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Chapter 1: Foundations of the Healthcare Intelligence Graph

1.1. Introduction

Healthcare intelligence graphs provide a blueprint for the integration of diverse health-related information into a common structure that supports graph analytics and navigational interfaces with interpretability at their core. The challenge is twofold: improving the quality and trustworthiness of the underlying data and enabling the discovery of new knowledge via methods that exploit the connectivity of a graph structure. Healthcare intelligence graphs realize a distinction between data gathering and data processing. Data come from clinical, administrative, genomic, and public health sources and are assembled in federated form to enable continuous updates. The data-processing layer allows data scientists or AI engineers to define the operations to be performed on a specific subset of the data and to control when and how they are executed. Analysts then provide the concise version of a dedicated task that can be interpreted, reused, and reasoned over by practitioners and decision-makers within the domain of interest.

Data quality, trust, and interpretability are at the heart of the current debate about the adoption and use of AI in the digital healthcare-sphere. Graph structures lend themselves naturally to the construction of social profiles and help determine contextual recommendation strategies in many online scenarios. Centrality, clustering, path analysis, and node/edge similarities are classic approaches used to extract, categorize, and exploit accessible information. Graph structures make it possible to define new targets for content-based and collaborative filtering. Moreover, irregularly connected graphs pose unique challenges that can obviously be addressed only from within the dedicated domain. Reasons for the interest in the role of maps and proactive usage exploration are thus implicit. Specific application needs within a visualization service help the introduction of personalized elements to the navigation experience.

1.2. Conceptual Foundations of Healthcare Intelligence

The creation of a healthcare intelligence graph is rooted in the search for a versatile knowledge graph that lends itself to diverse population health analytics. The research seeks to address fundamental questions: which datasets constitute the foundation? How can knowledge representation support the representation of health-related entities and their interrelationships? Which methods can fully leverage these data sources? The focus is on graph modeling, applying formal graph-analyzing algorithms to nodes and edges, and the production of knowledge-based processes consisting of nodes and edges that together form a decision-making pathway.

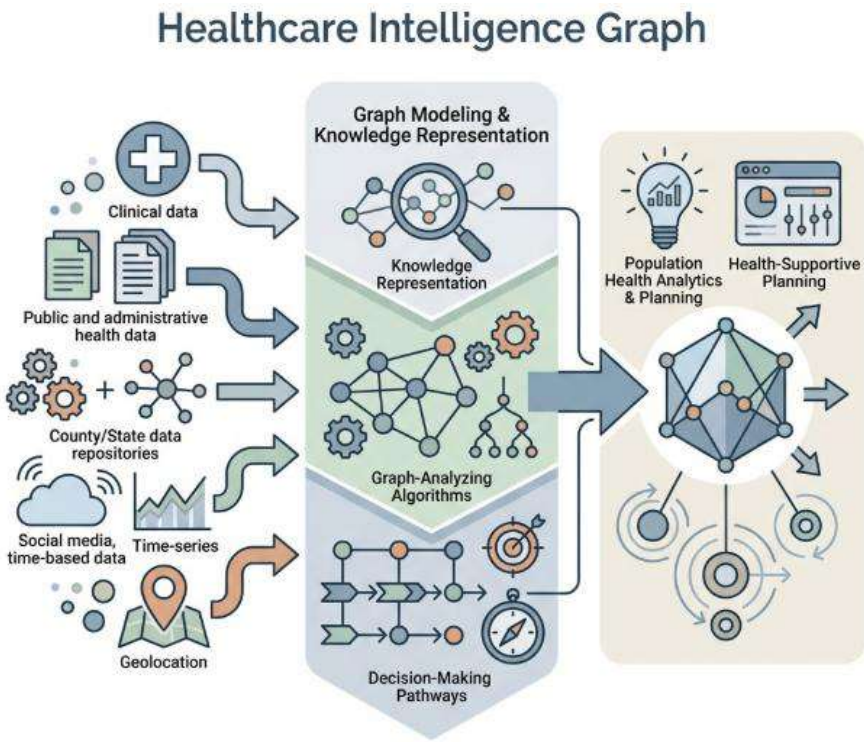

Fig 1.1: A Multi-Layered Knowledge Graph Architecture for Population Health Fusion and Decision Pathway Intelligence

