



Algorithmic analysis of B cells uncovers new populations critical to the immune response during *T. gondii* infection



Adrianna Alpern¹, Scott Souza², Kirk Jensen², David Gravano¹

¹Stem Cell Instrumentation Foundry, UC Merced

²School of Natural Sciences, UC Merced

BACKGROUND

Working with large amounts of data is very difficult and time-consuming, particularly when comparing more than three variables at the same time. Since our brains are incapable of visualizing structures beyond the third dimension, a tool that can map multiple variables on a two-dimensional map is needed. T-distributed Stochastic Neighbor Embedding, or tSNE, is a method used to visualize higher-dimensional data (data beyond 3 dimensions) on a 2-D graph, also known as dimensionality reduction. tSNE is able to do this by aiding in visualization of data points by similar qualities based on the multiple variables being compared. FlowSOM, a plugin tool used in Flowjo, a flow cytometry tool, can generate population clusters that can be visualized on a tSNE map. These two tools can be used together to organize and analyze large datasets with multiple variables in an efficient, convenient way, with much more objectivity. This study discusses the process of using tSNE and FlowSOM to study differences in immune response to *Toxoplasma gondii*, a parasitic organism that is known to cause potentially lethal symptoms in chronically infected mice. The mice used in the experiment were wild-type B6 mice and mutant *Bumble* mice. *Bumble* mice are genetic mutants that cannot produce *Nfkbid*, a protein that controls B-cell activation. Data used in this study are all provided by Scott Souza et al.

