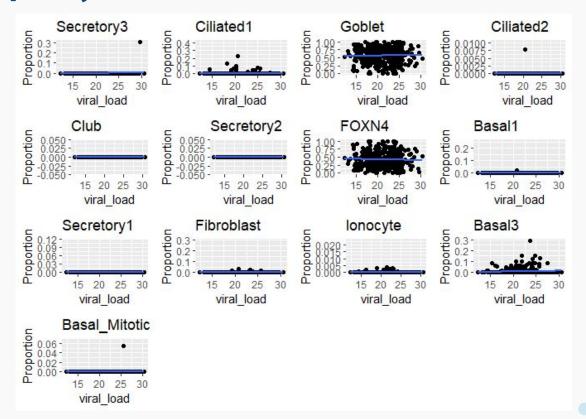
# Thank you! Questions?

# **Extra** slides

Figures that we made but are not part of the main presentation



## Cell type by viral load



#### **GO Terms**

