An Interoperable System for Disseminating Population Health Analytics in OMOP CDM: Health Risk Estimation Use Case

Hamed Abedtash

OHDSI Collaborators Meeting

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This project was originally conducted at Indiana University.



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Scope and Objectives

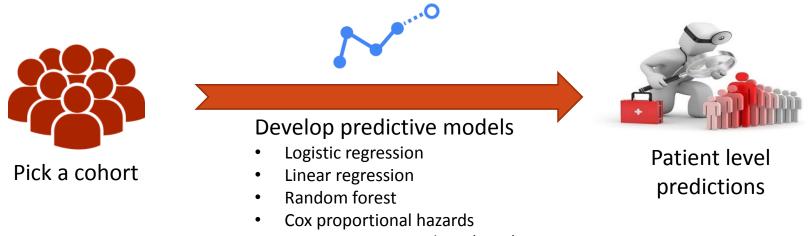
Explored challenges

- Collecting patient data for precision medicine
- Analyzing data to develop predictive models
- Testing predictive models
- Delivering risk estimations

Designed solutions

- To collect comprehensive medical records of patients
- To standardize patient medical records, both concept validations and dataset structure
- To standardize exchange of predictive models
- To provide a tool to enable testing and deploying health risk estimations in "plug-andplay" manner

Predictive models, How good they are?



- Support vector machine (SVM)
- Naïve Bayes network

Predictive models, How good they are?

Risk Prediction Models for Hospital Readmission: A Systematic Review Kansagara, D. et al. (2011). *Jama*, *306*(15), 1688-1698.

- Reviewed 7,843 papers, analyzed 26 unique models
- Poor-to-modest discriminative ability:
 - To risk-adjust readmission rates for hospital comparison with *c* statistic ranged 0.55-0.65
 - To identify high-risk patients for intervention early during a hospitalization with *c* statistic ranged 0.56-0.72
 - To estimate hospital discharge with c statistic ranged 0.68-0.83

Statistical models and patient predictors of readmission for heart failure: a systematic review

Ross, J. S. (2008). Archives of internal medicine, 168(13), 1371-1386.

- Poor-to-modest discriminative ability:
 - To patient readmission risk with c statistic of 0.60
 - To predict mortality after HF hospitalization with c statistic ranged 0.67-0.81

Problem No. 1

Predictive Models with poor-to-modest performance



Model development

- Not generalizable: Limited to the sample size
- Not reproducible: Not a good representative of the whole population; Limited to the patient characteristics in the training set
- Suboptimal results: Limited accuracy when tested on other data sources



Potential solutions

- Increase sample size of training set
- Include patients from all tiers of the population with diverse age range, race, ethnicity, genetic factors, history of diseases and comorbidities, therapies, etc.
- Compare the performance of different predictive modelling methods
- <u>We need a system that can integrate data from different centers with diverse data</u> <u>models in one matrices to run the machine learning algorithms.</u>

Challenges of Deploying Predictive Models

Development

Statistician/Data scientist

- Recode data
- Control for confounders
- Develop the model
- Evaluate the model



Deployment

IT programmer

Adding a new feature is always challenging and time limiting:

- Cross-map variables to the EHR data model
- Modify hard-coded variables



Due to the limitations in deployment:

Prediction

- Delayed use of predictive model
- Suboptimal predictions

Healthcare Provider

• Needs for an updated model

Problem No. 2

Complex and costly multi-center evaluation and deployment

Model deployment and evaluation

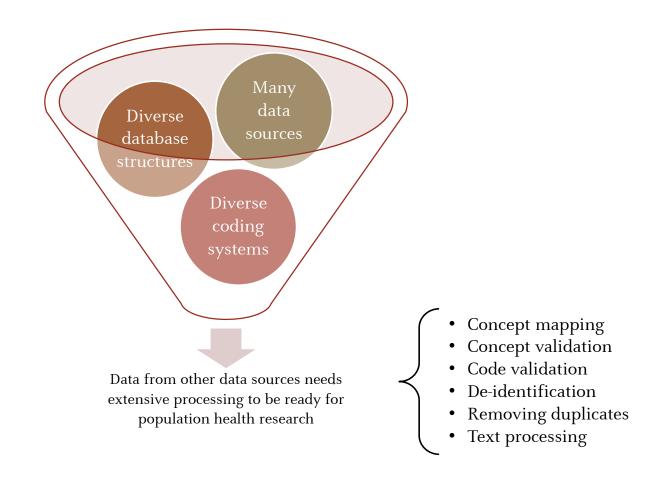
- Complex task: Different data models, Diverse coding systems
- Adding new excess costs: Development, Implementation, Maintenance, Training, Safety and privacy safeguards
- Many people are involved every time a new model is selected to be deployed or evaluated on multiple data repositories: Data Procurement Manager, IT Manager, Analyst, Computer Programmer, Statistician



Potential solutions

- Build a plug-and-play platform to deploy predictive models and generate predictions
- <u>We need an interoperable system, independent of the systems that runs the</u> <u>predictive models.</u>

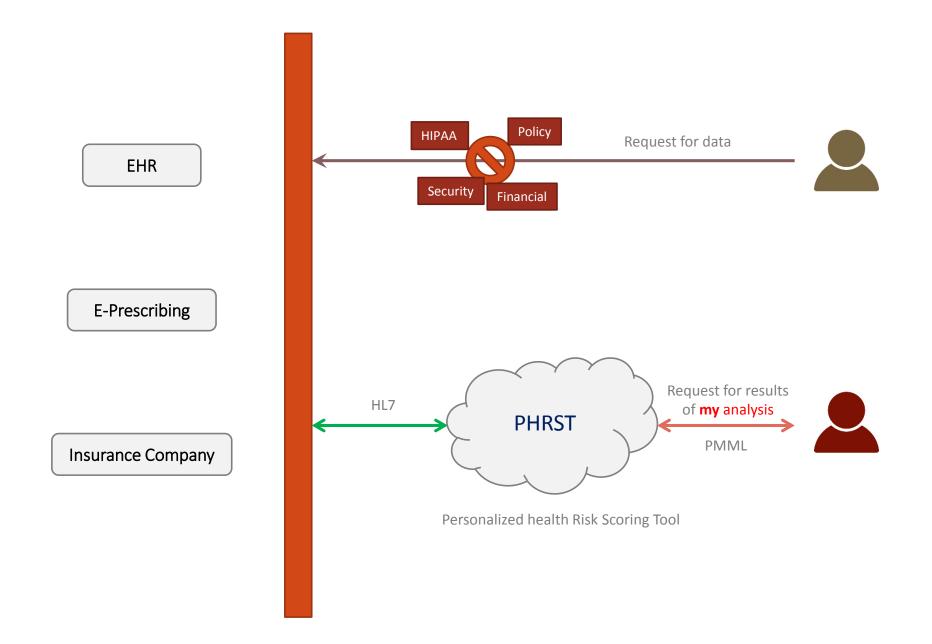
Problem No. 3 Limited access to ready-to-use data



Key Factors

Key factors to achieve goals of Precision Medicine to develop and deliver **risk estimation models**:

- "Generalizable" and "reproducible" predictive and risk scoring models
- "Comprehensive" and "ready-to-use" patient data repository
- "Convenient" evaluation of models on larger cohort of patients
- "Plug-and-play" deployment of predictive models