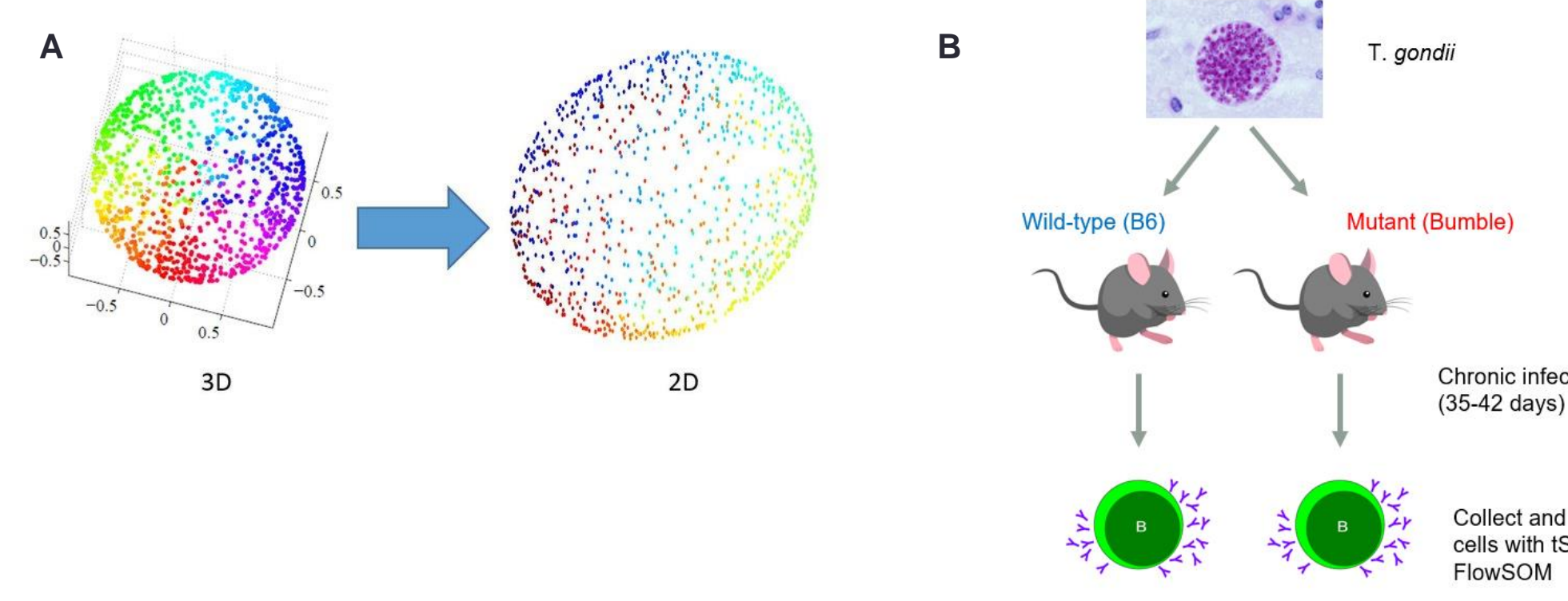


Figure 1. A visualization of dimensionality reduction, where a three-dimensional graph is reduced to two dimensions (Rosero et al., 2017) (A). General layout of experimental method by Souza et al (B).

METHODS

1. Collect mouse spleen and bone marrow cell data using flow cytometry (data from Scott Souza et al.).
2. Transfer data to Flowjo application.
3. Adjust parameter compensation in Flowjo.
4. Pregate for forward and side scatter, live cells, and B cells.
5. Downsample to get even sample sizes.
6. Export and concatenate data
7. Generate tSNE map.
8. Create populations using FlowSOM plugin.
9. Output Heatmap and Excel table for t-testing.
10. Select populations of interest for further analysis.