Concerns about data quality and interoperability have persisted in the healthcare domain for decades. A wide range of data is available, including clinical data from various sources, social determinants of health, public health data, and data from administrative sources. County and state health department data repositories often house additional data that inform health-related operational decisions. Healthcare incident researchers also utilize data sources such as social media feeds, time-series data, clinical guidelines, and geolocation data for health-supportive planning. Yet few healthcare systems leverage

such diverse data sources for thorough analytics. One promising avenue for achieving data fusion and knowledge graph creation is the application of a graph-based intelligence layer above existing data sources.

1.2.1. Data Sources in Healthcare

Deliverable systems and services of healthcare intelligence graphs depend on their input data. A variety of data sources in healthcare need to be recognized and integrated for analytics in healthcare decision support, using evidence from healthcare practice, to help predict possible events in the future based on data patterns and support decisions of public health actors or clinical staff. These data sources may belong to four major groups: clinical datasets, administrative datasets, omics datasets and public health datasets. Each of these groups serves a different purpose, has different roles in healthcare analytics, can use separate data models and data management systems, and generate results with a different meaning. Nevertheless, all possible healthcare analytics should explore, combine and exploit data from all the data groups. Some of the datasets are not publicly accessible and their use may need formal permission, while others are uploaded by different public health institutions and are provided with User License Agreements that define data sharing conditions.

Clinical datasets consist of patient electronic health records, which are collected during their interaction with clinical services. Such datasets give detailed, structured, patient-specific and temporally ordered information about diseases and their treatment. Clinical data support specific analytics targeting individual cases or small groups of subjects with similar diseases, provide information not available from any other source and allow detection of patient events that are very rare and have no public health data registered. Nevertheless, such datasets often are not well structured, have serious hidden biases and cover only small populations.

1.2.2. Knowledge Representation and Semantics

Knowledge representation and semantics are instrumental in determining the capacity of data to underpin valid discoveries, and thus the meaning and analytic complexity of the data. The majority of a healthcare intelligence graph can be constructed in a relational manner, but these representations are not semantically rich and cannot easily host real-world healthcare knowledge. Semantic databases complement the aforementioned approaches; however, health knowledge and reasoning are extremely complex, creating difficulties not found in the well-defined domains of other applications. Finally, modeling the data directly in a probabilistic manner is computationally intensive and hard to realize.

The most logical solution is therefore to construct an intelligent healthcare graph, whereby the datamodel, analytics, and applications are presented in a way that preserves the clinical meaning. An essential quality of a graph-based representation is its ability to explicitly define all components of the graph and not only the query engines concept. The graph structure enables the representation of the data in a node-and-edge-based design where data are reduced to their basic sense. An intelligent healthcare graph goes beyond this idea, formalizing all nodes and edges in alignment with clinical knowledge and meaning.

1.3. The Healthcare Intelligence Graph: Architecture and Components

Centralized representation of knowledge about healthcare data (e.g., patient records, clinical literature, and omics results) in a common framework. The Healthcare Intelligence Graph (HIG) is a multidimensional, multilevel, and multiparty representation of this knowledge. The basic architecture of the HIG consists of layers for raw-data storage and graph-structured knowledge representation. Data flow from data collection to user-facing applications passes through the data-preprocessing layer, which serves to clean, harmonize, distribute, and transform heterogeneous raw datasets into a unified knowledge representation that satisfies the analytic needs of clinical researchers, epidemiologists, and public health professionals. Raw-data sources include clinical databases, electronic health dossiers, clinical and epidemiological reports, global disease monitors, news reports, and omics data. Unstructured data may be transformed into well-structured knowledge through topics in natural language processing.

Three dimensions characterize the knowledge representation layer of the HIG: its components (nodes, edges, and properties), semantics (meaning of nodes and edges in the context of the healthcare problem), and knowledge representation approach (method of structuring representations of knowledge, or meaning). Graph-centric representation is the natural candidate in this case. Node and edge types, properties, and schemas form the graph data model. The presence of a rich set of standard vocabularies (ontologies), termed the Specializations Ontology, supports GraphML-based development of the data model. Graph schemas are aligned with widely used clinical classifications and taxonomies, and compatibility with heterogeneous terminologies is facilitated through mapping of the most commonly used terms in clinical narratives.

