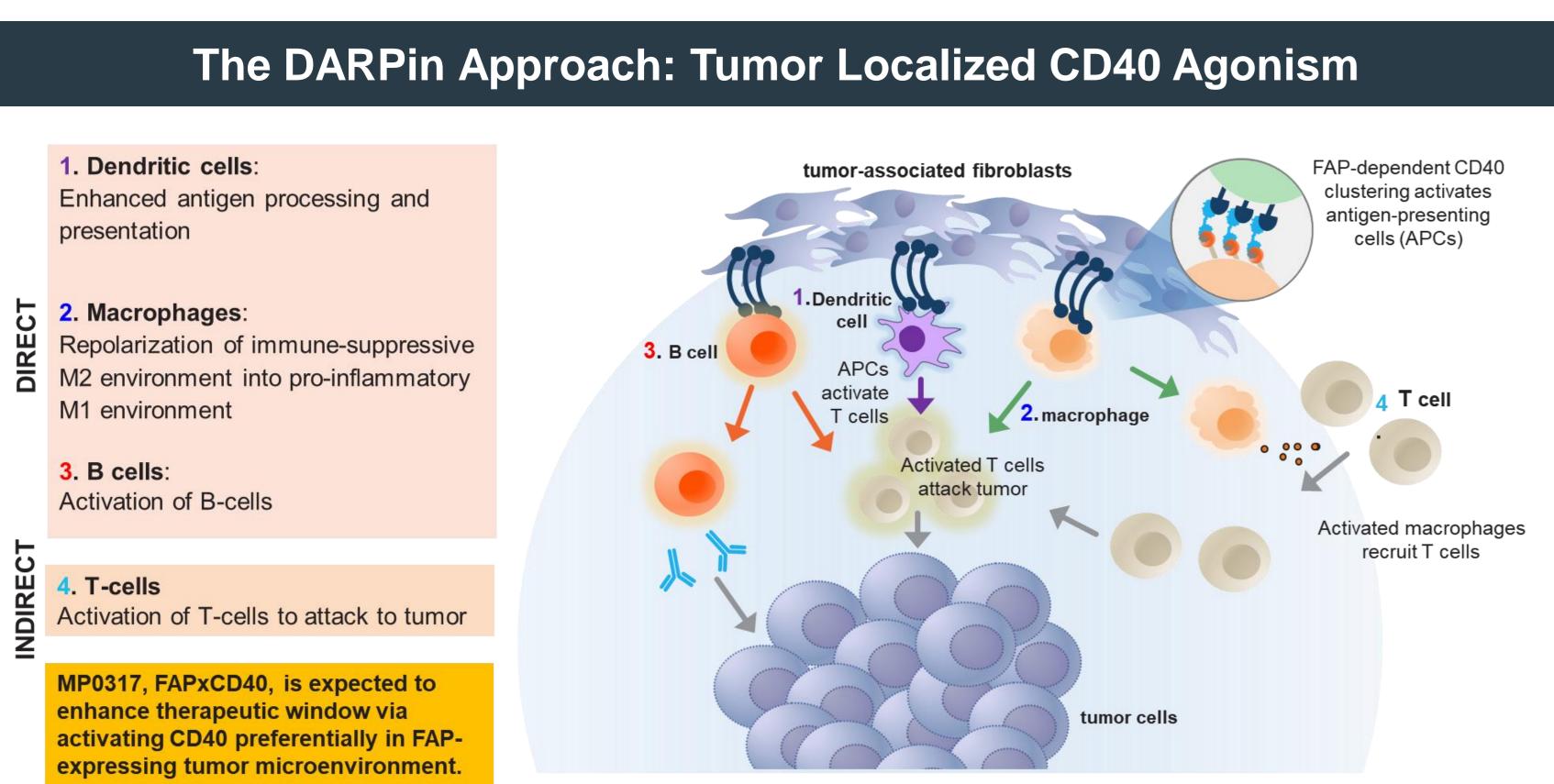
# Characterization of Tumor Infiltrating Dendritic Cells at the Single Cell Level