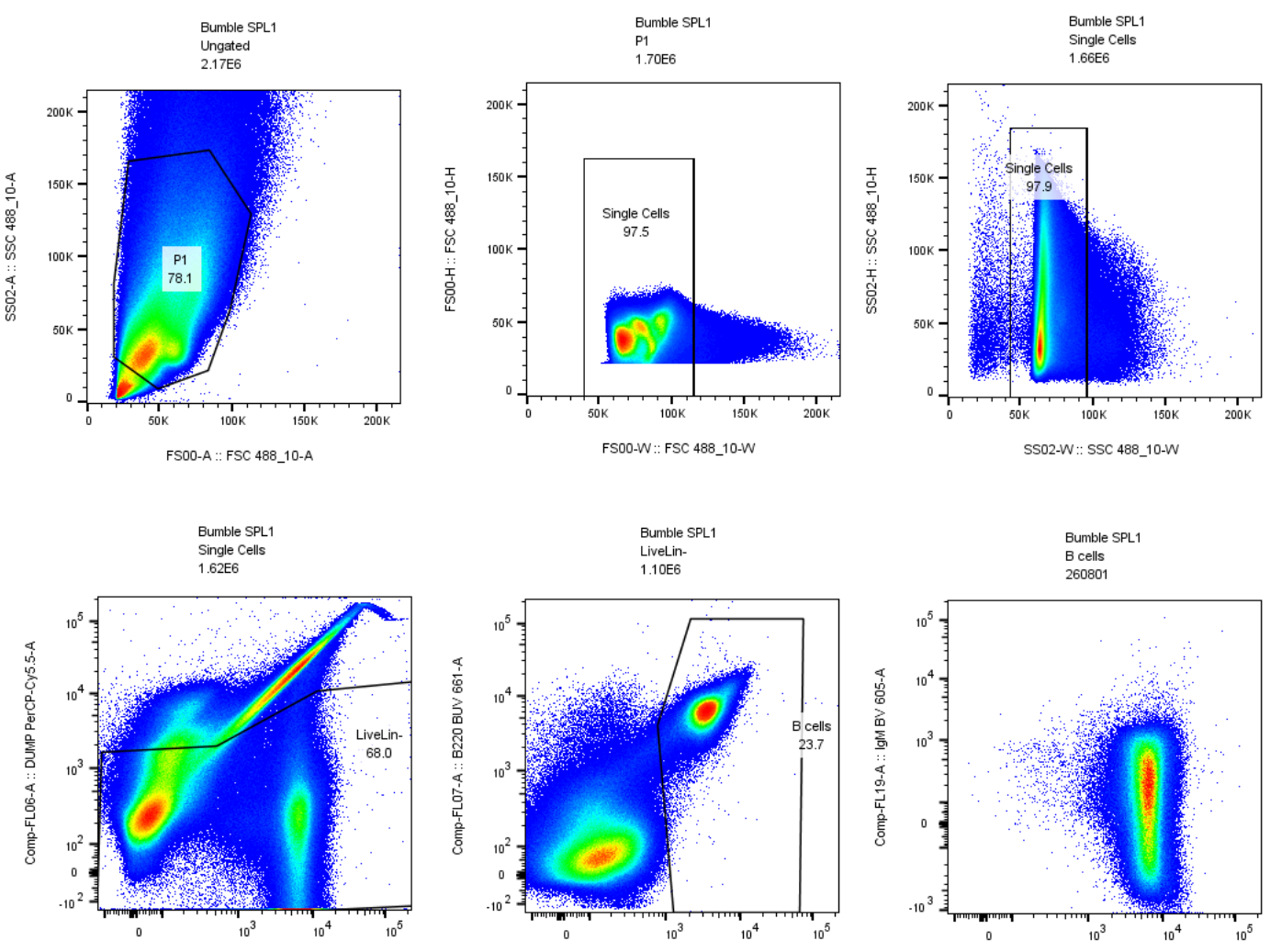


Fig. 2 : Mouse Cell Pregating method used in the Flowjo tool.