1.3.1. Graph Data Modeling for Healthcare

Data modeling is crucial when establishing a graph for a particular domain. It defines the nature of the represented knowledge and serves as a blueprint for the future analytical

study of the graph. Hence, the node and edge types and their properties need to be selected with special attention to their clinical meaning and semantics.

Nodes can represent any factual entity within the considered context, such as an individual patient, a disease, a drug, or a genetic variation. Edges represent relationships among the corresponding entities. Four principal node types can be identified for a knowledge graph in health care: Subject, Disease, Therapy, and Event. Each can be further decomposed into more specific subtypes. For example, Diseases include all clinical conditions, including symptoms and diagnoses, while Events encompass both clinical and administrative records for each patient.

1.3.2. Ontologies and Vocabularies

Graph data models integrate knowledge representation elements for real-world semantics. Healthcare data encompass diverse properties, necessitating distinct representations for nodes and edges. Carefully defined types and properties facilitate graph analytics by aligning with clinical concepts.

Data models embody domain knowledge through types, attributes, interrelations, and constraints. Predominantly, property graphs featuring heterogeneous labels and property sets, devoid of cardinality constraints, underpin various applications. Such flexibility accommodates personalized graphs driven by user-query-centric schemas. Property graphs excel in other use cases; however, their construction becomes challenging when analytical tasks assume a unified graph structure.

Node sets represent interconnected subjects of clinical interest; edges, the interrelations among these subjects. Varying properties accordingly constitute diverse data sources—biological, clinical, administrative, socio-economic—mapped to specific node sets. Population health properties type structures, while longitudinal EHR data address patient-level clinical propensities.

Edge structures dictate edges, such as co-occurrence for comorbidity links or velocity for epidemiological analysis. Empirical discoveries based on domain knowledge or statistical tests assign types, guiding analytical appropriateness. Snyder et al.'s screening for centrality and administration isolation serve as examples; validation adds further analytical assurance. Centrality nodes consistently rank highest across types.

To extend a core property graph model with domain knowledge, best practices in graph modeling for knowledge-graph-type representations delineate the definition of nodes and edges. Hence, nodes describe healthcare-relevant entities or phenomena stored in different types. The correctness and importance of these nodes align with the relevance

of the properties they host or processes they type, as defined by existing models or frameworks.

1.4. Methods and Algorithms

Tasks and algorithms for health analytics are identified first, and then the methods and infrastructure support required for their execution are specified. The analytic requirements defined in a prior research effort are adopted, and a comprehensive inventory of methods is compiled by reviewing the analytics description literature. For each of the tasks, the steps involved in preparing the data, including necessary transformations, filtering, and integration, are determined. The supporting infrastructure required for these preparations is then described.

Applying a broad understanding of healthcare analytics allows categorizing the methods required to support the Intelligence Graph. Tasks that directly exploit the graph structure include analytic operations on nodes and edges, such as assessing node centrality, clustering nodes, measuring shortest paths, and exploring and predicting graph links. These core operations are complemented by methods that go beyond the graph but are critical for many healthcare applications; that is, data preparation functions, such as the necessary transformations at the data sources, feature engineering for supervised learning, and narrative synthesis.

1.4.1. Node and Edge Analytics in Healthcare

Healthcare intelligence graphs enable advanced analytics fundamentally different from those performed on tabular representation or one-shot analysis of node or edge types. Individual and relational statistics are powerful tools to summarize a citation graph, but their application to patient health records is less informative. While clinical centrality, clustering, and path analysis are important, special attention must be given to link prediction and graph learning, because these methods derive features for a target task from the entire graph structure and usually outperform analogous supervised models that exploit specific histopathology.

Centrality reflects clinical significance: high indegree indicates disease severity, outdegree importance of risk factors. Central nodes likely receive visits from other patients in the same year and serve as leader nodes in comorbidity networks. Analysis of clustering co-occurrences points to substantial over-clustering of some graph substructures, while path-based techniques identify decision pathways followed by patients with certain conditions. Nodes and edges identified using such methods combine

clinical significance with graph-related features and serve as bases for prediction models such as supervised coming and going.