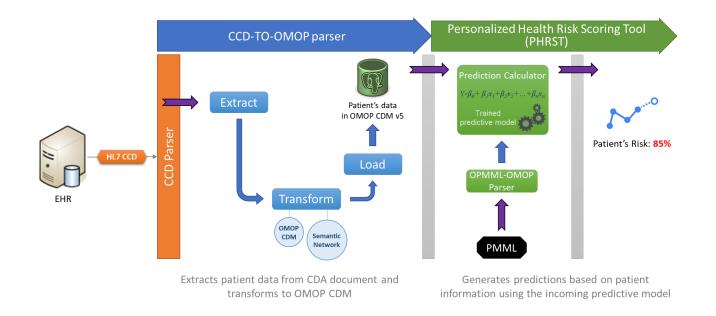


Personalized Risk Scoring Tool (PHRST)

PHRST is a tool that

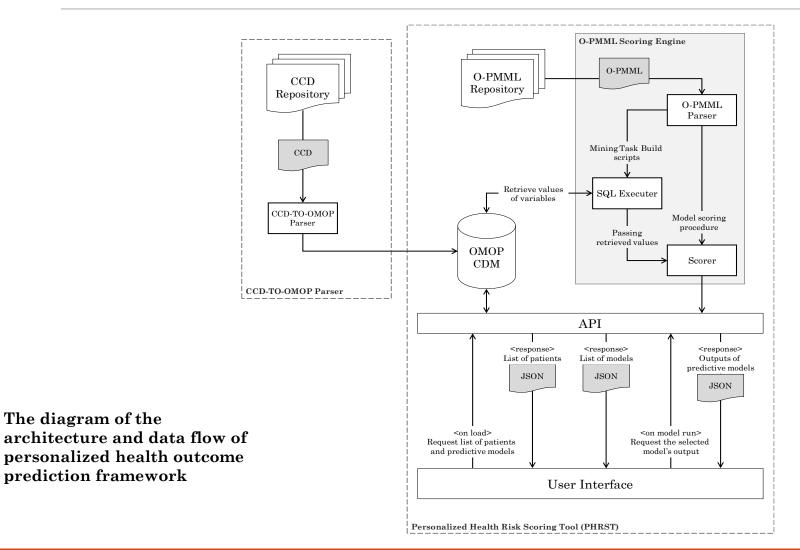
deploys (plugs) new analytics algorithms, runs (plays) the models on patient data, and returns the results

Plug-and-Play



The Interoperable System For Delivering **Personalized Predictive Analytics**

The diagram of the



The Interoperable System For Delivering Personalized Predictive Analytics

| tient List | Available Risk Scoring Models | Patient's Inf | ormation |
|---------------------------------------|---|---------------|----------------|
| tan Almond : 20170414123059 | Framingham Risk Score Panel | | Dario Martens |
| Dario Martens | Heart Failure in Atrial Fibrillation (10-year risk) | U | |
| 20170414091154 | Cardiovascular Disease (10-year risk) | | |
| goberto Armstead 20170413220837 | Cardiovascular Disease (30-year risk) | Patient ID | 20170414091154 |
| rissy Spearman | Congestive Heart Failure | DOB | 10/9/1946 |
| 20170414081338 | Oronary Heart Disease (10-year risk) | Gender | Male |
| Swyneth Weatherly # 20170414120043 | O Coronary Heart Disease (2-year risk) | | |
| Starla Yarbrough | Hypertension | | |
| d: 20170414193437 | Intermittent Claudication | | |
| awn Burrell | Diabetes | | |
| d: 20170413204411 | Stroke | | |
| nge Law d: 20170414062259 | Stroke after Atrial Fibrillation | | |
| Griselda Ahn | Stroke or Death after Atrial Fibrillation | | |
| d: 20170412235343 | | | |
| Giselle Aubin d: 20170413005458 | | | |
| Janita Baker | | | |
| d: 20170413011750 | • | | |

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The Interoperable System For Delivering Personalized Predictive Analytics



Personalized Health Risk Scoring Tool (PHRST)

Patient List Stan Almond

id: 20170414123059

Dario Martens

id: 20170414091154

Krissy Spearman

id: 20170414081338

id: 20170413204411

id: 20170414062259

Griselda Ahn id: 20170412235343

Giselle Aubin id: 20170413005458

Janita Baker

id: 20170413011750

Gwyneth Weatherly id: 20170414120043 Starla Yarbrough id: 20170414193437 Fawn Burrell