RESULTS

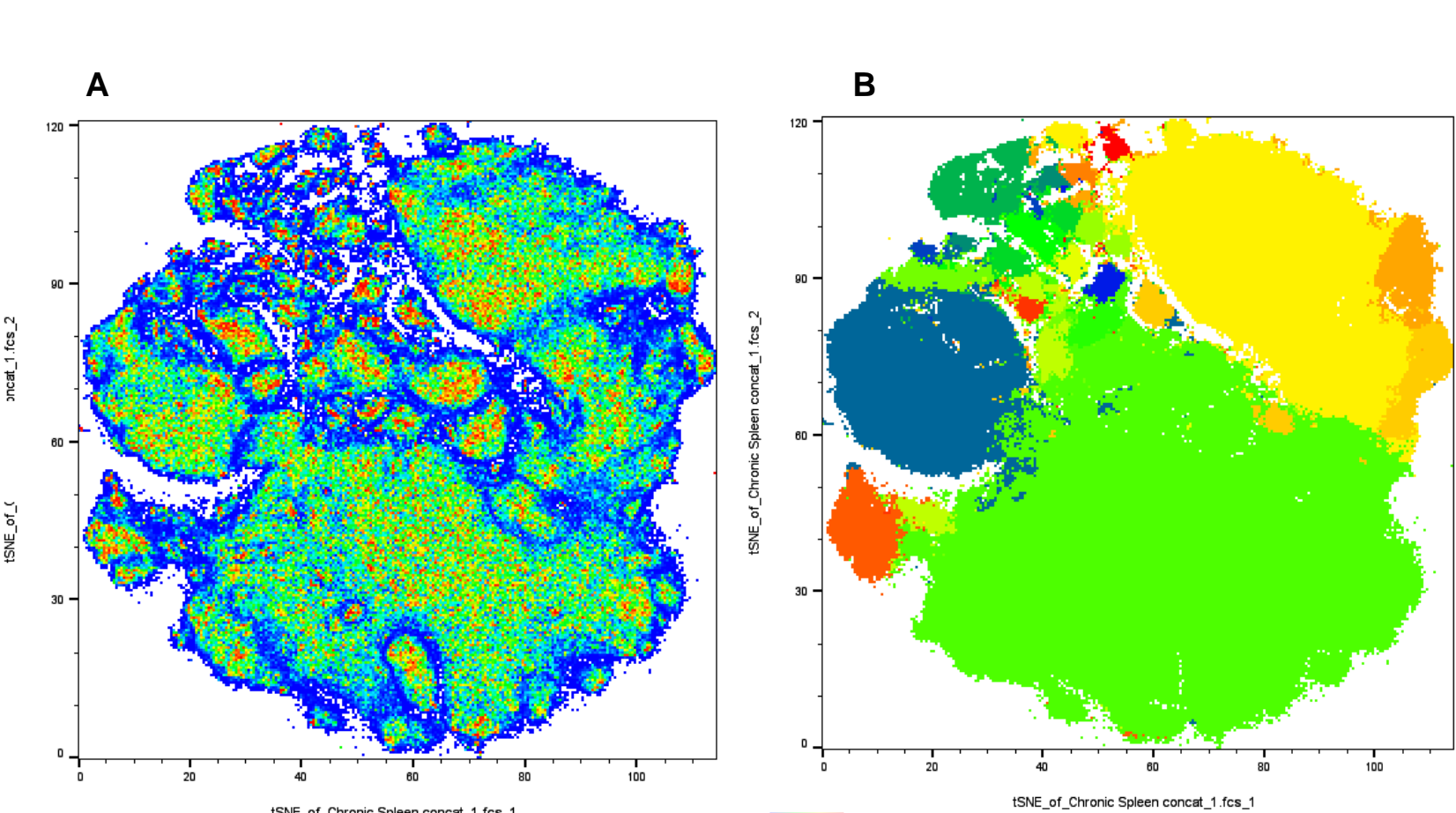
