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Intelligent, Interoperable, Relevance and Value Enrichment in Universal, Ubiquitous Electronic Health Records (EHRs)

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ABSTRACT

Electronic Health Records(EHR) are electronically maintained, linked, collections of allied, patient-related healthcare information collected during past encounters. They incorporate patient demographic information, encounter details, laboratory reports, prescription notes, past medical records, and other medical data. EHR creation is designed to support the future diagnosis, treatment, and decision making in patient care. However, since EHR technology is a burgeoning science, many facets lie under-used or under-utilized.Current implementations are confined to national boundaries managed by individual National Health Systems (NHS). Consolidated, universally interoperable EHR schemes are still a thing for the future; a migratory patient may not have his national EHR available in distant territories. Further, the examination of operational factors unearthed more inadequacies. Interoperability-related issues include the limiting network bandwidth causing inordinate delays, diverse local storage schemes at the various NHS clusters, the related requirement for synchronous vocabulary-related translation mechanisms at the various NHS-controlled boundaries causing inordinate delays, and the related security and access issues. These issues arise from the requirement for synchronous, query-messaging nature of information access and exchange. This paper articulates a novel, sound, and secure methodology for achieving true International Interoperability and uniform efficiency in ubiquitous Electronic Health Record systems.Utilizing intelligent machine learning processes, required query-messaging information is meaningfully aggregated enhancing the relevancy, access speed, and value-derivation from the given data.Asynchronous learning excludes the need for high available network bandwidth, upload and download delays associated with current synchronous database/cloud systems.Indeed, this overarching solution ensures seamless synchronous operation and high-end international interoperability, and would work in any ubiquitous EHR environment.

Keywords :*Health Level 7, Interpolated, Consolidated, Electronic Health Records, International Interoperability, Ubiquitous, Macrocosm.*

I. INTRODUCTION

The *Electronic Health Record* (EHR) is a dynamic, longitudinal data structure of recorded healthcare information. Typically, patient encounters, patient, healthcare provider, and medication-related demographic data, treatments, laboratory reports, prescriptions, and medical history make good *EHR* material; infact efficient *EHR* implementations should circumscribe the gamut of pertinent, captured healthcare data enabling efficient, speedy future diagnosis and treatment of patients and diseases. The *Health Information Management System Society* (HIMSS) defines *EHRs* as follows **[3]**:

"*The Electronic Health Record (EHR) is a longitudinal electronic record of patient health information generated by one or more encounters in any care delivery setting. Included in this information are patient demographics, progress notes, problems, medications. vital signs, past medical history, immunizations, laboratory data, and radiology reports. The EHR automates and streamlines the clinician's workflow*".

EHR interpolation in the *IT-driven* healthcare sector resulted in many parallel healthcare standards being instituted. For instance, *Health Level 7* (HL7) developed the *Electronic Health Record System Functional Model* (EHR-S FM) which"*provides a reference list of functions that may be present in an Electronic Health Record System (EHR-S)***[4]**. Functional profiles which are predetermined functional sets applicable to earmarked purposes, users, or environments, are created thereafter affording standardized descriptions of the specified scenarios. They are pertinent subsets of the complete function list in the *EHR-S FM*.The functional model therefore overarchingly refers to the allied *EHR* system, which in turn manifests in the form of one or more *scenario-related* functional profiles.

EHR systems in general are developed with the following merits in mind **[3][5]** :

- Improved Quality of Patient Care.
- Efficient Patients/Costs Monitoring.
- Filips to the Healthcare Industry.
- Improved Documentation and System Audit Readiness.
- Interoperability.
- Safety/Security.
- Quality/Reliability.
- Efficiency/Effectiveness.
- Improved Communication.

According to **[4],** an *EHR* standard regulates the exchange of valued, pertinent healthcare information. It provides common language parameters for the design and development of *EHR* systems.Efficient, seamless *International Interoperability*, defined herein as the global exchange of valued healthcare information with homogenous understanding amongst participating *healthcare service provider-oriented* computer systems, should be the goal and expectation of every *EHR* implementation.Present day *EHR* systems however, are mainly *institution-based* and *territorially-scoped* by individual *National Health Systems* (NHS). Many facets and perspectives of the *EHR science* are still unexplored, the possibilities for enhancement and advancement almost unbounded. *Interoperable EHR* schemes with *global consolidation* are still distant dream.Further, current implementations are *stricken* with operational issues such as limited network bandwidth, the requirement for synchronous vocabulary-related translation mechanisms at the various NHS-controlled boundaries due to diverse local storage schemes, and related security and access concerns. These issues arise from the *synchronous, query-messaging* nature of information access and exchange; ironically they trigger inordinate communication delays and really subvert *International Interoperability*. This paper propounds a sound, secure methodology for achieving seamless *International Interoperability* and global efficiency in ubiquitous *Electronic Health Record* (EHR) systems. Using intelligent machine learning and *EHR* aggregation, required stakeholder information is meaningfully aggregated for easy access and enhanced value-derivation.The *asynchronous learning* process excludes the need for high availability of network bandwidth, and avoids the upload and download delays associated with current, *synchronous, database/cloud-based EHR* systems.Accordingly, this paper is organized as follows; Section 2 presents a conceptual *EHR* overview, Section 3 presents details of the proposed *EHR* learning model, Section 4 articulates the proposed intelligent learning methodology, Section 5 presents study results, and Section 6 sums up with the *Conclusion* of the overall research findings.

II. ELECTRONIC HEALTH RECORD MACROCOSM

Conventionally, *healthcare-related* information was recorded by *area*, eg., laboratory, pharmacy, or emergency. These *unintegrated* subsystems had their own access procedures, patient identification schemes, and often diverse backend storage mechanisms (see Figure 1).