Link prediction is an essential graph task; accuracy hinges on empirical distributions of coming and going models. Despite temporal information typically contained in healthcare records, evaluations focus on the ability to predict undisclosed links rather than future events. Probabilistic measures transform edge strength into link feature vectors for downstream supervised or unsupervised models on temporal graphs. Evaluation features intelligent supervision to guide supervised models. Graph learning aims to generalize knowledge to the entire population from a subset of individuals, and unsupervised approaches outperform classical models.

1.4.2. Link Prediction and Graph Learning

Link prediction and graph learning aim to discover the long-term connections in the data. For instance, this can help predict the different courses of treatment for the same patients admitted for a specific disease along with the parameters that could lead the doctors to take the different alternative paths. Based on the success of these alternative treatment paths, the prediction of future resources can also help allocate and plan the need for doctors, hospital beds, and so on. These tasks can be performed using three approaches: supervised learning based on a table adjacency structure, unsupervised learning based on training by a secondary task defined from the original graph structure, and by graph learning, where the original structure can change during the training phase.

These three approaches have different strengths and weaknesses. In the first approach, the set of available links is used to describe a model capable of predicting the missing links; hence, the task is a supervised learning task such as classification or regression. The second one is more similar to an unsupervised task, where the training set is composed of pairs of nodes. For every node pair, the prediction task is to determine if there is a link connecting them or not. This kind of analysis is usually used in information retrieval literature but has not been explored in Healthcare Intelligence Graph applications. Finally, the last approach leverages the fact that graphs can change during the learning process and therefore, can be a most general approach.

1.5. Applications in Healthcare

Two broad categories define the knowledge-consuming tasks at the applied research level: the evaluation of analytical methods and algorithms, and the development of healthcare analyses. Although evaluation studies can be built around any type of data model, they need to exploit an instance suitable for benchmarking; for knowledge-

consuming tasks where evaluation is not the main goal, the node and edge analytics centrality, clustering, and path analysis methods have already been recognized as likely delivering clinically relevant insight and recommendations. Seven healthcare analyses factored through the whole of the Healthcare Intelligence Graph have therefore been presented: clinical decision support, risk assessment and scoring, population health, epidemiology, healthcare resource requirements, resilience planning, and visual interpretation support in response to queries formulated in natural language.