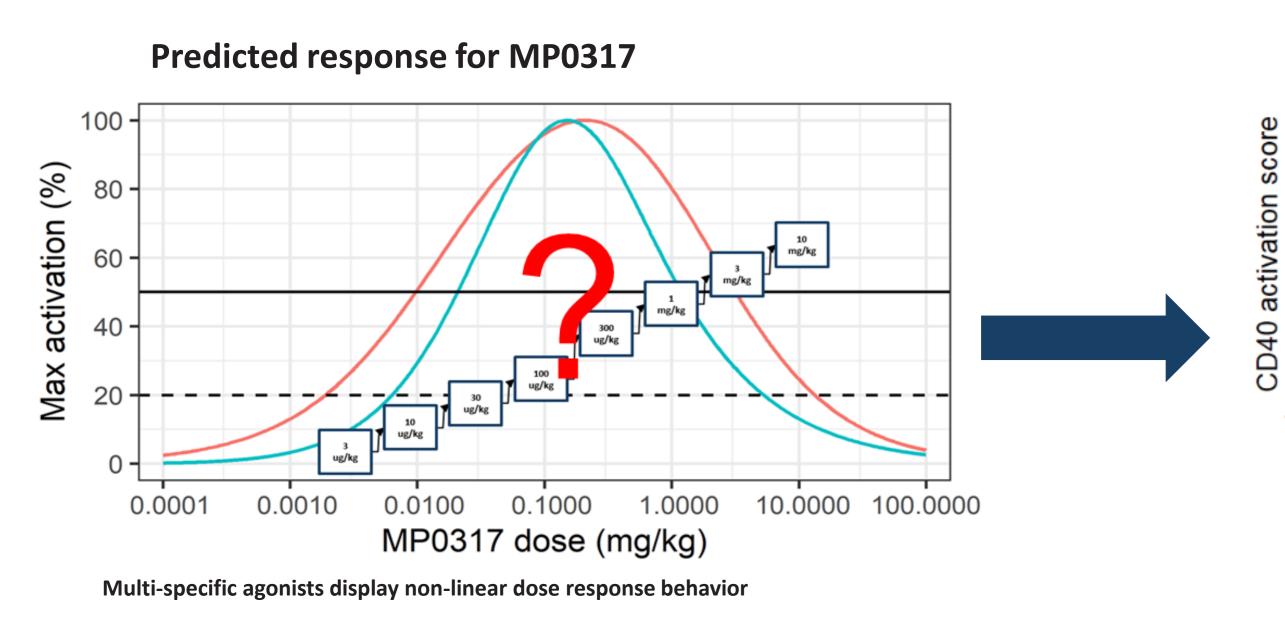
# Introduction

CD40 is an attractive target for cancer immunotherapy due to its central role in dendritic cell activation and subsequent T cell priming against tumor antigens. Molecular Partners has developed a DARPin, MP0317, that activates CD40 in a FAP dependent manner, localizing the activation to the tumor microenvironment. Compared to systemic CD40 activation, this approach, which helps avoid the sink effect, might allow dosing that reduces toxicity due to systemic immune activation. To support the translational understanding of MP0317's mode of action we used publicly available single cell sequencing data to develop a classifier for DC subpopulations, build an atlas of tumor infiltrating dendritic cells, and extract a signature specific to the CD40 expressing subpopulation. We plan to use this signature to evaluate changes in dendritic cell populations in clinical trials.