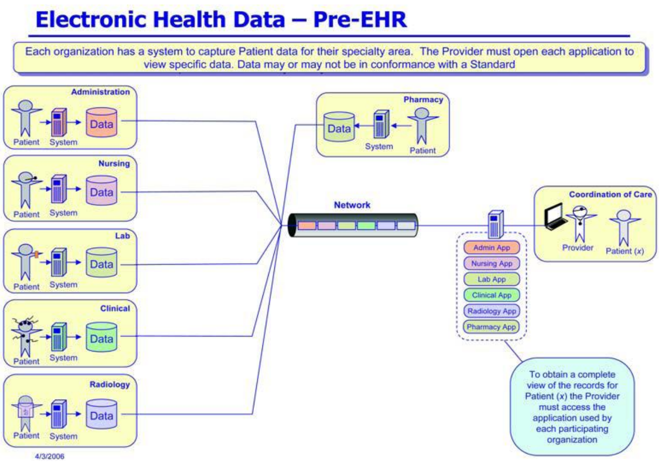

Figure 1. Electronic Health Data – Pre-EHR [3]

The mere diversity in subsystem development employing different vendors utilizing different languages and methods for user/patient identification and even access, subverted operational uniformity across all areas.Retrieval of an encompassing electronic record would thus require exhaustive login to all sub-applications and aggregating relevant patient record fragments. This unintegrated arrangement results in "*inordinately lengthy access times, vocabulary variations across silos, and gross data duplication, incompatibility, and inconsistency*" **[1]**.Further, the universal dispersion of allied electronic patient record fragments due to patient migration impedes efficient health record consolidation and access.Indeed the principal goal of this research was to devise an innovative, *learning-based, asynchronous* solution for efficient *EHR-based* system operation, mitigating if not totally eliminating the said inefficiencies due to poor, *unintegrated* organization, *query-messaging* type access and exchange, and associated delays, and line bandwidth concerns.

III. FEATURES OF THE PROPOSED INTERNATIONALLY INTEROPERABLE INTELLIGENT *EHR*-BASED LEARNING MODEL

i. Timely, up-to-date information provided at any node :

- Patients
- Diseases
- Treatments
- Treating Medical Practitioner
- Service Provider
- All-permutative relationships among above data entities.

ii. All pertinent healthcare information stored in global *Electronic Health Record* (EHR) schema, in multiple, universally-accessible healthcare service provider databases spread globally.

iii. Universal addressing of all healthcare *artifacts* – using *Object IDs* (OIDs*)* or*Universal User IDs* (IDs).

iv. *Unsupervised Learning* used during the "*relevance and value enrichment*" operation of the *EHR-based* information system. Populartechniques include *Bayesian Learning*, ***S****elf-Organizing Maps*, *Nearest-Neighbor Mapping*, *K-Means Clustering* and *Singular Value Decomposition*".

v. *Electronic Health Record* (EHR) information is *consolidated* and *learned asynchronously* for quick access eliminating *common vocabulary translation issues*, *access and security-related delays*, and *communication line concerns* inherent in conventional *query-messaging* type *EHR* schemes.

vi. *EHRs* are stored non-uniformly in respective *National Health Service* (NHS) and *Healthcare Service Provider* (HSP) repositories spread globally, in *national* and *intra-national* (*HSP*) clusters.

vii. Similar to *system start-up* in the mornings (or *system shut-down* the previous evening), list of required *EHR-related search artifacts*, eg.,*patient*, *disease*, *diagnosis*, *treatment*, *clinician*, or *HSP*, is fed into system and *learning* initiated.

viii. Absolutely NO synchronous *long-distance queries*, *messaging*, or *rummaging* in alien, distant databases necessary.

ix. *Learned* (required) information cached locally for prompt, speedy retrieval. Time-consuming download, upload procedures prevalent in current cloud-based systems eliminated.

x. "*Asynchronous Learning for Efficient Synchronous Operation*" - the Essential Slogan.

xi. System-related processes embedded in proposed *EHR-based* Learning Model

- Human-related : learning *Natural Language-based* Interaction vocabulary.
- System-related : includes the following sub-processes.

a) ***Updation*** – additions/insertions/deletions at nodes; affects global *EHR* schema (*Blend-in*).

b**)** ***Consolidation*** – Any record-based target *Resultset* filtered from pertinent kindred *EHR* sets composed by on-the-fly global consolidation (*Leaf Search Artifact-basedLink-in*). *Decentralized learning* at individual nodes.

c) ***Stratification***– Intelligent, dynamic, stratification of global network according to pre-defined guidelines– by *global*, *continent*, *country*, *economy*, *paid service-fee slab* etc. (*ClusterKey-basedLink-in*). *Centralized learning* applicable to entire network.

d) ***Rejuvenation*** – Intelligent, dynamic arrangement of global *EHR* fragments such that consolidation (*Link-in*) occurs according to *frequency* of information access. Facilitates access according to frequency of information use (*Access Frequency-basedLink-in*).
Decentralized learning at individual nodes.

e) ***Attenuation***– Intelligent, dynamic arrangement of global *EHR* fragments such that consolidation (*Link-in*) occurs according to *age* of information fragment. Facilitates access according to age (*Aging-basedLink-in*).*Decentralized learning* at individual nodes.