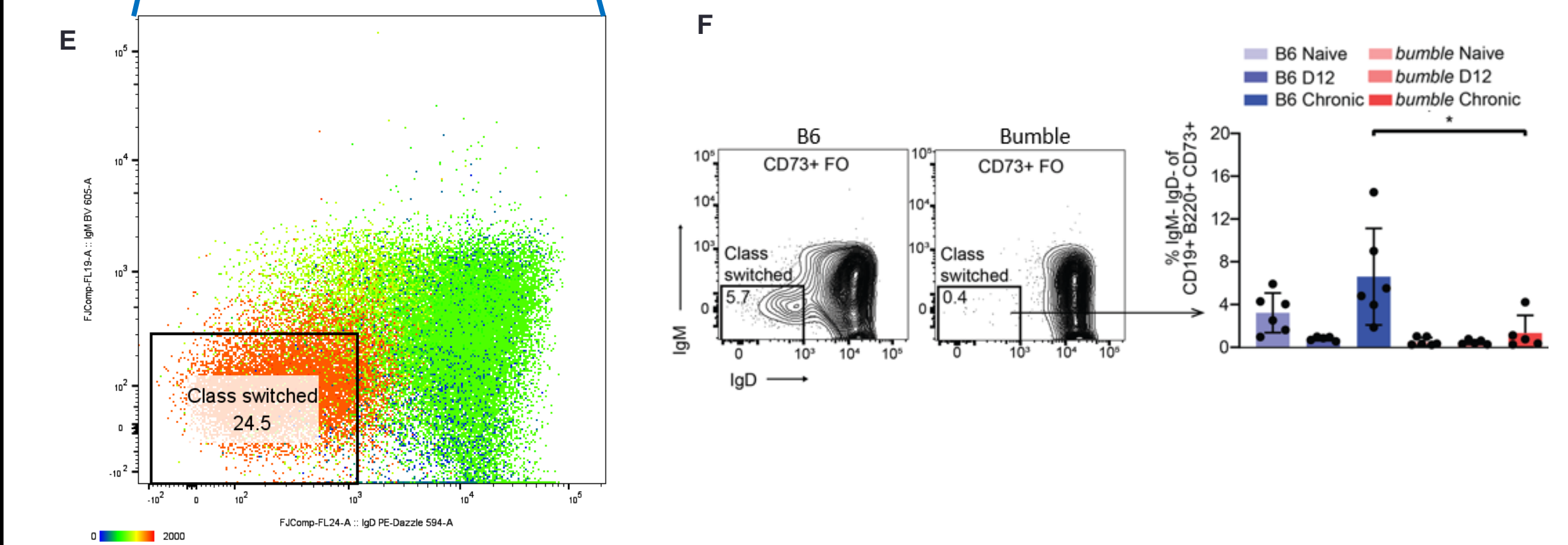
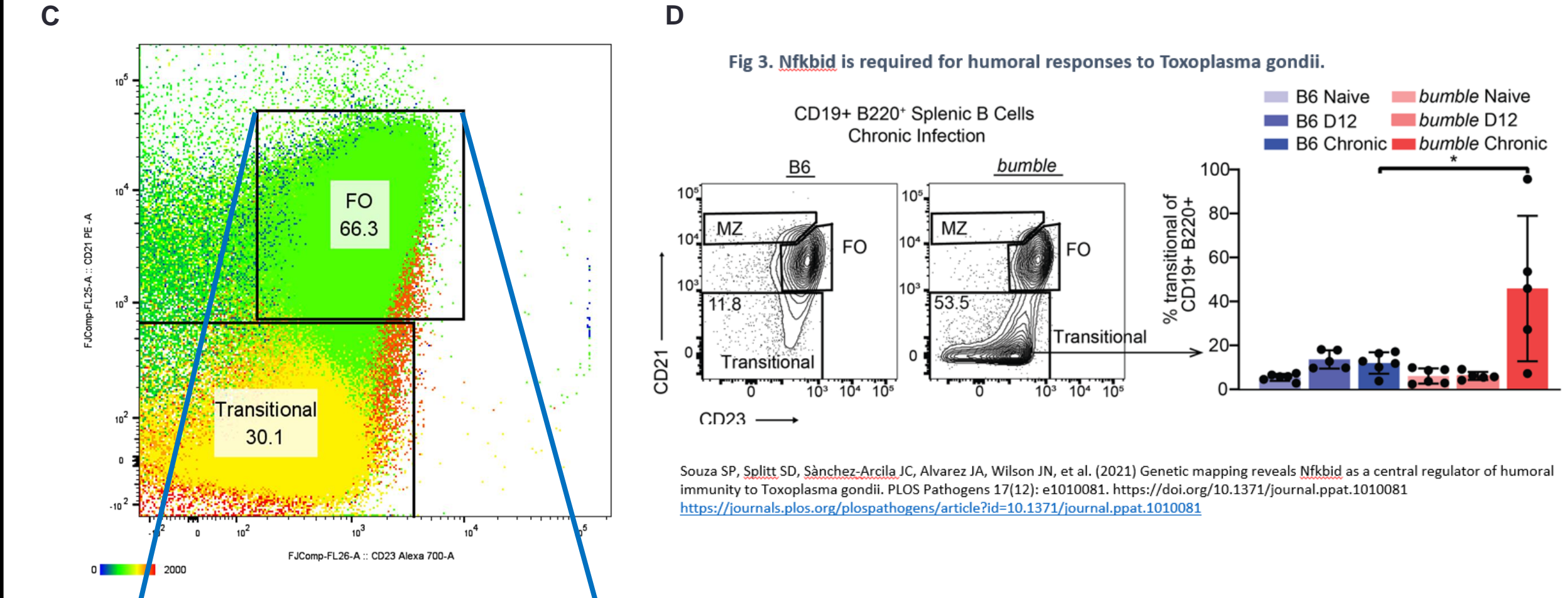