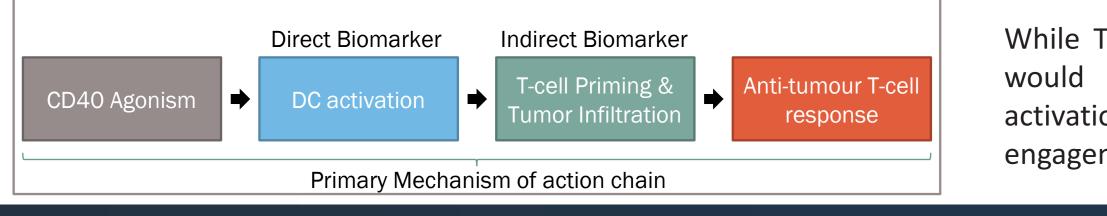
Tumor localized CD40 agonism. Our FAP-CD40 (MP0317) molecule DARPin activates antigen presenting cells in the tumor via FAP dependent clustering. CD40 agonism will activate antigen presenting cells (B cell, macrophages and dendritic cells) and, indirectly, T cells.

# Gene Signatures Can Serve as Pharmacodynamics Biomarkers in Early-Stage Clinical Trials



- For bispecific molecules the best dose is not always defined by the maximum tolerated dose
- Drug performance and optimal clinical phase 2 dosing must be informed by high quality biomarkers in early trials
- One of the biomarkers that can inform pharmacodynamics is the change in gene expression in tumor biopsies post treatment. However, in smaller patient cohorts changes in expression of individual genes can be hard to observe due to noise. As an alternative we can observe coordinated changes in genes relating to a biological mechanism or an immune cell type (gene signatures).

### **Reasoning for developing a dendritic cell signature:**



While T cell activation is a good biomarker we would also require a more direct one (DC activation). This will help show target engagement directly on antigen presenting cells.

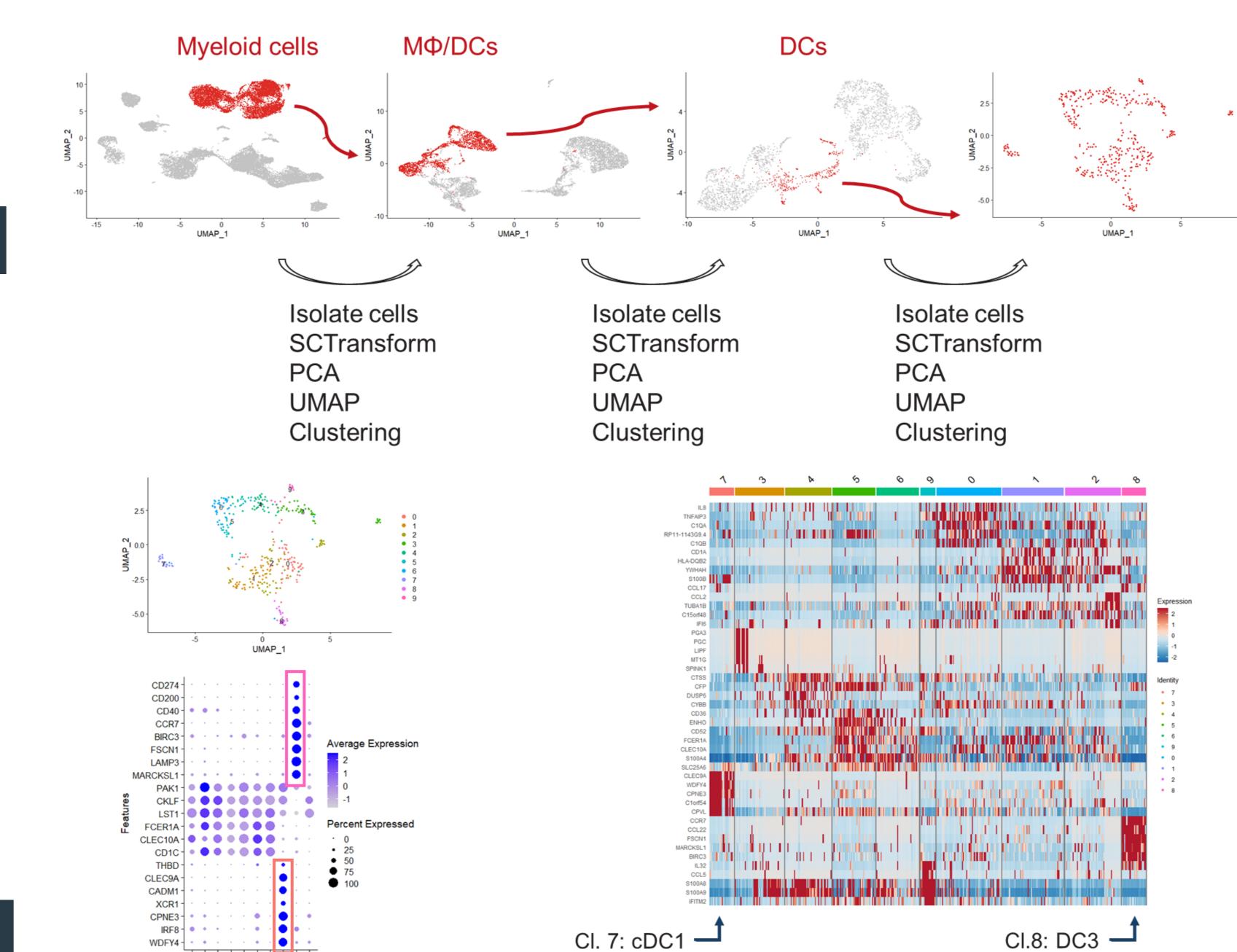
- , J. Exp. Med., 2020 Vol. 218 No. 1 e20200264 https://doi.org/10.1084/jem.20200264 2. Chen *et al.*, Met. Mol. Bio., 2018, 171810.1007/978-1-4939-7493-1 12
- 3. Becht *et al.*, Genome Biology, 2016, 17, 218
- 4. Maier et al, Nature 580, 257–262 (2020).