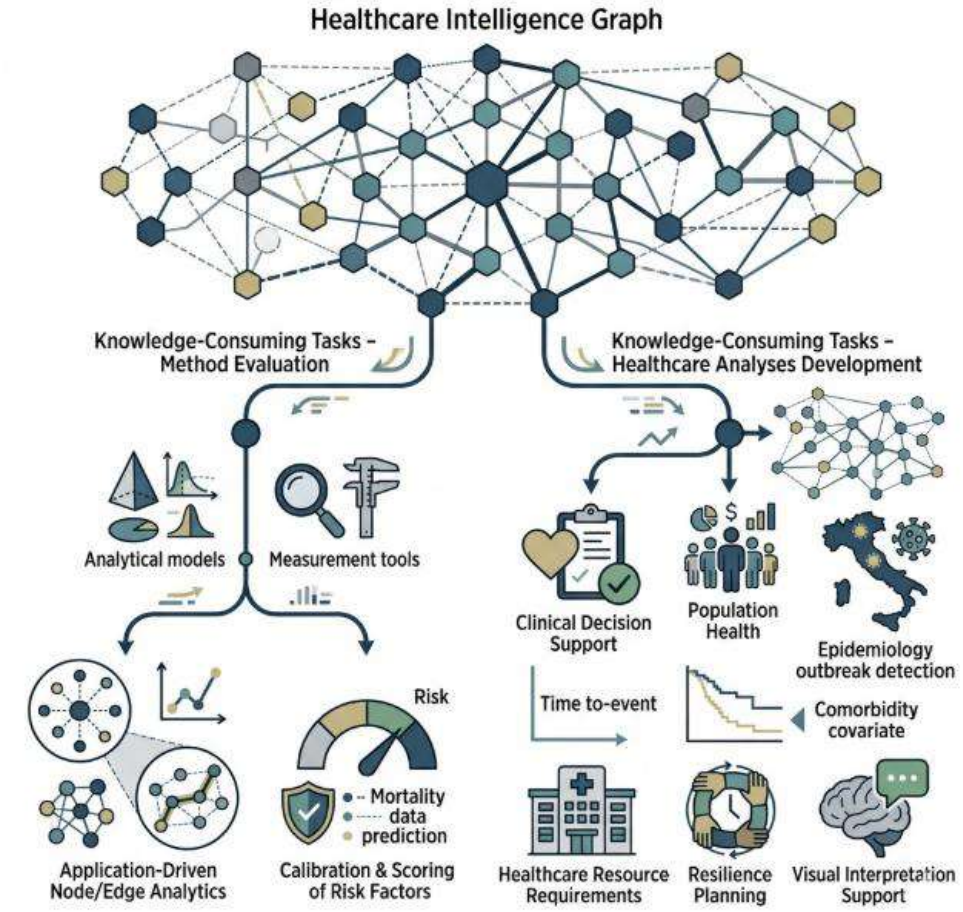

Fig 1.2: The Healthcare Intelligence Graph: A Structural Knowledge Base for Clinical Decision Support and Epidemiological Analysis

Healthcare use cases are identified for the Healthcare Intelligence Graph, covering the assessment of analytical methods and algorithms as well as high-level analyses such as clinical decision support and evaluation of healthcare resource requirements. The first use case is an application-driven evaluation of node and edge analytics; centrality, clustering, and path-analysis methods are investigated as a rule of thumb for gaining clinical interest. A second use case addresses the calibration and scoring of risk factors

and scores; risk factors for in-hospital mortality from coronavirus disease are derived leveraging information from the Healthcare Intelligence Graph. The third use case investigates the plot of a comorbidity covariate of great interest; the effect of aspirin treatment in patients diagnosed with coronavirus disease is studied with emphasis on time-to-event analysis. A fourth use case aims to detect temporal and geographical outbreaks of coronavirus disease in Italy; the analysis combines a distance-based approach with a dynamic spatial point process model. Data driving the third and fourth use cases come from a second-instance graph aimed at population health and epidemiology studies. Two further use cases examine local healthcare demand in terms of the required number of beds provided by COVID-19 outbreak contingency plans, and the allocation of healthcare personnel to regions on the basis of virus spread prediction. Socioeconomic Data and Applications Center Google .

1.5.1. Clinical Decision Support

Clinical decision support aims to offer context-sensitive information appropriate to specific clinical roles, thereby directing attention to the most relevant data for particular tasks. Such a capability has great potential for aiding physicians and advisors by answering questions such as: what is the most probable diagnosis for a patient? Which diagnosis would give the highest expected risk profile? Which intervention would minimize that risk profile? What combination of intervention and diagnosis is the most dangerous? Medical literature contains a wealth of knowledge that could be harnessed for such purposes. This includes decision pathways for a wide variety of diseases, scores for estimating disease risk probabilities, and guidance on treatment recommendation and evaluation.

Graphinsight has also been applied to these areas. Decision pathways for diverse diseases (including endocarditis, tuberculosis, and allergic rhinitis) have been reconstructed and made accessible to physicians. Risk scores derived from the hospital database have highlighted diagnoses with a high mortality rate, and recommendations have suggested the diagnosis, intervention, or combination that is most probable or dangerous. These endeavors have provided scientific support for traditional clinical wisdom and medical decision-making.

1.5.2. Population Health and Epidemiology

A growing body of research uses graphs for population health and epidemiology. Graphs have enabled epidemiologists to pinpoint the onset of COVID-19, the influenza virus, and other diseases before conventional surveillance systems and have assisted healthcare authorities in allocating resources during outbreaks. In population health, comorbidity

networks characterizing the association of diseases are valuable tools for preventive healthcare planning and decision-making. This body of work supplements the presentation of graphical analytics for clinical pathway and decision support systems.