Updation relates to *automated* (eg., using scripts) or *manual-input* based regular *insert*, *delete*, and *update* operations performed in the local database. Therefore, *Consolidation*, *Stratification*, *Rejuvenation*, and *Attenuation* constitute the actual intelligent, machine learning processes. Since *Stratification*, *Rejuvenation*, and *Attenuation* possess a similar *operational nuance* (all three entail hierarchical clustering with diverse *cluster-keys*, ie.,*Stratification* with *cluster-key* = global, continent, country, economy, paid service-fee slab, *Rejuvenation* with *cluster-key* = frequency of access, and *Attenuation* with *cluster-key* = age of data, they are algorithmically similar. It suffices therefore to present *learning* algorithms for *Consolidation* and *Stratification* only.

IV. INTELLIGENT LEARNING METHODOLOGY

a) Learning Overview

International Interoperability necessitates the universal referencing of healthcare *artifacts*, eg.,*Universal User IDs* (UUIDs) and *Object IDs* (OIDs)both facilitate universal reference [2], as indicated by the *probe sequence* shown in Fig.2.

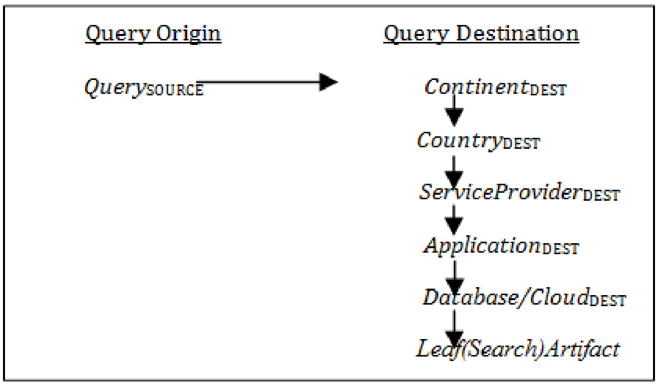

Figure 2. HL7 v3 Message - Query Probe Sequence [2]

Given this model, locally-maintained *UUIDs* for*query-target* reference are of the given form,

{$UUID \equiv [Continent_{DEST}, Country_{DEST}, SP_{DEST}, Application_{DEST}, DB\text{-}Cloud_{DEST}, LeafArtifact_{DEST}]$}

OID construction is similar and as such we have empirically,

{$OID \equiv 1.\ 999999_{C1}.999999_{C2}.999999_{SP}.999999_{A}.999999_{DB\text{-}C}.999999_{LP}$} where
C1–*Continent*, C2-*Country*, SP–*Service Provider*, A-*Application*, DB-C – *Database-Cloud*, and LP-*Leaf* ***(Search)Artifact.***

As presented above, this paper assumes the query probe sequence of
$Continent_{DEST} \longrightarrow Country_{DEST} \longrightarrow ServiceProvider_{DEST} \longrightarrow Application_{DEST} \longrightarrow Database/Cloud_{DEST} \longrightarrow$ *Leaf(Search)Artifact*

However, in essence, this would depend on the operational setup and configuration of the global healthcare network. The *Leaf (Search) Artifact* (L-SA) set as modelled herein is

L-SA = {*Patient*, *Disease*, *Diagnosis*, *Treatment*, *MedicalPractitioner*, *ServiceProvider*}

The delays associated with *querying* busy networks, synchronous data uploads, and downloads are eliminated; instead asynchronous intelligent learning, data enrichment, and relevance interpolation is proposed and applied. Archaic *Learning Algorithms* are utilized to *probe*, *filter*, and *locate*; focused, convergent learning techniques help retrieve and cache required *EHR* segments locally for prompt, speedy retrieval.

Learning *requirements-related Predicate*s constitute system-related interactive input. Input predicates are designed in order to preserve brevity of communication, ease of operator-learning, facilitate system-parsing, and promote future multi-linguilism. Two modes of interactive operation, *singular* and *batched* mode (using batch file-based predicate collections) are recommended. Typically, similar to *system start-up* in the mornings (or *system shut-down* the previous day), the list of required *EHR*-related search *artifacts*, eg.,*patient*, *disease*, *diagnosis*, *treatment*, *medical practitioner*, and *healthcare service provider* are fed into system and *Learning* initiated. Significantly, the *asynchronous* learning initiated is unaffected by system delays, network hogs, and line bandwidth unavailability associated with synchronous, query-based approaches prevalent in today's systems, "*Asynchronous Learning for Efficient Synchronous Operation*" being the motivation and goal of this solution. Prior requirements records of *search artifacts* are prepared and used for source predicate input, eg., daily patient appointments schedule for the current day's *beginning-of-the-day* system learning.

As mentioned in section 3., *learning* processes constitute both human and system-related learning; human learning related to system users and operators acquiring conversance of the predicate-based interactive vocabulary, and intelligent system learning aimed at network-wide healthcare data enrichment and relevance interpolation, ie., data *updation*, *consolidation*, *stratificatio*n, *rejuvenation*, and *attenuation*. However, *updations* per se(data *additions*, *insertions*, *deletions*) are procedural, performed locally in the service provider/national database/cloud; these do not entail a *learning* endeavour. *Learning* processes should ensure the incorporation of up-to-date system updates in the *globally consolidated and learned*, *kindred EHR* chunks. Therefore the pertinent, intelligent, system-related *learning* processes are *consolidation*, *stratificatio*n, *rejuvenation*, and *attenuation* which are described later in this section.