Rigoberto Armstead id: 20170413220837 Scoring Date

Cardiovascular Disease (10-year risk)

15

10

5

0

Risk (%)

Scoring Date Age TCL HDL SBP Treated Smoker Diabetic Risk Hypertention (yrs) (mg/dL) (mg/dL) (mmHg) 2014-07-21 50 170 47.5 149 No No No 6.12 % 2014-10-01 50 170 42.7 149 No No No 6.59 % 2015-02-25 51 170 42.7 149 No No No 6.89 % 2013-04-06 49 170 47.5 149 Yes No No 7.86 % 2013-06-11 49 170 47.5 149 Yes No No 7.86 %

Patient's Information Gwyneth Weatherly Patient ID 20170414120043 DOB 1/20/1964 Gender Female

6.9%

Cardiovascular Disease (10-year risk)

Latest update: 2015-02-25

01-Jul-13 01-Oct-13 01-Jan-14 01-Apr-14 01-Jul-14 01-Oct-14 01-Jan-15 Date

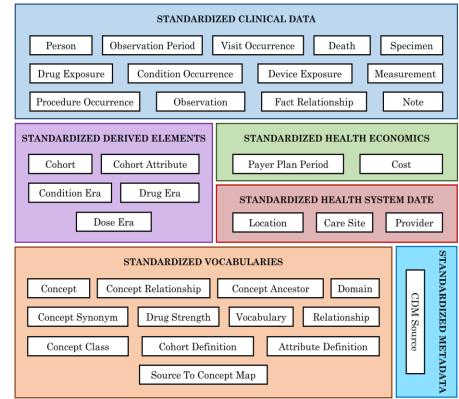
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HL7 Consolidated-Clinical Document Architecture (C-CDA)

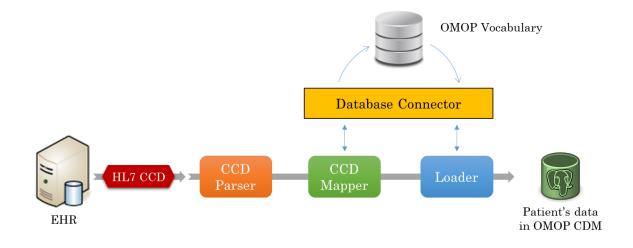
```
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    Medication: Albuterol inhalant<br/>
    Instructions: 2 puffs QID PRN wheezing<br/>
    Status: Active<br/>
 </text>
 <entry typeCode="DRIV">
   <substanceAdministration classCode="SBADM" moodCode="EVN">
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     <effectiveTime xsi:type="PIVL TS">
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     </effectiveTime>
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      codeSystem="2.16.840.1.113883.6.96"
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      <consumable>
        <manufacturedProduct>
          <manufacturedMaterial>
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             codeSystemName="RxNorm">
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           </code>
            <name>Pro-Air Albuterol</name>
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        </manufacturedProduct>
     </consumable>
    </substanceAdministration>
```

OMOP Common Data Model Version 5.1 conceptual model



CCD-TO-OMOP package

- *CCD parser*: Extracts demographics, medicines, conditions, care provider encounters, laboratory test results, and observations data from CCDs.
- *CCD Mapper*: Transforms the data into intermediate OMOP tables—which are instantiated from the OMOP CDM module—for further processing.
- *Loader*: Loads the transformed data from the intermediate tables into an OMOP CDM database.