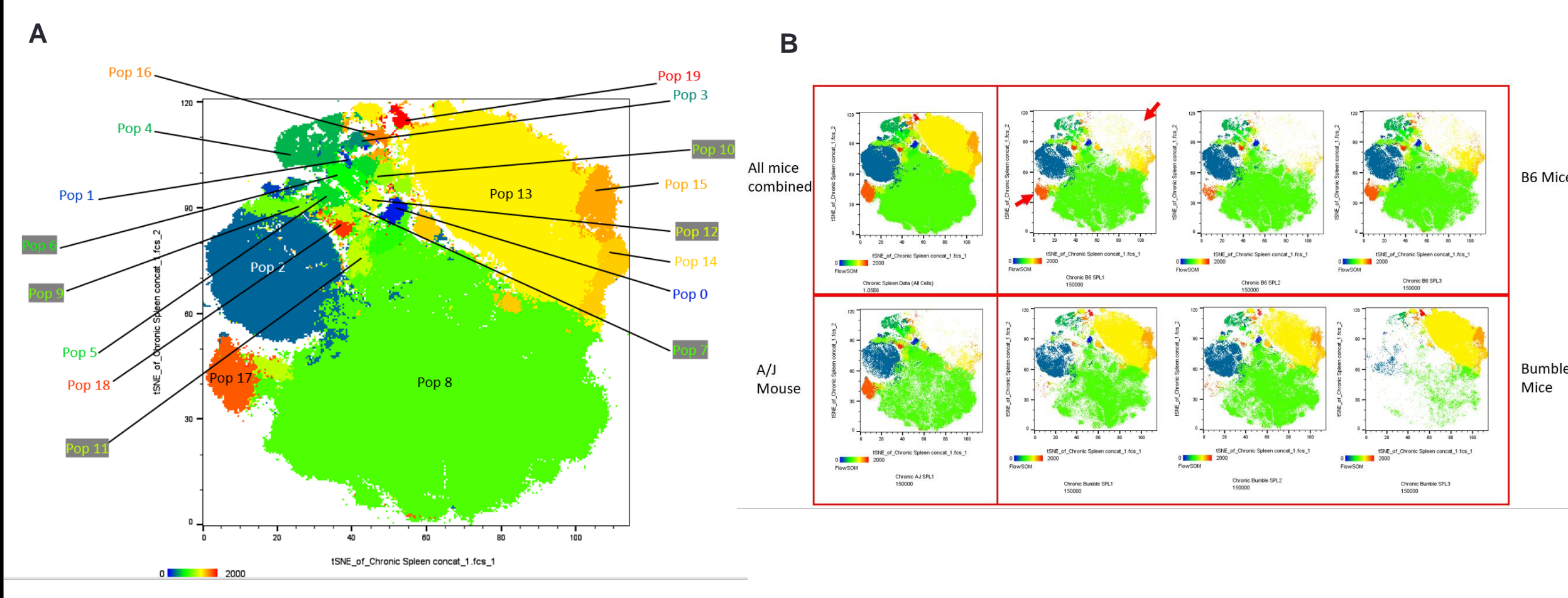