In general, record-based storage schemes are utilized universally in *EHR* repositories, as shown in Figure 4. A veritable plethora of such schemes exist, from the inceptive *Hierarchical* and *Network* models to the present-day conventional *Relational*, *Object-Oriented*, *Object-Based*, and *Hybrid* models. All these record-based structures suffer from the *Data Sparseness* syndrome; first cuts with populated data may leave large-scale gaps in fields for non-existent or unavailable data. Conventional *relational* techniques overcome these storage deficiencies through multi-level *Normalization*. Other models may use similar techniques. However, this paper presumes a reasonably full complement of stored data in all repositories, to make the proposed learning processes efficient, fruitful, and worthwhile. Further, for convenience, the conventional *relational* model is presumed in all repositories; this can be seamlessly extrapolated to all record-based models as needed.

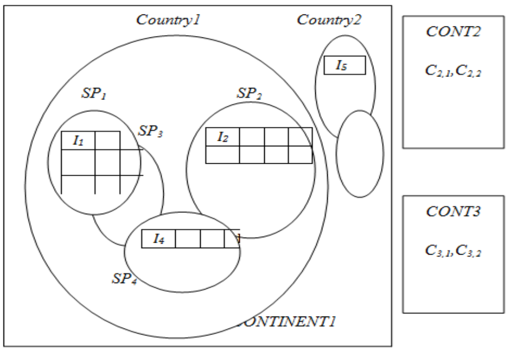

Figure 3. Universal Electronic Health Record Storage

SP_i: Service Provider i
I_x :*EHR* Information Database, where x = Database Number
CONTi : Continent, where i = Continent Number
$C_{p,q}$: Country q in Continent p

b) Learning Predicates for Input

Learning Predicates were designed with brevity and universal uniformity in mind. Given the modelled query probe sequence, the *maximal*, *semantically-meaningful*, *convergent* learning predicate set $\theta(LP)$ takes the *Quintuple* form

$\theta(LP)$ = [*Global*, *Continent*, *Country*, *ServiceProvider*, *Leaf(Search)Artifact*]

Any random learning predicate set $\phi(LP)$ would contain five or lesser number of elements in each member, eg.,

$\phi(LP)$ = {[*Continent*, *Country*, *ServiceProvider*, *Leaf(Search)Artifact*], [*Continent*, *Country*],
[*Country*, *ServiceProvider*, *Leaf(Search)Artifact*], [*Continent*, *Leaf(Search)Artifact*],
[*Country*, *Leaf(Search)Artifact*], …………………………}

Learning can be initiated with any one as the *Head Learning Artifact* (HLA), ie.,*Global*, *Continent*, *Country*, *HealthService Provider* (HSP) or *Leaf Search Artifact* (LSA); the learned *EHR* knowledge chunks would encompass the allied remaining *artifacts*. Typically, the five *HLAs* would be defined as random access fields in the local storage repositories, eg.,*Primary*, *AlternateKeys* in a *Relational* database arrangement. However, it is important to note that *efficient*,*focused*, and *convergent* learning necessitates the specification of at least one *Sentinel Learning Artifact* (SLA) in the input *learning predicate*. *SLAs* constitute relatively static datasets, eg., *Global*, *Continent*, *Country*, as opposed to the dynamically mutating *non-SLA* datasets *HSP*, and *LSA*. *SLAs* spearhead and searchingly drive forward the *Learning* process, efficiently consolidating related globally-spread *EHR* chunks on-the-fly, finally converging on the coherent, relevant *EHR-Target-Cluster* (ETC). The terminal *ETC* of any input *learning predicate* signals a completed *learning thread*; a completed batch of input *learning predicate-related ETCs* constitute the consummation of a *Learning session*.

c) Learning Algorithms

Two unsupervised *learning* algorithms are presented. For *efficiency*, *convergence*, and *operational versatility*, learning is *multi-threaded* but *directed*, starting at the highest specified *sentinel* artifact and flowing towards the required *leaf search artifacts* (LSA). Of paramount significance is that actual target *LSAs* become available a few clicks away together with their allied *surround*, improving the relevance, accuracy, and semantics of the required information. Clarifications, verifications and validations can be performed locally with enhanced efficacy and greater value extraction than conventional means.

i)*Consolidation :**Learning* of *pertinent*, *kindred*, global *EHR* segments, readied for exhaustive and comprehensive knowledge provision during synchronous operation. Learning techniques used are trivial *K-Nearest Neighbour* for the fan-out phase, and *Bayesian learning* for related global *EHR* consolidation.

Procedure *Consolidate* (input :*scope*, *required-lsa-value*; output : *consolidatedResultSet*);
{ read *scope*; /* either *Global*, *Continent* or *Country* */
If scope = *countryValue*goto Skip2;
/* learning the scoped *Continents* using trivial *K-Nearest Neighbour learning* (single-step) */
generate-learn *memberlist* m_i; $i \in N$, $1 \le i \le k$, k is number of *Continents* in list
generate-learn *memberlist* m_i associated probabilities;
if m_1 <>*continentValue* then [n_i]= [m_i],goto Skip1;
{store m_i; $i \in N$, $1 \le i \le k$, k is number of items in list
for each m_i
/* learning the scoped *Countries* using *K-Nearest Neighbour learning* */
{generate-learn *memberlist*n_i; $i \in N$, $1 \le i \le l$, l is number of countries in list
generate-learn *memberlist* n_i associated probabilities;

Skip1: if n_1 <>*countryValue*goto Skip2;
{store n_i; $i \in N$, $1 \le i \le l$, l is number of items in list
for each n_i within each m_i
/* generate and learn *ServiceProviders* who relate to each n_i */

