Virtual reality to memorize complex 3D shapes

Benjamin Lelouch[1], Corentin Bodson[1], Jules Herrmann[1]. Mentored by Leo Blondel[2]
[1] Frontiers of Life Bachelor, Paris Cité University, Center for Research and Interdisciplinarity (CRI)
[2] Université de Paris, INSERM U1284, CRI

Abstract

Thanks to keener microscopy techniques, microscopy data are of **increasingly high complexity**. Analysis of this data by humans requires **sharpened visualization tools**. To this end **Virtual Reality** (VR) could be a tool of interest, as it immerses the user in a virtual environment along with its data. We conducted an experiment comparing the ability of a user to **memorize and recall 3D objects** using **VR or traditional desktop** visualizers we developed. These 3D objects correspond to the shape encapsulating small moving particles. This process yielded **no significant difference** between the user's results and the null distribution. Nonetheless, we observed a significant **progression in VR** not observed when using the desktop version of our software.

Intro

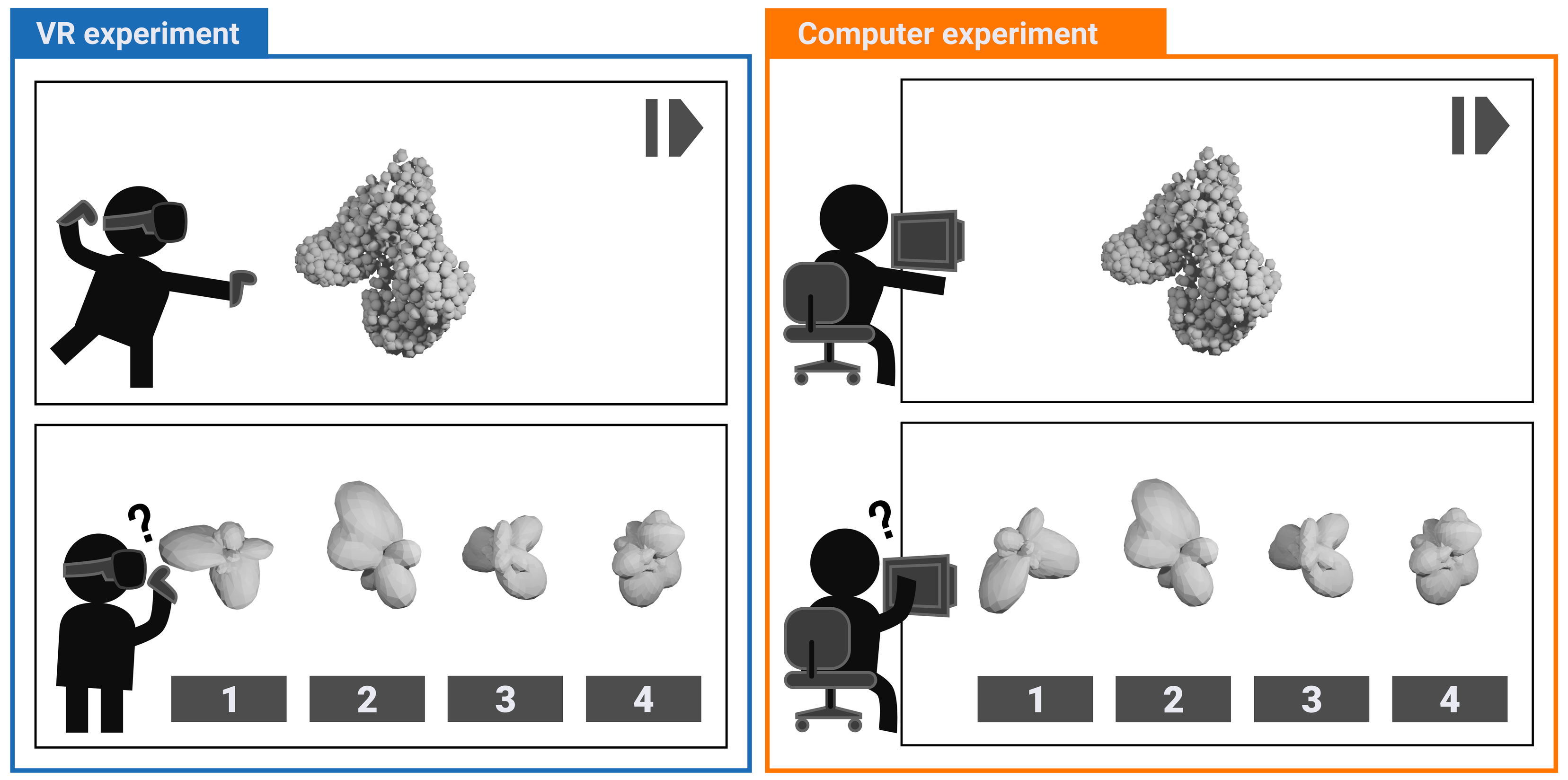
Light Sheet Fluorescence Microscopy (LFSM) is a technique that allows 3D video imaging of biological samples[1]. To this day, these datasets are most commonly displayed on **desktop 2D screens** while Virtual Reality (VR) could provide **more intuitive analytics** capacity for 3D + time datasets.