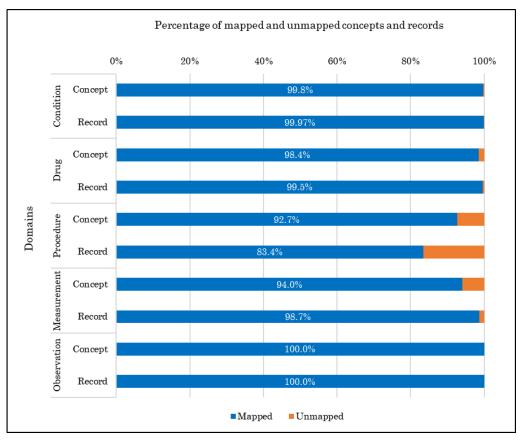
CCDs

- Continuity of Care Document: A summary of patient medical records
- Randomly selected 250 deidentified CCD documents
- HL7 version 3 (V3) consolidated clinical document architecture (C-CDA) Release 1.1 standard from Regenstrief Institute

Processed OMOP CDM tables

- Person : patient demographics
- Observation Period : periods of observing patient health events
- Visit Occurrence: visit encounters
- Condition Occurrence: diagnoses and health conditions
- Condition Era: continuous intervals of diseases and conditions
- Procedure Occurrence: procedure records
- Drug Exposure: administered medications
- Drug Era: continuous intervals of medication use
- Measurement: results of medical evaluations
- Observation: clinical observations

Overall mapping performance of concepts and records to OMOP CDM vocabulary by domain.



- We have standard for exchanging patient information, why not for predictive models?
- Predictive Model Markup Language (PMML)
 - Introduced in 1997 by the Data Mining Group
 - XML-based architecture
 - Mainly used in finance, banking, AI, auto industry
 - Very few studies in the literature on using PMML in healthcare



PMML Versioning:

- 1997: release 0.7
- 1998: release 0.9
- 1999: release 1.0
- 2000: release 1.1
- 2001: release 2.0
- 2004: release 3.0
- 2009: release 4.0
- 2011: release 4.1
- 2014: release 4.2
- 2016: release 4.3 (latest)

PMML Consortium:

- IBM
- MicroStrategy
- SASActian
- Experian
- Zementis
- Equifax
- FICO
- Fiserv
- KNIME
 - Open Data Group
- RapidMiner

- Togaware Pty Ltd
- Angoss
- KXEN
- Microsoft
- Oracle
- Portrait Software
- Prudsys
- Salford Systems
- SAP
- Software AG

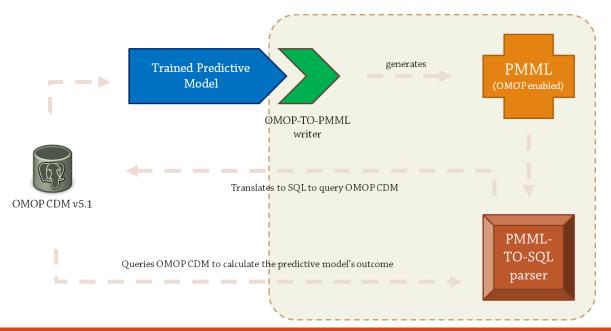
Tibco

• StatSoft

0

The "plug-and-play" requirements for sharing OMOP-based predictive models

- All concepts and mining tasks are compatible with OMOP CDM.
- The PMML must contain data mining from database.
- The PMML must contain the transformation processes of participating variables.
- The PMML must contain the predictive model's specifications: model type, participating variables, coefficients, matrices, correlations, ...
- The PMML must contain the processes to compute outputs of the model.



