1. Define your research scope
   1. Aim to use machine learning and possibly deep learning to identify possible fraudulent trends or activity using public Medicare Data.
   2. We plan to use 3 years of Medicare part b and part d data along with labels joined from the LEIE to generate some insights about Medicare FWA. Since there are few fraud cases in the vast amount of Medicare data, we plan on mining these cases for insight and then using clustering techniques and other unsupervised methods to try and identify fwa behavior.
   3. The data sets are quite large and combining them can be a bit of an issue. The public Medicare data sets are not released at the patient/event level. They are instead aggregated on NPI and other characteristics [13 – others I’m sure]. This means our team will have to join some large datasets together to get access to the relevant features we need.
2. Previous Research
   1. Anomaly detection is employed in many different areas for fraud detection. The assumption being that anomalous events or activity is likely to be fraudulent when compared with the rest of the body. Teams have used Spatial Density using imLOF (Improved Local Outlier Factor) [11]. As well as unsupervised methods such as Isolation Forest and Unsupervised Random Forest [2], Deviation Clustering and GMM [16]. Further past teams have seen that Local Outlier Factor (non-improved), K-Nearest Neighbors, and autoencoders are suboptimal performers [2]. Though there is some debate over LOF. [16 and 2]
   2. Past research has seemingly only focused on single years [2,12,13, etc] and used either a Supervised Learning design [6] or a combination of unsupervised and supervised [13,2]. Our design will follow the latter.
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17. Application of Bayesian Methods in Healthcare Fraud - Ekin, Leva, Ruggeri, and Soyer
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