Indeed, VR was found to **enhance scientific investigation** in various sectors that require users to interact and comprehend 3D + time datasets[2,3,4]. In this context, our mentor researcher Leo Blondel developed a VR software for visualizing large 3D+time microscopy datasets produced by LFSM[5].

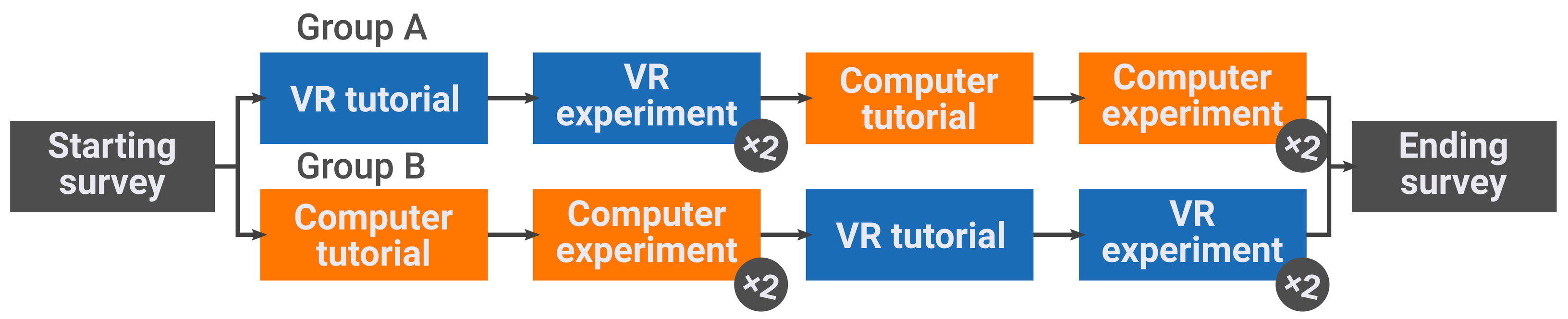
Our project aimed at measuring the impact of using a VR headset or a flat 2D screen on a user's ability to interpret 3D time-evolving objects corresponding to the shape encapsulating moving particles.

We exposed users to a **video sequence** of time-evolving complex datasets. These datasets are composed of small cell-like particles moving along complex organized patterns. Users were asked to observe the global shape drawn by the particles. They were then shown a set of 14 3D meshes. Seven of these were extracted from the sequence, later referred to as "true shapes", while the later called "false shapes" were randomly generated. Participants were asked to **sort the true shapes** in the chronological order corresponding to the observed sequence. This procedure was executed **twice in VR and twice on a desktop 2D screen** for each participant with two different datasets.

VR and computer results distributions did not differ significantly. In fact, these distributions did not prove to be significantly different when compared to the null distribution. Therefore, **no significant impact** could be assessed on the user's ability to track the changes in global shape when using the VR or the desktop version of our software. However, a significant and notable **progression** in users' ability to tell true shapes from false was observed in the **VR version**.