Benefits

- Standard format for sharing predictive model's specifications between data systems to apply on the destination data
- Independent of original and destination systems' data models
- Supports variety of machine learning algorithms
- Small, sharable, and human readable text file
- A specialized parser receives the model, extracts specifications, and runs the model



Analytics tools that support PMML

| Analytic Tool | Export PMML | Import PMML |
|---------------|------------------|------------------|
| SAS | PROC PSCORE | SAS Model Manger |
| R | pmml package | pmml package |
| KNIME | PMML writer node | PMML reader node |
| SPSS | SPSS Modeler | SPSS Modeler |

The Structure of PMML

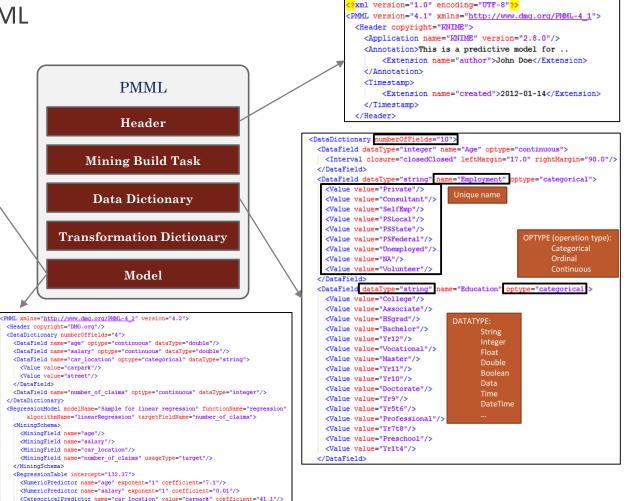
ModelStats: Represents variable statistics

- Univariate
- Multivariate
- Anova

Models: Detailed specification of the models. Supports multiple models in one PMML.

Supported models:

Association Rules Baseline Models Cluster Models General Regression k-Nearest Neighbors Naive Bayes Neural Network Regression Ruleset Scorecard Sequences Text Models Time Series Trees Vector Machine

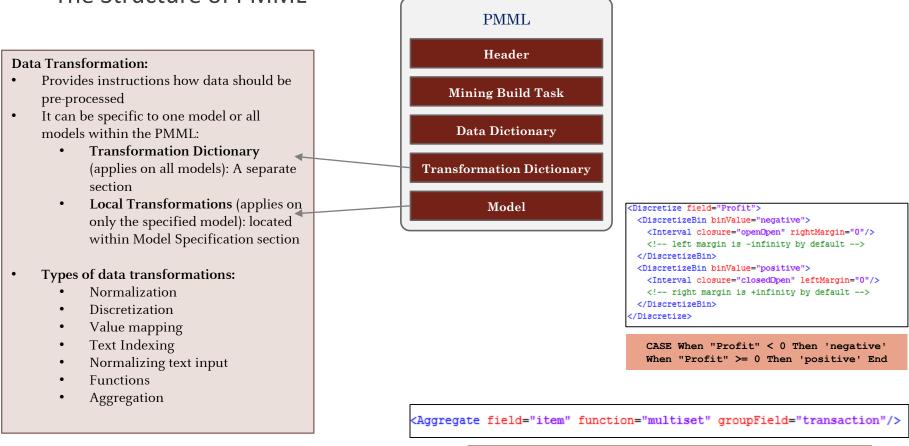


</RegressionTable>

<CategoricalPredictor name="car location" value="street" coefficient="325.03"/>

</PMML>

The Structure of PMML



Types of functions: Count, Sum, Average, Min, Max, Multiset

Framingham 10-year risk of cardiovascular disease

- Predictors
 - Age
 - Diabetes
 - Smoking
 - Treated and untreated Systolic Blood Pressure
 - Total cholesterol
 - HDL cholesterol
 - BMI replacing lipids in a simpler model

 $\sum \beta X = 3.06117 \times \ln Age + 1.12370 \times \ln Total \ Cholesterol - 0.93263 \times \ln HDL + 1.93303 \times \ln SBP_{not \ treated} + 1.99881 \times \ln SBP_{treated} + 0.65451 \times Smoker + 0.57367 \times Diabetic$

Risk of CVD in 10 *years for men* = $1 - 0.88936^{\exp(\sum \beta X - 23.9802)}$

 $\sum \beta X = 2.32888 \times \ln Age + 1.20904 \times \ln Total Cholesterol - 0.70833 \times \ln HDL + 2.76157 \times \ln SBP_{not treated} + 2.82263 \times \ln SBP_{treated} + 0.52873 \times Smoker + 0.69154 \times Diabetic$

