Advancing Public Health Informatics through Big Data Analytics and Synthetic Health Data Generation, a Novel Multicloud Synthetic Syndromic Surveillance Cloud-Native Architecture

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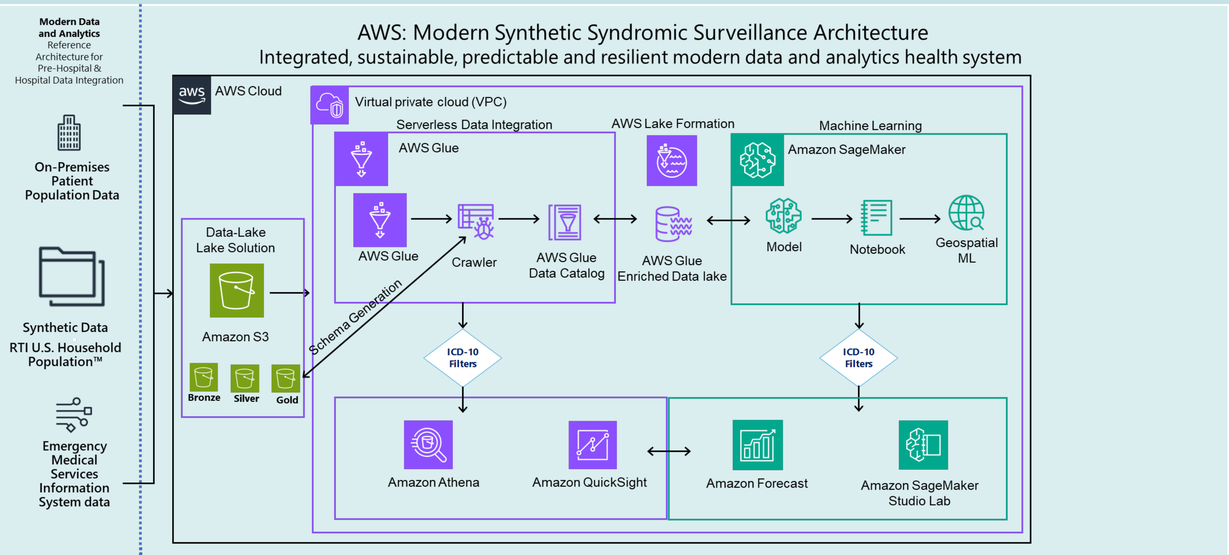
Background

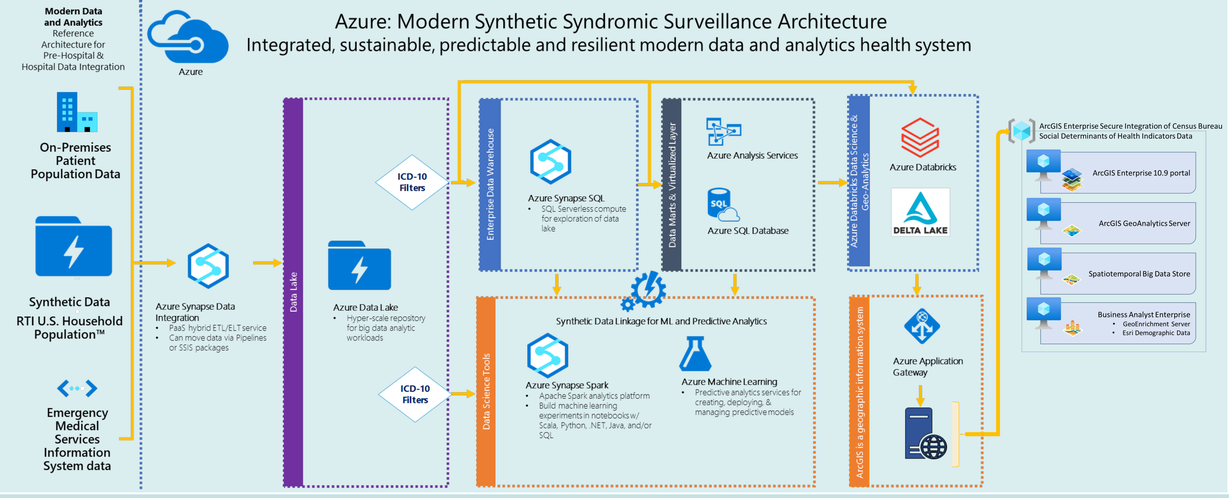
The use of machine learning to build predictive models often requires the harmonization of disparate data sources. For instance, at our institution at the University of Illinois at Chicago, we have found a need to meld real-time geographic data with hospital data and enriched geospatial information. This required a complex architecture for data analytics over cloud services which had not been published in the literature over the past decade. This poster aims to discuss the construction and design of synthetic syndromic surveillance cloud architecture for hospital data integration. Our project aims to present the design and construction of a multi-cloud synthetic syndromic surveillance cloud-native architecture that can integrate hospital data from various sources. The proposed architecture will provide a comprehensive and efficient solution for integrating and harmonizing diverse data sets in the healthcare domain, enabling the development of more effective predictive models.