Figure 3. tSNE and FlowSOM can be used in tandem to visualize higher dimensional data. tSNE allows for a two-dimensional view of higher-dimensional data (A). FlowSOM can generate colored population clusters for easier viewing and analysis (B).

RESULTS



G: Populations of Transitional gate			H: Populations of FO gate			I: Populations of Class Switched Gate		
Population number	Percent of gate	# of events	Population number	Percent of gate	# of events	Population number	Percent of gate	# of events
FlowSOM Pop0	0.057	179	FlowSOM Pop0	0.63	4411	FlowSOM Pop0	0.99	117
FlowSOM Pop1	0.19	536	FlowSOM Pop1	0.19	1513	FlowSOM Pop1	0.19	23
FlowSOM Pop2	0.08	2763	FlowSOM Pop2	17.3	120247	FlowSOM Pop2	0.97	115
FlowSOM Pop3	0.12	368	FlowSOM Pop3	0.18	1229	FlowSOM Pop3	0.40	47
FlowSOM Pop4	1.60	5050	FlowSOM Pop4	0.032	224	FlowSOM Pop4	8.45E-3	1
FlowSOM Pop5	0.99	3109	FlowSOM Pop5	0.042	296	FlowSOM Pop5	0.22	26
FlowSOM Pop6	0.24	768	FlowSOM Pop6	0.055	386	FlowSOM Pop6	0.18	21
FlowSOM Pop7	0.050	158	FlowSOM Pop7	0.97	6788	FlowSOM Pop7	0.23	27
FlowSOM Pop8	0.32	26167	FlowSOM Pop8	74.5	521077	FlowSOM Pop8	1.34	159
FlowSOM Pop9	0.073	231	FlowSOM Pop9	1.20	8402	FlowSOM Pop9	2.60	306
FlowSOM Pop10	1.06	5218	FlowSOM Pop10	0.19	1319	FlowSOM Pop10	0.63	75
FlowSOM Pop11	0.53	1672	FlowSOM Pop11	1.71	11966	FlowSOM Pop11	10.3	1223
FlowSOM Pop12	0.041	130	FlowSOM Pop12	0.014	101	FlowSOM Pop12	0	0
FlowSOM Pop13	0.93	71650	FlowSOM Pop13	0.051	357	FlowSOM Pop13	8.45E-3	1
FlowSOM Pop14	5.95	18735	FlowSOM Pop14	0.50	3504	FlowSOM Pop14	8.45E-3	1
FlowSOM Pop15	5.96	18757	FlowSOM Pop15	2.67E-3	18	FlowSOM Pop15	0	0
FlowSOM Pop16	0.60	1804	FlowSOM Pop16	4.29E-3	30	FlowSOM Pop16	0.16	19
FlowSOM Pop17	1.80	4967	FlowSOM Pop17	2.30	16559	FlowSOM Pop17	78.5	926
FlowSOM Pop18	0.72	2252	FlowSOM Pop18	0.16	1108	FlowSOM Pop18	3.27	397
FlowSOM Pop19	0.90	2845	FlowSOM Pop19	1.43E-4	1	FlowSOM Pop19	0	0