Within population health and epidemiology, outbreaks of infectious diseases and the evolution of infectious disease mortality are common concerns. Networks, for both transmission and co-infection among diseases, are among the solutions used by researchers in these fields. Their aim is to detect, analyze, and manage infectious diseases more promptly and effectively than existing systems. Indeed, a greater depth and visibility of information in diagnostic tests, vaccination rates, age-specific disease contacts, disease transmission rates, and immunity detection improve the performance of existing epidemiological models. Graph analytics provide a supplemental layer of intelligence that makes the data and model more useful and usable. Such early detection allows deployment and definition of effective disease control and preventive strategies — for example, schools closure and airport screening.

1.6. Evaluation, Validation, and Ethics

Evaluation, validation, and ethical concerns are paramount. No analytic method is universally valid under all circumstances, and graph algorithms are no exception. Graph mining provides connectivity, relationship types, and proximity patterns, using these results often for tasks of great importance. Thus, assessing fitness for use is crucial. Besides method quality, the quality of data generated by potential or existing uses of GIGs is pertinent. Data quality must be satisfied for the resulting products or processes to be useful or trusted. Although the provision of disease risk scores goes through a safety approval process, supervisory boards do not examine all possible decision advice systems accessible via classification or recommender models. Ethical issues also demand investigation. The high potential for bias in GIGs may lead to automated systems or decision support giving wrong or misleading advice. Data used to produce any risk scores or decisions must not be biased against any group or entity represented by the available information and, if possible, should promote fairness. Inappropriate governance of data provision can lead to privacy issues. The GDPR offers insight into use-case testing. If those intended or driven by the data subject have strict data-compliance rules, these must also apply to processes or systems exploiting data originating from them or a data subject under the influence of the GDPR.

Guidelines and evaluation metrics applicable to any database are insufficient for comprehension in GIGs. Graph narratives require distinct evaluation layers and metrics. Adequate processing entails the assessment of transparency, reproducibility, and interpretation of both the whole narrative and the final narrative component—be it a GIG application, an analytical task, or any other GIG's supporting action. The importance of

evaluation during use case creation and testing is evident, as is the necessity of quality and compliance in the knowledge and inference layers. Process, data, and outcome auditing for bias must be integral to the creation of nodes, edges, and labels.

1.6.1. Evaluation Frameworks for Graph Narratives

Evaluation is essential to assess the efficacy of analytics, as well as the functional quality of the systems on which the analytics are deployed. In the case of the analysis of graphs, quantitative indicators of the quality of the graphs, the results from their analysis, or both, are commonly employed. An additional category of evaluation is the testing of algorithms involved in the preprocessing and preparation of the graph topology and associated features. For graphical narratives, the evaluation of the adequacy of the description through a graph-based insight can be more subjective than the application of predictive algorithms. Nonetheless, sensitivity analysis of parameters is valuable to assess the robustness of the conclusions.

A graphical description assembles the historical and current information related to a situation; thus, one of the aims of such a description should be an accurate summary of a period around the event analyzed. This should be a procedural consideration for experimenting within either clinical or pop-health contexts. It is a general principle to analyze selection criteria scientifically in clinical and healthcare-related scenarios because of the high clinical significance that a sound study can have. Therefore, the analysis of the most appropriate time period in which a risk score is computed, or in which communication traffic through the graph is followed, should be systematically explored. This analysis should also quantify the minimum number of patients needed to obtain a proper risk score or traffic characterization to help direct future research and validate less populated paths in the hierarchy.

1.6.2. Bias, Fairness, and Accountability

Bias and fairness are prominent issues in most machine learning applications, especially those affecting lives, such as healthcare analytics. Supervised algorithms may propagate biases present in the training data, while unsupervised models without control are more prone to discovering correlations between attributes that are not causal in nature. Bias in link-prediction algorithms emerges unintentionally from the training set but may stem from the selection of the graph schema as well, as it defines the edges used for training. Three main sources of bias may be detected in relation to the data: labels hidden in the data (e.g., race or gender), model training (training set), and deployment (reduced or biased population).