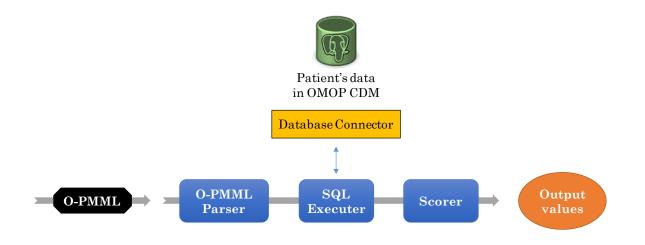
Risk of CVD in 10 years for women = $1 - 0.95012^{\exp(\sum \beta X - 26.1931)}$

xml version="1.0" Framingham 10-year risk of PMML version="4.3" xmlns="http://www.dmg.org/PMML-4_3" xmlns:xsi=" http://www.w3.org/2001/XMLSchema-instance" xsi:schemaLocation="http://www.dmg.org/PMML-4_3 //www.dmg.org/v4-3/pmml-4-3.xsd"> cardiovascular disease <Header copyright="Copyright (c) 2017 Hamed Abedtash {hamed.abedtash@gmail.com}" description= "Framingham 10-year risk of cardiovascular disease for women"> <Extension extender="omop"> <OmopCdm version="5.0.1"/> </Extension> <Extension name="author" value="Hamed Abedtash"/> <Application name="OMOP-PMML Writter" version="0.1"/> Added new schema in <Timestamp>2017-04-30 16:52:26</Timestamp> </Header> **Mining Build Task section** finingBuildTask> <Extension name="age" extender="omop": <InputFields> <InputField name="INDEX DATE" displayName="Index date (YYYY-MM-DD)" optype="continous" <!-- Data dictionary includes unprocessed data from database --> D" displayName="OMOP Person ID" optype="continuous" dataType= <DataDictionary numberOfFields="??"> < !-- Risk score: the risk of CVD --> displayName="Database schema" dataType="string"/> <DataField name="risk" displayName="10-year CVD Risk" optype="continuous" dataType="double"/> <!-- Age: The age of patient at the index date, coming from PERSON table --> ar from date '@INDEX DATE')-year of birth as AGE from <DataField name="age" displayName="Age" optype="continuous" dataType="double"/> n id=@PERSON ID; <!-- Total cholesterol: Total cholesterol measure at the index date --> <DataField name="TCL" displayName="Total Cholesterol" optype="continuous" dataType="double"/> op"> < --- HDL: HDL measure at the index date --> <DataField name="HDL" displayName="HDL" optype="continuous" dataType="double"/> TE" displayName="Index date (YYYY-MM-DD)" optype="continous" <!-- Treated for Hypertension (True/False): Whether patients has been taking medications for D" displayName="OMOP Person ID" optype="continuous" dataType= systolic blood pressure in the last 30 days of the index date --> <DataField name="HTNTRT" displayName="Treated for Hypertension (y/n)" optype="categorical" dataType displayName="Database schema" dataType="string"/> ="boolean"> <Value value="1"/> ct meas.person id, meas.measurement concept id, <Value value="0"/> max.MEAS DATE </DataField> nct person id, measurement concept id, value as number, < --- Systolic Blood Pressure --> rom @SCHEMA.measurement <DataField name="SBP" displayName="Systolic Blood Pressure" optype="continuous" dataType="double"/> ent concept id in (3027114) and measurement date < EX DATE', 'YYYY-MM-DD') <!-- Smoker: True/False, whether patient is a current smoker --> n id=@PERSON ID) meas <DataField name="smoker" displayName="Smoker(y/n)" optype="categorical" dataType="integer"> nct person id, measurement concept id, <Value value="1"/> t date) over(partition by person id,measurement concept id) as <Value value="0"/> easurement </DataField> ent concept id in (3027114) and measurement date < <!-- Diebtes: True/False, whether patient is diabetic --> EX DATE', 'YYYY-MM-DD') <DataField name="diabetic" displayName="Diabetic(y/n)" optype="categorical" dataType="integer"> n id=@PERSON ID) measmax <Value value="1"/> measmax.person id and meas.measurement date=measmax.MEAS DATE) m tcl <Value value="0"/> </DataField> 27 </DataDictionary>