Skip2 :
{generate-learn *memberlist* o_i;$i \in N$, $1 \le i \le q$, q is number of *HSPs* in list
generate-learn *memberlist*$o_i$associated probabilities;
if o_1 <>*lsa*
{storeo_i; $i \in N$, $1 \le i \le q$, q is number of *HSPs* in list
for each o_i within each n_i within each m_i
/* using *Bayesian learning and selection* */
{generate-learn *memberlist* records p_i where *key* = *required-lsa-value*;
$i \in N$, $1 \le i \le r$, r is number of *required-lsa* records in list
generate-learn *memberlist* p_i associated *Bayesian* branch probabilities
for records where *key* = *required-lsa-value*};
exit();
}
}
}
}
}
/* Completes *generate-and-learn* phase of *LSA chunking* and related *Bayesian Network* (BN) *creation* */
/* Link-in Consolidation */
for each m_i
{for each n_i
{for each o_i (*HSP*) in *created* (*learned*) BN
{*consolidatedResultSet* = append-cache(*required-lsa-value* records) r times;
consolidatedResultSet = append-cache([m_i, n_i, o_i, p_i] paths) r times};
};
};

return*consolidatedResultSet* ;
}

On completion, the *learning* process (*preprocessing*) would have *aggregated* and cached the required and relevant *LSA-relatedEHRchunks* for speedy inquiry.

ii) *Stratification*

Procedure *Stratify* (input : *cluster-key*; output : *stratifiedResultSet*[ ]);
{ read*cluster-key*; /* either *Continent*, *Country*, *Economy*, *Paid-Service-Fee-Slab* */
If *cluster-key* = *countryValue* goto Skip2;
/* learning the scoped *Continents* using trivial *K-Nearest Neighbour learning* (single-step) */
generate-learn *memberlist* m_i; $i€N$, $1 \le i \le k$, k is number of *Continents*
generate-learn *memberlist* m_i associated probabilities;
if m_1 <>*continentValue* then [n_i]= [m_i],goto Skip1;
{store m_i; $i€N$, $1 \le i \le k$, k is number of *Continents*
for each m_i
/* learning the scoped *Countries* using trivial *K-Nearest Neighbour learning* (single-step) */
{generate-learn *memberlistn*$_i$; $i€N$, $1 \le i \le l$, l is number of *Countries* per *Continent*
generate-learn *memberlistn*$_i$ associated probabilities;

Skip1: if n_1 <>*countryValue*goto Skip2;
{storen_i; $i€N$, $1 \le i \le l$, l is number of items in list
for each $n_i$within each m_i
/* generate and learn *HSPs* who relate to n_i within each m_i */

Skip2 : {generate-learn *memberlisto*$_{i,}$; $i€N$, $1 \le i \le q$, q is number of *HSPs* in list
generate-learn *memberlist* o_i associated probabilities;
ifo_1 <> *lsa*
{store o_i; $i€N$, $1 \le i \le q$, q is number of *HSPs* in list
for each o_i within each n_i within each m_i
/* using *Bayesian learning and selection* */
{generate-learn *memberlist* records p_i and associated *paid-service-fee-slabs*;
$i€N$, $1 \le i \le r$, r is number of *lsa* records in list
generate-learn *memberlist*records p_i*'s* associated *Bayesian* branch probabilities
for associated *paid-service-fee-slabs*};
exit();
}
}
}
}
}

/* Completes *generate-and-learn* phase of *LSA Hierarchical Structuring* and related *Bayesian Network* (BN) *creation* */
/* Link-in based on *Hierarchical Structuring* */
for each m_i
{for each n_i
{for each o_i (*HSP*) in *created* (*learned*) BN
{*stratifiedResultSet* [j]= append-cache(*required- paid-service-fee-slab*$_j$records);
stratifiedResultSet[j] = append-cache([m_i, n_i, $o_{i,}$, p_i] paths) } $1 \le j \le 3$
};
return*stratifiedResultSet* [ ];
}

On completion, the *learning* process (*preprocessing*) would have *aggregated* and cached the required and relevant *cluster-key-related, hierarchically-structured*, *EHRchunks* for speedy inquiry. The system will operate and provide rights and accessibility to the global *HSP* membership based on *paid-service-fee* slabs. Note that the *learning* algorithms for *Rejuvenate* and *Attenuate* are similar; they just utilize different *cluster-keys*.

The *asynchronous learning* performed at every *HSP* node precedes the actual synchronous, global *EHR*-based healthcare system operation. During operation, all connectivity is deemed *local* but with a *global feel*; costly real-time long distance links and access delays completely eliminated. The system will operate as learned with minimal or no intervention until a new learning paradigm is launched, causing *re-learning* and *re-configuration* of the local operational environment. The *overlay* of learning processes is also possible as required eg, *Rejuvenation* atop *Attenuation*. The *Learning* would so structure data according the clinician's requirement.

d) Implementation

System Implementation warrants a great deal of indepth thought; automating *learning* processes requires and is facilitated by overarching uniformity in data storage, access, manipulation, and archival processes. However, given the geographical spread of the envisaged, ideal, asynchronous-learning-driven, intelligent *EHR* healthcare solution, with interpolated stratifications by *continent*, *country*, *economy*, or even *paid-service-provider-membership-fee*, it is expected that diverse storage schemes, access and manipulation mechanisms exist, cordoned by stringent security. The successful operation of the proposed *asynchronous-learning-drivenEHR* solution with *International Interoperability* requires the easy, unhindered access to globally-spread healthcare data repositories with the most current data, and appropriate translation mechanisms handling mixed language and vocabulary issues. The *learning* algorithms presented herein need to be *embellished* with proper scripting and coding in order to afford seamless access, parsing, and homogenous understanding through precision semantics, of the *learned* data. Convenient, easily accessible, *available-data mirrors* is a innovative yet *super-efficient* approach to *hawk* required *LSA* data amongst the participating *membership*. Distinct and separate from the main *HSP* repositories, these frequently-refreshed *data mirrors* can embed high-end technology for super-fast and effortless universal access and visibility. The main *HSP* data stores can be protected and securely-cordoned from any external interference or access.