Sources of bias in data, models, and deployment must be assessed, as well as strategies to mitigate them. Bias in data can be mitigated by identifying test bias through the fictitious setting of fair distances. In a broader sense, fairness can be understood as the absence of any discriminatory influence in the model outcomes, suggesting interventions on bias causes and not simply on the model training. Example strategies include modified training-data-generation procedures, adding fairness to the optimization objectives, and model outputs in resources made available for downstream tasks.

Ensuring bias-free decisions is key for any production model. A model that supports, for instance, hospital-appointment submissions should propose appointments to available doctors, thereby satisfying a fairness property. The task should remain, as far as possible, fair so that all distinct patient populations are served fairly in terms of number of appointments. The potential for such appointments can be guaranteed through bias-sensitive training, meaning that upon selection, a supervisor will favor every group with the same score.

The systemic blank-spot principle also applies, meaning that the repository must contain sufficient data about all population segments to enable sound decision making. Otherwise, patients belonging to a less-represented group may face more considerable exposure and risk, as their tailor-made knowledge may not be so well established. Adopting the systemic blank-spot principle for the entire model deployment constitutes a pivotal strategy for any production system.

Bias in training-data generation should be addressed through a special algorithm that identifies and recommends how to fill distribution gaps among populations with respect to sensitive variables. The solutions can be presented as suggestions to the responsible authority in a given domain to achieve greater fairness.

1.7. Implementation Considerations

Practical data analytics support the development of a Healthcare Intelligence Graph for varied healthcare analytics. Analytic node-centric tasks focus on node and edge properties and related algorithms. Such analytic tasks serve as building blocks for higher-level analytical tasks. Analyses based on centrality, clustering, and path-finding in addition to aspect-oriented analytic tasks enrich clinical decision support and population health. The Healthcare Intelligence Graph opens up link-prediction research to supervised and fully unsupervised approaches in health care. Risks and uncertainties associated with link prediction are recognized.

Link prediction, that is, predicting the existence of an edge between unconnected nodes in the graph, has been identified as a support for clinical decision processes, resources for epidemic investigations, and models of virus-disease relationships. It introduces

complicated data resourcing and processing practices. Some approaches require labelled training data, and the selection of the features for the model influences the predictive performance. Fully unsupervised methods, based on the structure of the graph, do not suffer the same dependency. Unsupervised feature-learning methods can be considered semi-supervised, with the labelled data involved at the output end. Analyses of the weights of the embedding features, if made available, show the connection with domain knowledge.

1.7.1. Data Governance and Compliance

Healthcare processing and information systems, in particular, are increasingly challenged to address privacy and data governance issues. Personal Health Information (PHI) may include a name, a residential address, a telephone number, a date of birth, a patient's fingerprints, or even pictures or images of a person, and so forth. The Health Insurance Portability and Accountability Act of 1996 (HIPAA) governs the use of such information. To uphold mutually supportive data principles, the data subjects should not only be informed about the intended processing of their data but also provide consent. The consent must be voluntary and can be withdrawn at any time. Moreover, users of the systems with privileged access to PHI must be carefully monitored, as they may abuse their common access privileges to carry out malicious internal attacks. A Privacy Preserving Data Access Control Algorithm (PPDACA) guarantees that private data is disclosed only to its legitimate owner.

Profound control of data access ensures that users are only able to access data that they are authorized to do so. For instance, an analyst may use SQL-like queries to obtain the global view through a view manager that validates the data request against the request's inner privacy level before transmitting it to the underlying services. Compliance with laws, regulations, guidelines, and specifications that meet ethical, legal, and quality requirements are core elements of data governance, implementing preventive and detective technology. Deployment in systems that adhere to such requirements is essential in the era of Big Data.

1.7.2. Scalability, Performance, and Maintenance

To ensure the Healthcare Intelligence Graph maintains a reasonable response time, the breadth of data analysis that can be performed, and the possibility of real-time features and capabilities, scalability, performance, and maintenance considerations are crucial. For the developed system to be an effective tool for researchers and health authorities alike, it must be able to process voluminous data and respond in a timely manner while also keeping up with the rate of new data generation. The generated graph is expected to

grow asymptotically with the increases in size in the underlying data sources. The data volume and its growth rate are therefore key determinants of scalability, along with the frequency of processing and serving.