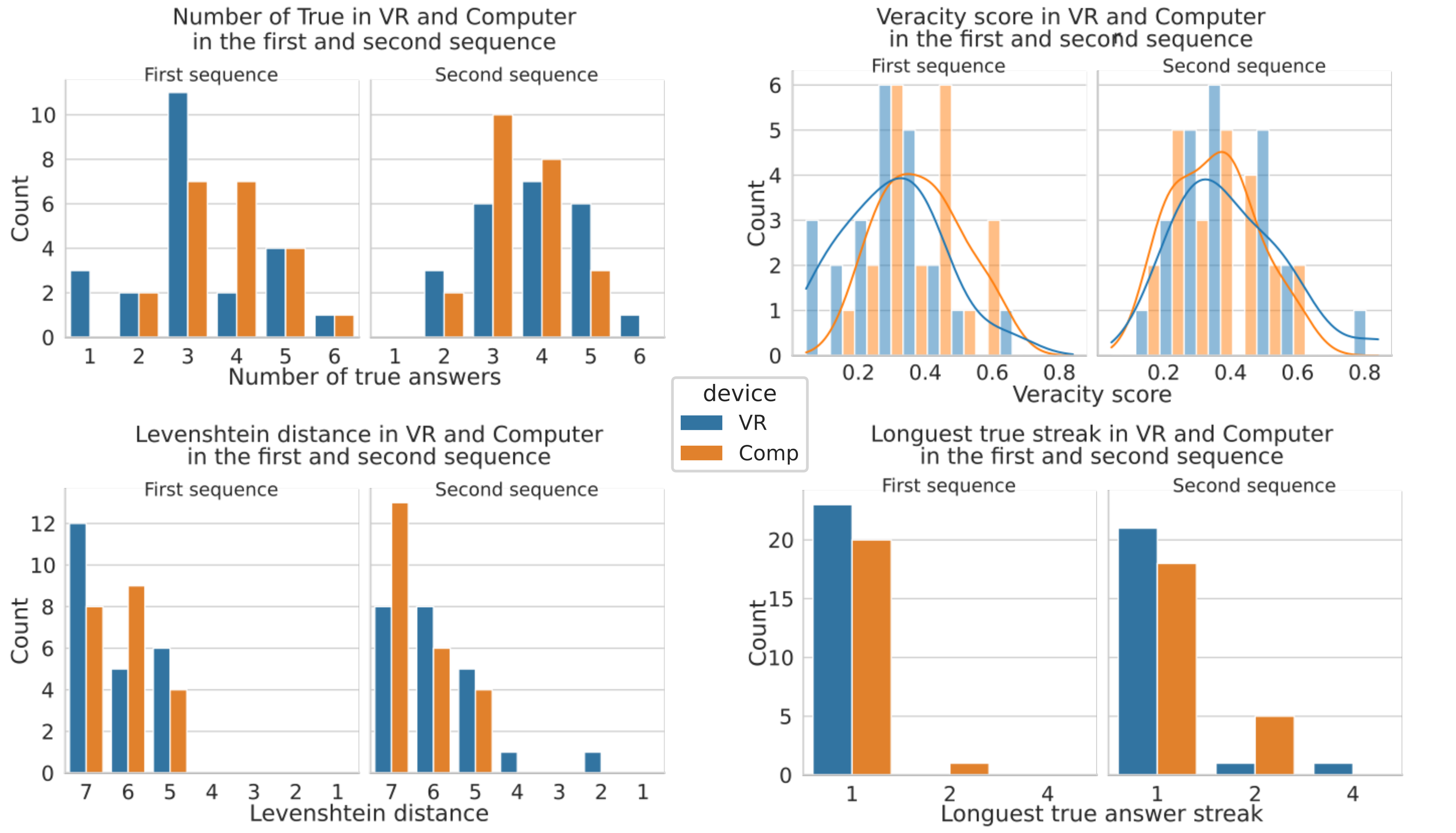
VR tutorial
VR experiment
Computer tutorial
Computer experiment



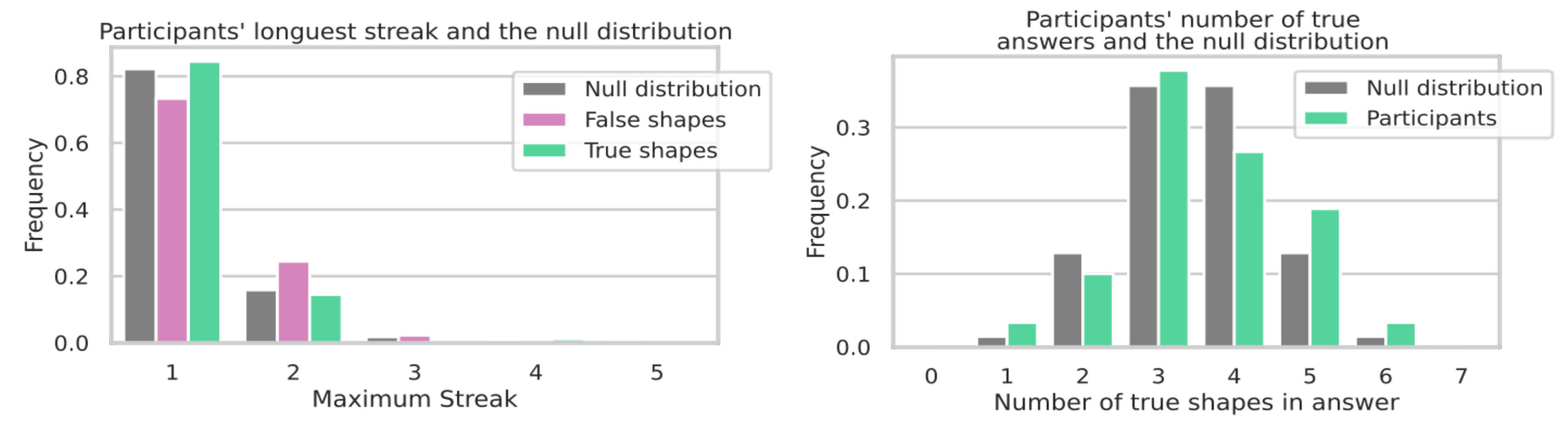
Code : https://github.com/drblobfish/score-diving-4th-dim
Bibliography : https://www.zotero.org/groups/4625494/score-4d-microscopy/library
CRI project : https://projects.learningplanetinstitute.org/projects/rRiHhgY3/summary