V. RESULTS

The *Machine Learning* algorithms presented herein utilize *Bayesian* and trivial *K-Nearest Neighbour* learning techniques.

i. *Bayesian Learning*

The simplest form of the Bayes' Theorem as presented in **[13]** is

$$P(A|B) = \frac{P(A)\,P(B|A)}{P(B)},$$

where*A* and *B* are events.

- $P(A)$ and $P(B)$ are the respective probabilities of *A* and *B*.
- $P(A \mid B)$, is the conditional probability of *A* given that *B* is true.
- $P(B \mid A)$, is the conditional probability of *B* given that *A* is true.

However, according to [12] when considering an entire sample space *S*of *n* events $A_1, A_2, A_3, \ldots A_n,$ all *mutually-exclusive*, and if any random event *B* of *S* is such that $P(B) > 0$, then we have

$$P(A_k \mid B) = \frac{P(A_k \cap B)}{P(A_1 \cap B) + P(A_2 \cap B) + \ldots + P(A_n \cap B)}$$

Since $P(A_k \cap B) = P(A_k)P(B \mid A_k)$, *Bayes' theorem* can be rewritten as [12]

$$P(A_k \mid B) = \frac{P(A_k)\,P(B \mid A_k)}{P(A_1)\,P(B \mid A_1) + P(A_2)\,P(B \mid A_2) + \ldots + P(A_n)\,P(B \mid A_n)}$$

ii. *K-NearestNeighbour*

K-Nearest Neighbour (KNN) algorithm essentially selects the *k* closest neighbours out of possible *n* options where *k*, *n*are parameters ($k \leq n$). The selection criterion used is allied to the problem space and solution envisaged; *Euclidean* and *Least Mean Squares* (LMS) distances are popular criteria. Hence the *KNN* set is these instances would be the *k closest neighbours* in terms of *Euclidean* or *LMS* distances.

1-Nearest Neighbour (INN) is a special case of the *KNN*, selecting the single closest neighbour.

In our study, we will be using a trivial form of the *K-Nearest Neighbour*technique, the selection criterion being the *step-distance*. A *single-stepfan-out* distance will be used to *learn* the new *membership* at each new transition.

iii. *Learning Probabilities*

Both *SLAsContinent* and *Country*constitute relatively static datasets. We have,

$[Continents] = [C_i], \; i \in \mathbb{N}, \; 1 \leq i \leq 5$

eg., $[Continents] = [America, Africa, Europe, Asia, Australasia] = [Am, Af, Eu, As, Au]$

$P[C_i] = 1/5 = 0.2 \quad i \in \mathbb{N}, \; 1 \leq i \leq 5$

Note : Presently some sources prescribe a *Hepta-Continent* model consisting of [*North America*, *South America*, *Antartica*, *Africa*, *Europe*, *Asia*, *Australasia*], but we will stick to the conventional and familiar *Penta-Continent* model.

[*America*] = [*Antigua and Barbuda, Argentina, Brazil, Bahamas, Barbados, Canada, ... Cuba, ...USA*]

Let *num* denote the number of countries in any continent. Thus [14],

$num[C_1 = Am] = 38 \quad \Rightarrow P(C_{1,p}) = 1/38 = 0.0263, \quad p \in N, \; 1 \leq p \leq 38$
$num[C_2 = Af] = 57 \quad \Rightarrow P(C_{2,q}) = 1/57 = 0.0175 \quad q \in N, \; 1 \leq q \leq 57$
$num[C_3 = Eu] = 52 \quad \Rightarrow P(C_{3,r}) = 1/52 = 0.0192 \quad r \in N, \; 1 \leq r \leq 52$
$num[C_4 = As] = 50 \quad \Rightarrow P(C_{4,s}) = 1/50 = 0.02 \quad s \in N, \; 1 \leq s \leq 50$
$num[C_5 = Au] = 14 \quad \Rightarrow P(C_{5,t}) = 1/14 = 0.0714 \; t \in N, \; 1 \leq t \leq 14$

Total countries according to above source = 38+57+52+50+14 = 211

However, *HSPs* and *LSAs* represent dynamically mutating *non-SLA* datasets.
The *HSP membership* globally are*dynamic* and *variable*, denoted by

$globalHSPs = [hsp_{p,a}, hsp_{q,b}, hsp_{r,c}, hsp_{s,d}, hsp_{t,e}]$
$p, q, r, s, t \in N, \quad 1 \leq p \leq 38, \; 1 \leq q \leq 57, \; 1 \leq r \leq 52, \; 1 \leq s \leq 50, \; 1 \leq t \leq 14$
$a, b, c, d, e \in N, \; 1 \leq a, b, c, d, e \leq n$, n is the *upper-bound* on *HSPs* per country.