Figure 4. Using tSNE and FlowSOM to find populations of interest in mouse spleen cells. We used FlowSOM to divide the data into 20 populations, ranging from populations 0 to 19 (A). FlowSOM clusters can also be organized based on mouse type to compare the populations of each mouse (B). Gating within CD23 vs. CD21 graph for FO and transitional cells (C). In the FO gate, we compared IgD and IgM and made another gate, class switched (E). Both tables show consistency with gating methods used in published work by Souza et al (D, F). Analyzing FlowSOM population statistics in the FO gate and the transitional gate reveals which populations make up the majority of each gate (green boxes). According to the data, it seems that the FO gate is made up mostly of Population 8 and Population 2 (F). On the other hand, the transitional gate is made up largely of Population 13 (G). The populations that make up the class switched gate are mainly Population 11 and Population 17 (H).

RESULTS

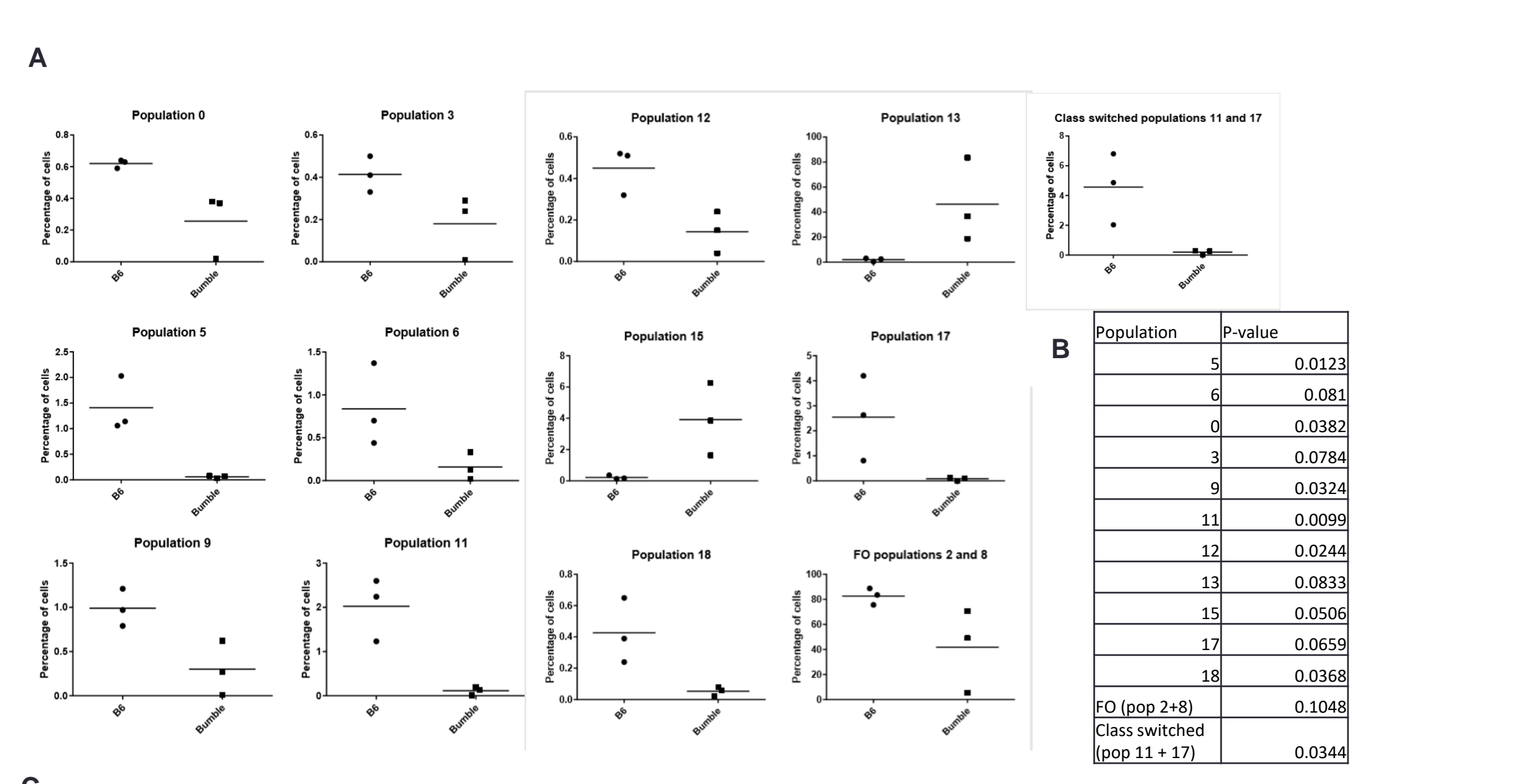


Figure 5. FlowSOM can generate plots and heatmaps to compare and contrast different populations, as well as find the differences in qualities. Box plots show the percentage of cells from each mouse strain in a population (A). An unpaired two-tailed t-test shows the p-value for each population to check its significance (B). FlowSOM produces a heatmap showing the expression of each cell marker. The warmer the color, the greater the amount of the marker present (C).

CONCLUSION

By using tSNE and FlowSOM, the data in this experiment became much easier to analyze, and the data showed clear differences in B cell activity in wild-type versus *Bumble* mice. With these tools, organizing and analyzing large amounts of data with lots of variables became much faster and more accurate. Despite these benefits, it is important to note that this isn't a perfect algorithm, as it is prone to errors made when collecting data from flow cytometry, requires human intervention to calibrate any over- or under-compensation, and has issues with distinguishing data taken at different time points. Nonetheless, it is a great tool for understanding high-dimensional analysis, and hopefully will be utilized and refined in the future.

ACKNOWLEDGEMENTS & REFERENCES

Funding provided by the UC Merced Student Success Internship Program and ISAC SRL Emerging Leader award to David M. Gravano.

We would like to thank the UC Merced Stem Cell Instrumentation Foundry flow cytometry core for technical support.

References

- Rosero, Paul & Diaz, P. & Salazar Castro, Jose & Peña, Diego & Anaya Isaza, Andres & Alvarado Pérez, Juan & Therón, Roberto & Peluffo, Diego. (2017). Interactive Data Visualization Using Dimensionality Reduction and Similarity-Based Representations. Lecture Notes in Computer Science. 10125. 334-342. 10.1007/978-3-319-52277-7_41.
- Souza SP, Splitt SD, Sánchez-Arcilla JC, Alvarez JA, Wilson JN, Wizzard S, Luo Z, Baumgarth N, Jensen KDC. Genetic mapping reveals Nfkbid as a central regulator of humoral immunity to Toxoplasma gondii. PLoS Pathog. 2021 Dec 6;17(12):e1010081. doi: 10.1371/journal.ppat.1010081. PMID: 34871323; PMCID: PMC8675933.
- Van Gassen S., et al. FlowSOM: Using self-organizing maps for visualization and interpretation of cytometry data. Cytometry A. 2015 Jul;87(7):636-45.