VR vs Computer

Participant's answers were evaluated by different scoring functions : 1) the number of true shapes in the shape selected by the participant, 2) the longest streak (LS) of sorted adjacent true shapes, 3) the Levenshtein distance between the participant's answer and the correct answer and 4) the sum of the distances of each true shape to its correct positions, named "veracity score".

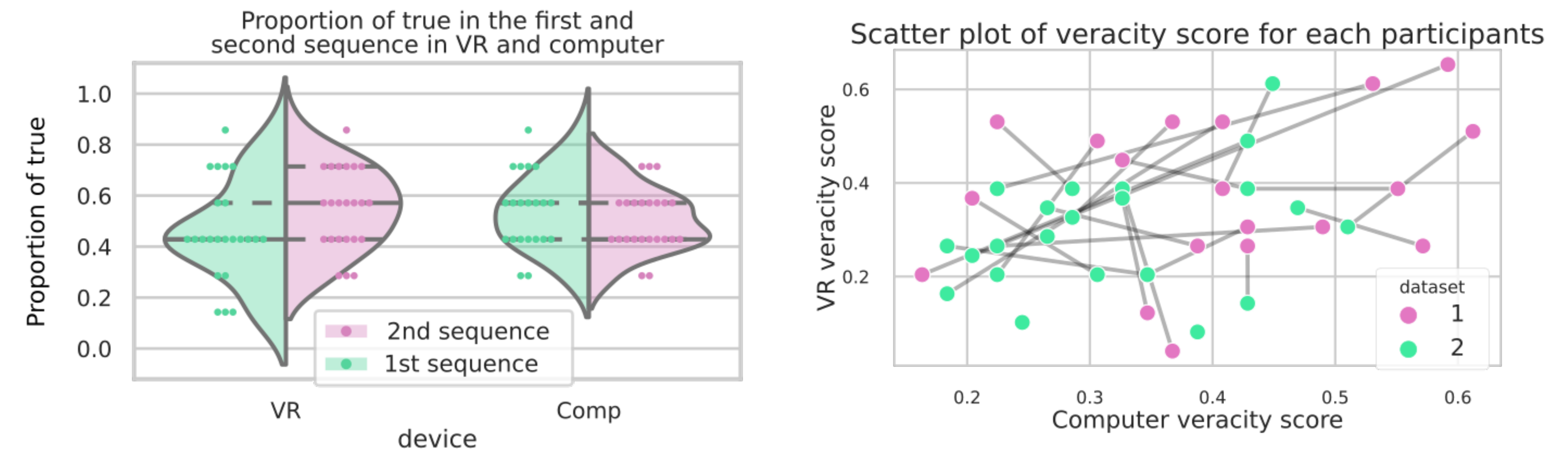


Comparison of scores between Computer and VR with respect to experiment order. For almost all experiments we observe no significant difference (Mann-Whitney U test (MWUt) : p-values<0.05). However, for the first experiment, participants had significantly lower Veracity Scores in VR than Computer (MWUt: p-value=0.023). They also obtained a lower Levenshtein distance for the second experiment, which however was just above the p-value threshold for significance (MWUt: p=0.06).



Comparison of the distribution of the number of true answers with a hypergeometric distribution (N=14, K=7, n=7). No significant differences were found. This shows that the experiment was too difficult and that participants mainly guessed rather than used their memory.

