## Academic Statement

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Images, sound or genomic sequences are all objects that modern computers can handle due to one key idea: the idea of high dimensional geometry. Even something as diverse as a tweet can be written as a (long) vector where the ith entry denotes how many copies the tweet contains of the ith word in the English language. Looking at data as points in a geometry allows us to use the concept of distance to represent similarity, and of isoperimetry to understand inherent structure in data domains. Different applications lead to different geometries, but only recently did we fully understand the most basic one – the Euclidean geometry.

In my thesis, I worked on multiple problems related to search and data structures. In Ahle et al. (2016) we showed that there are certain limits to how fast you can search in any geometry. We proved that the existence of a very fast algorithm would allow other too fast algorithms in the fundamental computational area of boolean satisfiability, breaking the so-called Strong Exponential Time Hypothesis. The work was extended in Abboud et al. (2017) starting the field of approximate hardness for polynomial algorithms. Another key idea in high dimensional algorithms is randomization. It turns out that even simple high dimensional problems, like packing spheres tightly, are very hard mathematically. Meanwhile simply placing the spheres at random locations works very well, this has problems related to the predictability and fairness of the computation. Today all the most efficient algorithms in the field have some chance of failing without any chance of verifying their results! In Ahle (2017) I found a way to solve this problem for the two most common geometries, and in? the results were extended to cover the Euclidean case as well. My most recent work includes a unified approach to LSH for distances on set/boolean data and explicit feature embeddings of polynomial kernels, giving new state of the art results in linear methods in machine learning.

Research Plan At Columbia, I will tackle the most important problem in search: Edit Distance. The edit distance between two strings like SIMON and SALOON is the minimum number of insertions, deletions or substitutions required to turn one into the other. In this particular case, the answer is 3: delete an O and change AL into SI. Given a database of strings and a query, we would like to quickly retrieve the most similar string in the database. This problem is deeply linked to natural language processing Sidorov et al. (2015) and computational biology McGrane and Charleston (2016), and as of yet a very big computational mystery.

Practical solutions include transforming strings into sets (using so-called k-mers) in which case my recent work Ahle (2019) gives the state of the art algorithm. Another approach embeds the strings into a geometry called L1 which is related to the Euclidian geometry and allows fast search. Unfortunately both transformations distort the edit distance a great deal, which makes the approach less than ideal.

I believe that a more direct approach will yield much better algorithms, leading to many breakthrough from machine learning to biology. A very recent development of papers Chakraborty et al. (2018); Haeupler et al. (2019) have introduced many new ideas on edit distance, and Andoni et al. (2018) has shown that all geometric search can be viewed through so-called non-linear spectral cuts, giving us a more principled path for research. I will study these quantities from both an upper and lower bound perspective. For upper bounds, new analytical methods developed in my recent papers allow studying candidate algorithms that this far has been a mystery. For lower bounds, new hypercontractive inequalities I have discovered give a new view at spectral cuts. Omri Weinstein is the topmost expert on lower bounds for data structures, and working with him, and other experts and Columbia University, will make this project much more likely to succeed.

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