Let B = Getting a *required-lsa-value EHR*

Applying *Bayes' Learning*

$$P(hsp\text{-}Am_{p,a} \mid B) = \frac{P(hsp\text{-}Am_{p,a})\, P(B \mid hsp\text{-}Am_{p,a})}{P(hsp\text{-}Am_{1,a})\, P(B \mid hsp\text{-}Am_{1,a}) + P(hsp\text{-}Am_{2,a})\, P(B \mid hsp\text{-}Am_{2,a}) + \ldots + P(hsp\text{-}Am_{38,a})\, P(B \mid hsp\text{-}Am_{38,a})}$$

$p \in N, \; 1 \leq p \leq 38 \quad 1 \leq a \leq n$, *n* is the *upper-bound* on *HSPs* per country

$$P(hsp\text{-}Af_{q,b} \mid B) = \frac{P(hsp\text{-}Af_{q,b})\, P(B \mid hsp\text{-}Af_{q,b})}{P(hsp\text{-}Af_{1,b})\, P(B \mid hsp\text{-}Af_{1,b}) + P(hsp\text{-}Af_{2,b})\, P(B \mid hsp\text{-}Af_{2,b}) + \ldots + P(hsp\text{-}Af_{57,b})\, P(B \mid hsp\text{-}Af_{57,b})}$$

$q \in N, \; 1 \leq q \leq 57 \quad 1 \leq b \leq n$, *n* is the *upper-bound* on *HSPs* per country

$$P(hsp\text{-}Eu_{r,c} \mid B) = \frac{P(hsp\text{-}Eu_{r,c})\, P(B \mid hsp\text{-}Eu_{r,c})}{P(hsp\text{-}Eu_{1,c})\, P(B \mid hsp\text{-}Eu_{1,c}) + P(hsp\text{-}Eu_{2,c})\, P(B \mid hsp\text{-}Eu_{2,c}) + . + P(hsp\text{-}Eu_{52,c})\, P(B \mid hsp\text{-}Eu_{52,c})}$$

$r \in N, \; 1 \leq r \leq 52 \quad 1 \leq c \leq n$, *n* is the *upper-bound* on *HSPs* per country

$$P(hsp\text{-}As_{s,d} \mid B) = \frac{P(hsp\text{-}As_{s,d})\, P(B \mid hsp\text{-}As_{s,d})}{P(hsp\text{-}As_{1,d})\, P(B \mid hsp\text{-}As_{1,d}) + P(hsp\text{-}As_{2,d})\, P(B \mid hsp\text{-}As_{2,d}) + \ldots + P(hsp\text{-}As_{50,d})\, P(B \mid hsp\text{-}As_{50,d})}$$

$s \in N, \; 1 \leq s \leq 50 \quad 1 \leq d \leq n$, *n* is the *upper-bound* on *HSPs* per country

$$P(hsp\text{-}Au_{t,e} \mid B) = \frac{P(hsp\text{-}Au_{t,e})\, P(B \mid hsp\text{-}Au_{t,e})}{P(hsp\text{-}Au_{1,e})\, P(B \mid hsp\text{-}Au_{1,e}) + P(hsp\text{-}Au_{2,e})\, P(B \mid hsp\text{-}Au_{2,e}) + . + P(hsp\text{-}Au_{14,e})\, P(B \mid hsp\text{-}Au_{14,e})}$$

$t \in N, \; 1 \leq t \leq 14 \quad 1 \leq e \leq n$, *n* is the *upper-bound* on *HSPs* per country

iv. *Learning Transitions*

Suppose the following results were returned by the *learning* run for input *learning predicates* :

a) [*Global*, *required-lsa*= Tom]
b) [*Global*, *Cluster-key* = service-fee-paid]

Table 1 : Learning Run Results

	SLAs	**Non-SLAs**
Consolidation	Asia, Sri Lanka	*HSP* = eclipse, goodhealth, *required-lsa*= Tom
	Europe, Sweden	*HSP* = happyheart
		required-lsa = Tom
Stratification	Global	*Cluster-key*=service-fee-paid ; 3 slabs a, b, c

Using the *Bayesian* form given in [12] where *S* is a sample space of *n* events $A_1, A_2, A_3, \ldots A_n,$ all *mutually-exclusive*, and if any random event *B* of *S* is such that $P(B) > 0$, then we have
Considering the previous result,

$globalHSPs = [hsp_{p,a}, hsp_{q,b}, hsp_{r,c}, hsp_{s,d}, hsp_{t,e}]$

$p, q, r, s, t \in N, \quad 1 \le p \le 38,\ 1 \le q \le 57,\ 1 \le r \le 52,\ 1 \le s \le 50,\ 1 \le t \le 14$
$a, b, c, d, e \in N, \quad 1 \le a, b, c, d, e \le n$, n is the *upper-bound* on *HSPs* per country.

For this example, let $n = 10$, n is the *upper-bound* on *HSPs* per country. Using the following *Bayes'* form [12] where S is a sample space of *n mutually-exclusive* events $A_1, A_2, A_3, \ldots A_n,$ and *B* is any random event of *S* is such that $P(B) > 0$, then we have

$$P(A_k \mid B) = \frac{P(A_k \cap B)}{P(A_1 \cap B) + P(A_2 \cap B) + \ldots + P(A_n \cap B)}$$

For *required-lsa* (*B*) = "Tom"

$$P(hsp\text{-}happyheart \mid B=\text{"Tom"}) = \frac{P(hsp\text{-}happyheart \cap B=\text{"Tom"})}{\sum P(hsp_{SWEDENc} \cap B=\text{"Tom"})} = 1 \qquad 1 \le c \le 10$$

$$P(hsp\text{-}eclipse \mid B=\text{"Tom"}) = \frac{P(hsp\text{-}eclipse \cap B=\text{"Tom"})}{\sum P(hsp_{SRILANKAd} \cap B=\text{"Tom"})} = 1/2 \qquad 1 \le d \le 10$$

$$P(hsp\text{-}goodhealth \mid B=\text{"Tom"}) = \frac{P(hsp\text{-}goodhealth \cap B=\text{"Tom"})}{\sum P(hsp_{SRILANKAd} \cap B=\text{"Tom"})} = 1/2 \qquad 1 \le d \le 10$$