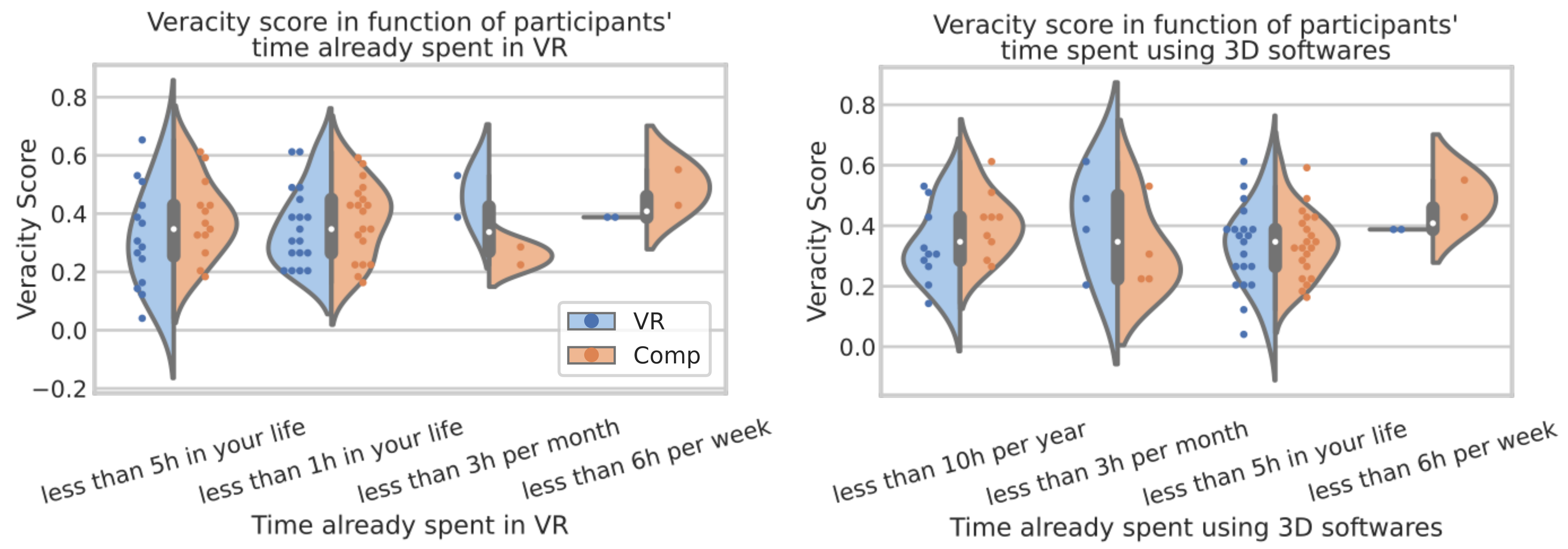
Comparison of the distribution of the longest streak (LS) taken both forward and backward with the null distribution. Null distribution sampled with 10 000 random draws. We find the LS of false shapes to be significantly longer than under the null hypothesis (MWUt: p=0.01). This suggests participants might have used primarily the fact that adjacent shapes look similar instead of relying only on their memory. However, no significant difference was found between the null hypothesis and LS of true shapes.



Comparison of veracity score between the first and second sequence with respect to device. Participants improved their proportion of true answers between the experiments. This improvement is significantly higher in VR than with 2d screens. (MWUt: p=0.023).

Relation between the veracity score in VR and computer with respect to dataset used. Dataset 1 is significantly associated with higher veracity scores (MWUt: p=0.005). For dataset 2, the veracity score of each participant in VR and with a 2d screen could be positively correlated (pearson correlation: r=0.42, p=0.064). This would suggest some participants performed better than others, independently of the device used. The extraneous factors responsible for the general success of participants are, as yet, unknown.

Other extraneous factors



Distribution of veracity scores with respect to the participant experience with VR and 3D softwares. No link was found between these variables. However, our sample was biased towards participants with no or very little experience with VR : only 2 participants (10%) had used VR more than 5h in their life.

Correlation matrix of all the measured variables. We only kept the significant correlation (p<0.05, Pearson correlation for ordinal variables and point biserial correlation for dichotomous variables). The score functions are coherently correlated.

Discussion

Our lack of clear results is mostly due to the **difficulty** of the participants' task. To assert that VR permits a better memorisation and recall of the global shape of 3D time-evolving datasets this study should be performed anew using **simpler datasets**. We observed a better progression between the first and second experiment in VR than with 2D screens. This could be caused by the fact that the majority of the users had scarcely ever used a VR set before and hence needed more time and practice in a tutorial phase. This might also mean that this learning effect might continue with VR if more experiments were performed. This would require a **longer experimental setup**, where participants would be exposed to a larger number of datasets.

Selected bibliography

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