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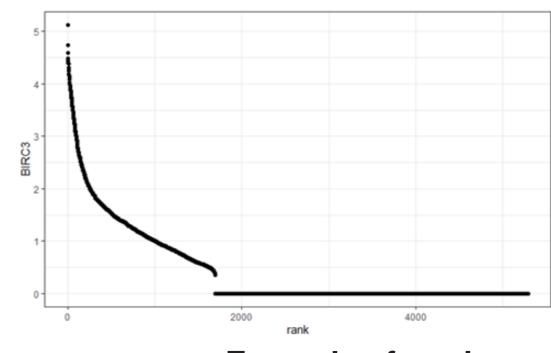
# **Classifier for DCs: Training Set**

of iterative clustering:



Three populations (cDC1, DC3 and cDC2/moDC, as defined in reference 1) were identified: The DC1 group (cluster 7) corresponds to the conventional type I dendritic cells. We then observe a continuum of states across clusters 0 to 6 that starts with the conventional type II DCs and goes towards an intermediate macrophage/dendritic cell population. The DC3 in cluster 8 group corresponds to a mature state of DCs rather than a lineage and its presence has been recently shown in tumors [1,4].

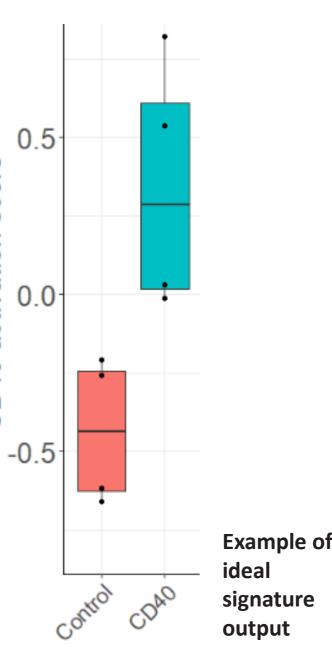
# **Classifier for DCs: Algorithm**



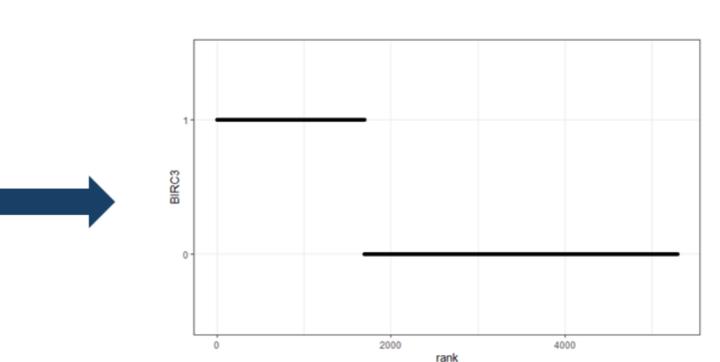
### Algorithm steps:

0 1 2 3 4 5 6 7

- Binarize data to avoid batch effect bias when training the classifier, the expression data of the 4 datasets was converted to 0 or 1
- . Train random forest classifier on all available features
- Select 200 features with highest discriminatory potential
- 4. Retrain classifier on those 200 features
- 5. Cells are first classified as cDC1 or DC3 using the classifiers and as moDC/cDC2 using the principle of exclusion

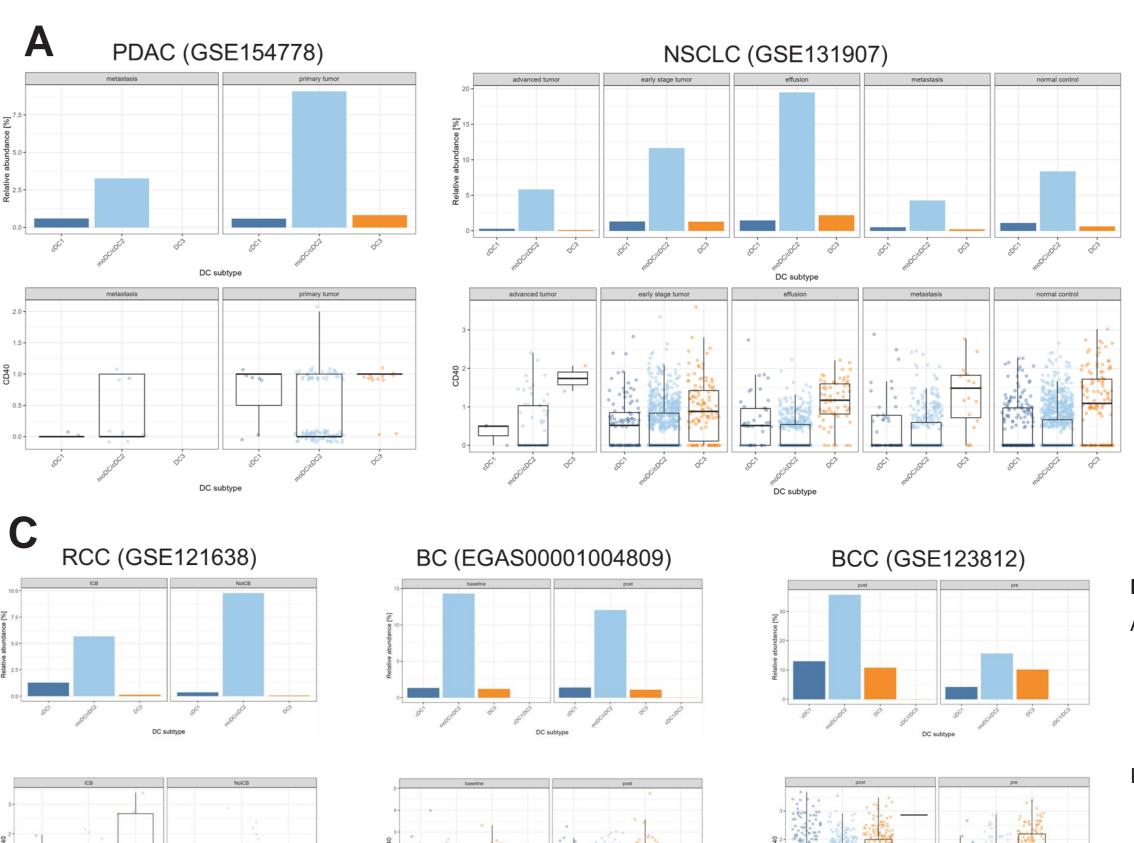


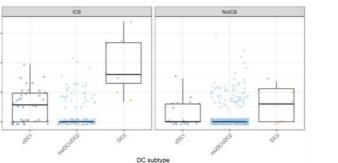
### To obtain training data, multiple publicly available scRNA-Seq datasets were analyzed and annotated manually using the principle