Table 2 : Probabilities and Learned Results

Transit No.		**Consolidation**	**Stratification**
1	**Probability**	$P[C_i] = 0.2,\ i \in N,\ 1 \le i \le 5$	$P[C_i] = 0.2,\ i \in N,\ 1 \le i \le 5$
	Learned Result (*trivial KNN*)	America, Africa, Europe, Asia, Australasia	America, Africa, Europe, Asia, Australasia
2	**Probability**	[0.2x0.0263, 0.2x0.0175, 0.2x0.0192, 0.2x0.02, 0.2x0.0714] = [0.0053, 0.0035, 0.0038, 0.004, 0.0143]	[0.2x0.0263, 0.2x0.0175, 0.2x0.0192, 0.2x0.02, 0.2x0.0714] = [0.0053, 0.0035, 0.0038, 0.004, 0.0143]
	Learned Result (*trivial KNN*)	Antigua and Barbuda, Argentina, Brazil, Bahamas, Barbados …..211 countries.	Antigua and Barbuda, Argentina, Brazil, Bahamas, Barbados …..211 countries.
3	**Probability (*n*=10)**	[0.2x0.0263x0.1, 0.2x0.0175x0.1, 0.2x0.0192x0.1,	0.2x0.0263x0.1, 0.2x0.0175x0.1, 0.2x0.0192x0.1, 0.2x0.02x0.1, 0.2x0.0714x0.1] =

		0.2x0.02x0.1, 0.2x0.0714x0.1] = [0.00053, 0.00035, 0.00038, 0.0004, 0.00143]	[0.00053, 0.00035, 0.00038, 0.0004, 0.00143]
	Learned Result	{[America …….], [Africa ……….], [Europe, ……...Sweden, happyheart,……], [Asia, ..Sri Lanka, eclipse, Sri Lanka ,goodhealth ……], [Australasia …...]}	{[America …….], [Africa ……….], [Europe, .. Sweden, happyheart,*a*, …….], [Asia, .. Sri Lanka, eclipse, *b*, Sri Lanka ,goodhealth, *b* ……], [Australasia …...]}
4	**Probability (After Bayes' Learning)**	{0, 0, 0.0038, [0.004x0.5, 0.004x0.5] , 0} = {0, 0, 0.0038, [0.002, 0.002], 0}	{…, …, 0.0038, 0.004+0.004 , …} = {…, …, 0.0038, .008, …..}
	Learned Result (*Bayes'*)	{[Europe, Sweden, happyheart, Tom], [Asia, Sri Lanka, eclipse, Tom], [Asia, Sri Lanka, goodhealth, Tom]}	{[Europe, Sweden, happyheart, *a*], [Asia, Sri Lanka, eclipse, goodhealth, *b*]}

VI. CONCLUSION

This research studied indepth the use *Machine Learning* techniques for *Electronic Health Records* (EHR) system operation in the global healthcare industry.It was determined that present practice dictated the *synchronous* operation of *EHR-based* healthcare systems, giving rise to difficulties in access and data transmission . Further, since *EHR* creation, maintenance, and use is confined to convenient healthcare-provider and national boundaries, the underlying diversity in the data storage mechanisms and associated vocabularies require homogeneity in access, use, and understanding. Currently, no scalability potential existsnor *modalities* for *synchronous* global *EHR* consolidation, causing grave hindrance to our principle goal of true *International Interoperability*.Also, these *unorganized*, *non-homogenous* clusters of *EHR* implementations infuse and breed alarming inefficiencies into the total network;*unintegrated organization* engenders *inordinately-lengthy access times*, *vocabulary variations*, and *gross data duplication*, *incompatibility*, and *inconsistency*.These ricochet on other performance factors such as *safety and security*, *quality and reliability*, and *efficiency and effectiveness*. This paper articulated a sound and secure methodology to achieve efficient *International Interoperability* amongst all participating *HSPs*.Through *asynchronous machine learning*, earmarked *EHR* clusters are *consolidated and learned*, affording *interoperable*, *current*, *relevance* and *value-enriched EHR* data to all stakeholders. Utilizing two proven *learning* techniques, namely *Bayesian* and *K-Nearest Neighbour*, two *learning* algorithms were presented, namely, *Consolidation* and *Stratification*.

As previously mentioned, the successful operation of the proposed *asynchronous-learning-drivenEHR* solution requires the easy, unhindered access to globally-spread healthcare data repositories. Convenient, easily accessible, *available-data mirrors* is a innovative yet *super-efficient* approach to *hawk* required *LSA* data amongst the participating *membership*. Distinct and separate from the main *HSP* repositories, they are really *HSPshowcases* containing the available, most current data and may also incorporate *common-vocabulary-related* translation mechanisms enhancing the value of the *hawked* data. These frequently-refreshed *data mirrors* can embed high-end technology for super-fast and effortless universal access and visibility. The main *HSP* data stores can be protected and securely-cordoned from any external interference or access. Summing up, it is *satiating* that the new *learning-based EHR* system development solution is not only efficient and convergent towards our prime goal of *International Interoperability*; rather its capacity to circumvent or eliminate stereotypical *line*, *access*, and other *real-time issues* prevalent in present-day *Distributed Systems* makes it a practical and worthyinterpolation to the development paradigm. Indeed it represents a true endorsement of the slogan "*Asynchronous Learning for Efficient Synchronous Operation*"; a global snapshot of pertinent consolidated healthcare information presented at your local computer.

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