The generated Healthcare Intelligence Graph can be utilized not only as a repository of knowledge but also as a tool for real-time and near-real-time analytics. A real-time system must have the ability to instantly respond to incoming data and trigger dedicated processes on new events. A near-real-time system must have the ability to continuously query an event stream, processing new events as they arrive and producing new output whenever the processing cycle is completed without significant delay during normal operation. The health intelligence graph can become a real-time system by integrating a stream-processing capability into its architecture. This is possible because the underlying data sources (population data, public health information, healthcare service demand) represent event streams that can be processed on a continual basis.

1.8. Case Studies and Practice Guidelines

Three case studies cover major applications of the Healthcare Intelligence Graph: supervised learning with node attributes and links, clinical decision support, and pop-health analysis. Each study elucidates the analytical pipeline and distills lessons, reflecting on success and limitation factors; the last study focuses on preparation. A continuation recommends actionable steps for others seeking to implement similar technologies, drawing on both lessons learned and the literature.

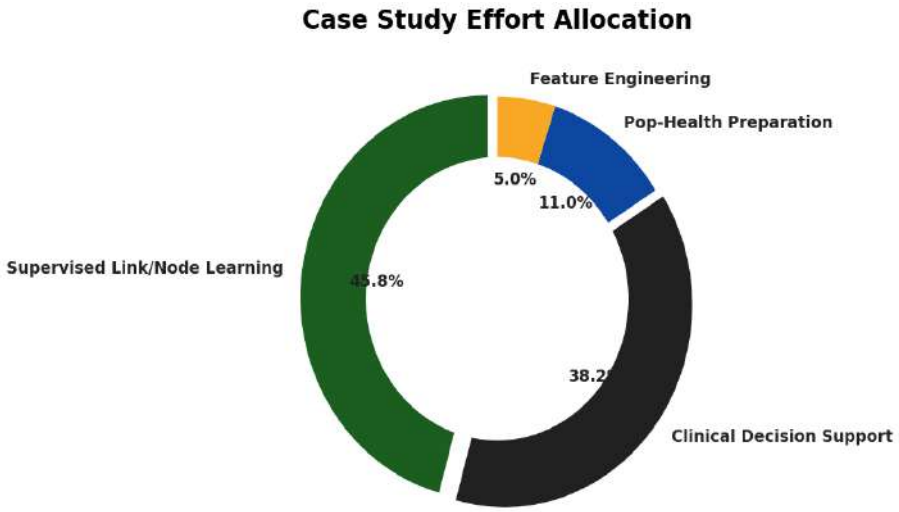

Fig 1.3: Case Study Effort Allocation

Node and edge analytics serve as building blocks for the first case study, supervised learning to identify future heart failure. Both link prediction and graph learning are relevant, as these enable modeling with edge attributes and support undocumented edges in the supervised data. Graph-derived features from these processes should cependant be considered preliminary; user-defined, expert-driven, and other automatically learned features facilitate greater insight. Evaluation welcomes standard methods, as these are crucial for comparison and repeatability. Datasets from the US National Heart, Lung, and Blood Institute maintain the requisite quality while exploring key graph aspects.

1.9. Conclusion

Intelligent healthcare systems are pivotal for data-driven decision making in clinical settings, public health institutions, and private companies involved in healthcare. Connecting disparate data sets from clinical, administrative, and third-party sources provides depth and breadth for knowledge extraction that would not be possible using single data sources. This consolidated healthcare dataset has been referred to as the Healthcare Intelligence Graph (HIG), a formal representation of healthcare knowledge designed to address the patterns of knowledge representation, querying, evolution, explanation, and learning present in healthcare analytics. Knowledge order is specified, from the clinical knowledge required for patient care to the higher-order knowledge embedded in the shape of the HIG. The specific need-to-know basis of each user drives the representation of these questions in data-management terms.

The proposed architecture addresses these data-management issues, allowing users with varied needs to access the same information in a way that meets their requirements, by interfacing onto the consolidated knowledge graph. Users with a need for explanations, those wishing to perform data analytics or evaluation, and states parties that want to influence the knowledge shapes present in the HIG all have different requirements: ontology development, central issues for knowledge-graph creation, store management, and a shared control of knowledge across the data sources.

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