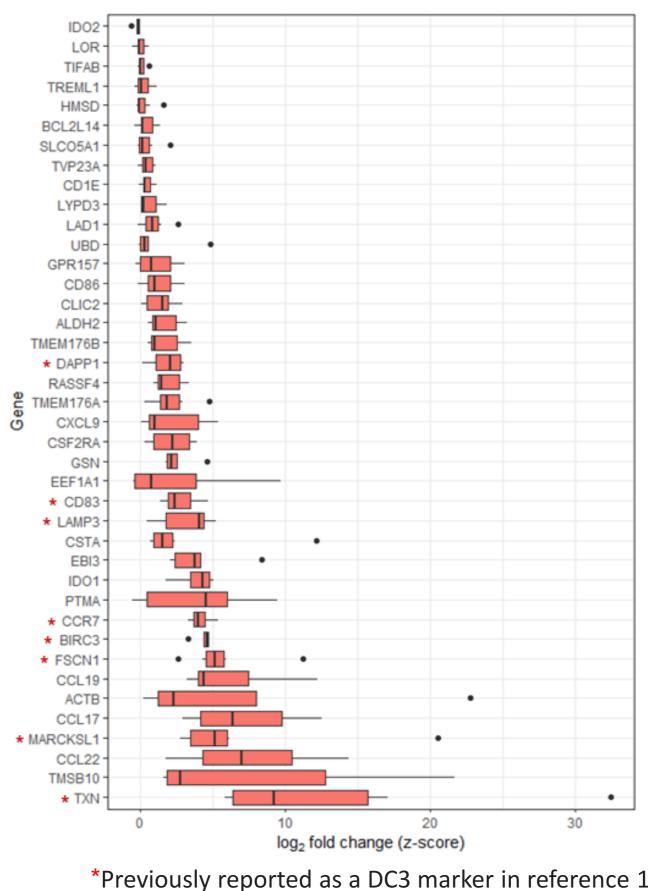


### Example of rank expression and binarization for gene BIRC3

Summary of classifier performance:
Confusion Matrix and Statistics
Reference Prediction 0 1 0 6910 26 1 13 494
Accuracy : 0.9948 95% CI : (0.9928, 0.9963) No Information Rate : 0.9301 P-Value [Acc > NIR] : < 2e-16
Sensitivity : 0.9981 Specificity : 0.9500 Pos Pred Value : 0.9963 Neg Pred Value : 0.9744 Prevalence : 0.9301 Detection Rate : 0.9284



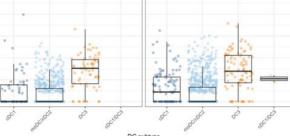


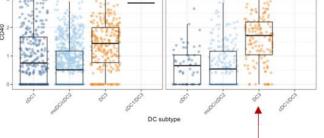


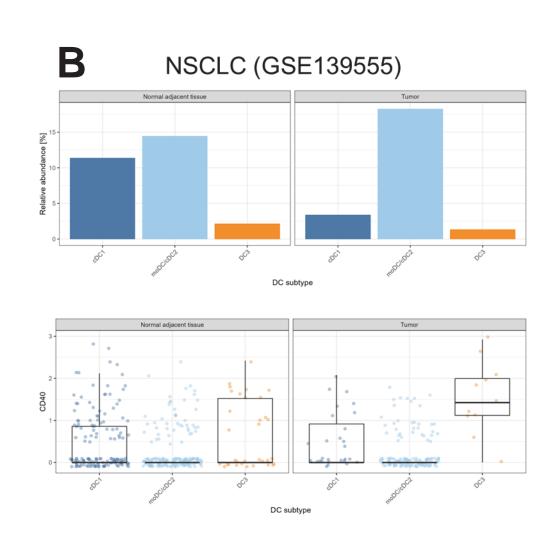
Using differential expression analysis (one versus all) and the most predictive features from our classifier we define a gene signature for the DC3 group. We are planning to use this signature in evaluating clinical biopsies together with previously established signatures for DC1 and DC2 populations [2,3].