Methods

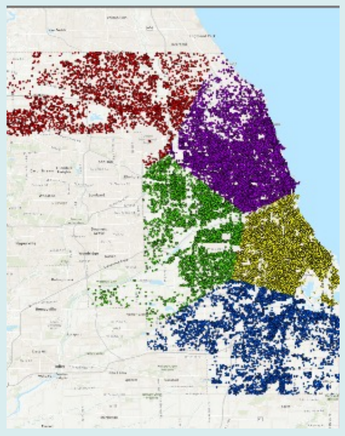
The open-source cloud computing data analytics architecture that we used is shown in our Research Design section. Data can be obtained from various sources, including patients from an electronic health record. We used Illinois patient data acquired from the COMPdata Informatics and statistically matched the patient records with household population records from the RTI U.S. Synthetic Household Population™ database. After filtering with ICD-10 codes, the data is ingested into S3 buckets. Afterward, the data is stored in a hyper-scale repository Amazon Data Lake where it is cleansed and enriched with the help of orchestrated Glue Jobs using AWS Glue Crawlers. AWS Glue Data Catalog helps in data cataloging and classification where raw CSV files are converted into Parquet, and both the data files are merged and stored in S3 cleansed bucket. The S3 Analytics bucket creates a final data frame with cluster labels from geospatial clustering algorithms like K-means, DBSCAN, Gaussian Mix, and OPTICS. The result thus generated is fed to ArcGIS Enterprise for geospatial analytics. In addition, predictive models can be created, deployed, and managed as part of a synthetic syndromic surveillance system. Likewise, under Azure, the data is stored in a hyper-scale repository Azure Data Lake. After filtering with ICD-10 codes, the data is ingested into an Azure Synapse SQL Server. Azure pipelines help to clean and filter the data inside the Azure SQL data warehouse. Data analysis can be performed using Azure Synapse Spark as an analytics platform and Azure Machine Learning for its analytic services. We can move the data into ArcGIS Enterprise for geospatial analytics

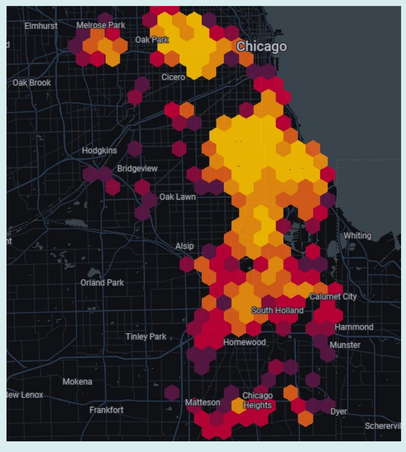
Research Design

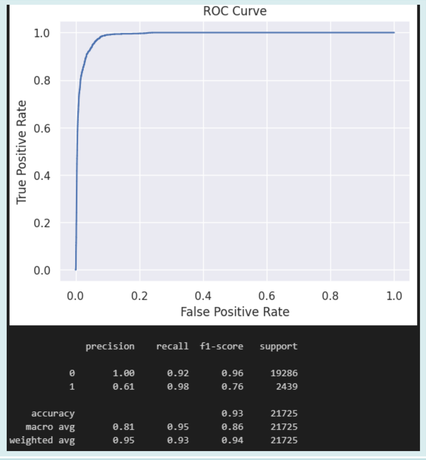




Results







	precision	recall	f1-score	support
0	1.00	0.92	0.96	19286
1	0.61	0.98	0.76	2439
accuracy			0.93	21725
macro avg	0.81	0.95	0.86	21725
weighted avg	0.95	0.93	0.94	21725

Conclusion

The presence of health data, synthetic data, and the lack of interoperability between these forms for research necessitates designing a new system to perform modern data analytics efficiently. Such experiments often require the use of a complex data warehouse as well as a cloud computing environment. Here we have described an open-source architecture that we have developed to successfully build our unique synthetic syndromic surveillance systems.

Future Plans

We plan to improve our team-based data science processes through frequent data acquisition from the Illinois Department of Public Health and continued synthetic linkage to COMPdata Informatics. This will allow us to provide up-to-date spatial analysis for improved community health advocacy. We have also decided to focus more on feature engineering, model training, and model evaluation.

Acknowledgements

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