- We developed a classifier to call out these cells in multiple datasets originating from different tumor types.
- We quantified their abundance and CD40 expression across tissues and tumor stages and derived a gene signature that will be used for assessing pharmacodynamics effects in phase I clinical trials.
- This signature is currently being validated in *ex vivo* assays. • This analysis also supports the hypothesis that earlier stage tumors would have a higher chance to respond to anti CD40
- immunotherapy

## DC Abundance and CD40 Expression Across Tumors:





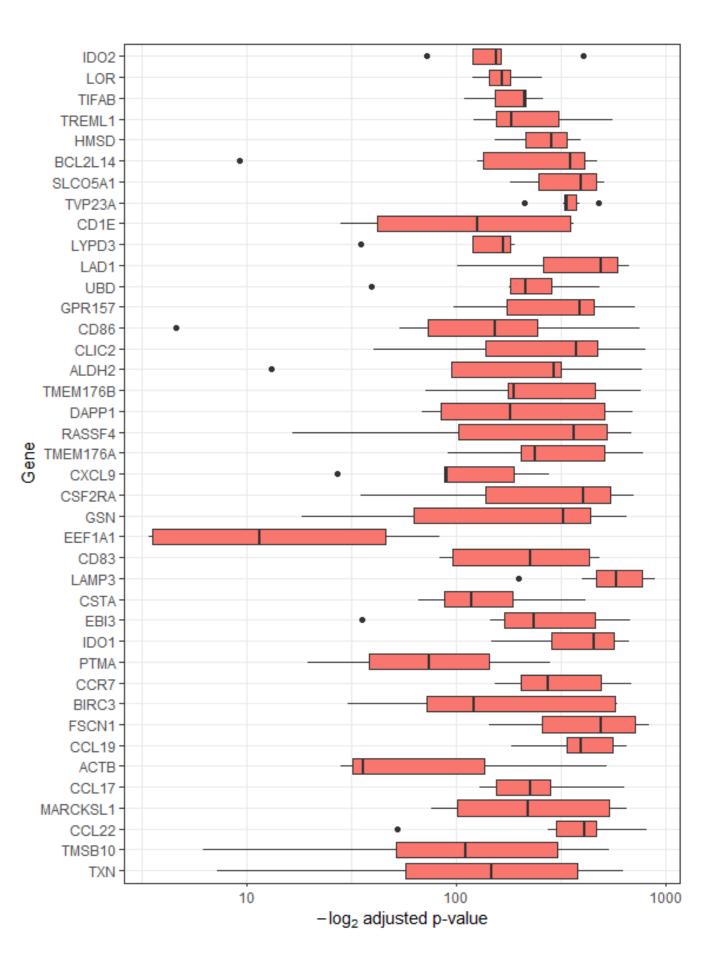


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DC Abundance & CD40 expression across tumor stages A. Abundance (out of myeloid compartment) of DCs across tumor stages in PDAC and NSCLC. Abundance of both DC1 and 3 subtypes decreases in more advanced stages. DC3 group has the highest CD40 expression

- In early-stage tumors the DC abundance is higher than in normal tissues. CD40 expression is also higher in tumor infiltrating DC3s compared to normal tissue ones.
- Immune checkpoint blockade increases abundance of DC1. Expression of CD40 is maintained on the DC3 compartment.

# DC3 Signature for Use in Bulk RNAseq Analysis



# Conclusions

• We have identified three types of tumor infiltrating DCs, in agreement with recent literature<sup>1</sup>