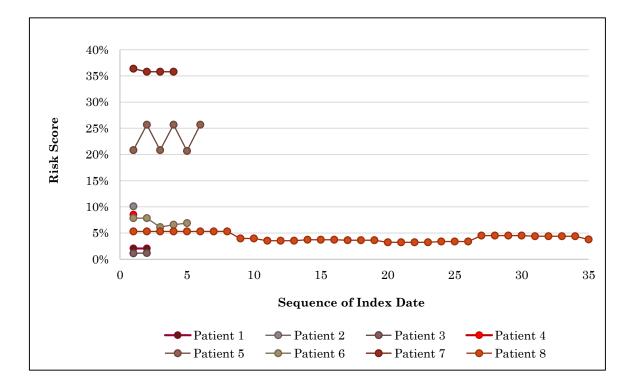
| | Data transformation | | | | |
|---|--|---|--|--------------------------|--|
| Framingham 10-year risk of | | | | | |
| <pre>CDerivedField name="logAge"</pre> | | dataType="double" optype="continuous"> | | | |
| cardiovascular dispaso | cardiovascular disease | | | | |
| <pre><rreidker <="" field="ag" pre=""></rreidker></pre> | | e"/> | | | |
| | | | | | |
| | | | | | |
| | - | dataType="double" optype="continuous"> | | | |
| | <pre><apply function="ln"></apply></pre> | | | | |
| (1) Define production model (s) | <pre>/FieldDef field=UTC</pre> | <u>ት"/></u> | | | |
| | Defines predictive model <regressionmodel algorithmname="Cox</th></tr><tr><th>proportional-hazards regression" functionname="regression" isscorable="true" modelname="framingham10ycvdmen"></regressionmodel> | | | SSION algorithmutame Cox | |
| <pre><miningschema></miningschema></pre> | | | | | |
| <pre><miningfield name="hazard" usagetype="predicted"></miningfield></pre> | | | | | |
| <miningfield name="logAge" usagetype="active"></miningfield> | | ."/> | | | |
| <miningfield name="logTCL" usagetype="active"></miningfield> | <pre><miningfield name="logTCL" usagetype="active"></miningfield></pre> | | | | |
| <miningfield name="logHDL" usagetype="active"></miningfield> | <miningfield name="logHDL" usagetype="active"></miningfield> | | | | |
| <miningfield name="logSBP_TRT" usagetype="active"></miningfield> | | rue then put logSBP_NOTTRT=0 and return logSBP_TRT=ln of SBP> dataType="double" optype="continuous"> | | | |
| | <pre></pre> (MiningField name="logSBP_NOTTRT" usageType="active"/> | | | | |
| < <u>MiningField name="smoker" usageType="active"/></u> < <u>MiningField name="diabetic" usageType="active"/></u> | | p"/> | | | |
| | | | | | |
| | | OTTRT" dataType="double" optype="continuous"> | | | |
| <output></output> | <output></output> | | | | |
| <outputfield dat<="" name="predicted_hazard" optype="continuous" th=""><th>al" dataType="boolean"></th></outputfield> | al" dataType="boolean"> | | | | |
| "predictedValue" isFinalResult="false"/> | "HTNTRT"/> | | | | |
| <outputfield datatyp<="" name="hazard_ratio" optype="continuous" th=""><th>pe="integer">1</th></outputfield> | pe="integer">1 | | | | |
| "transformedValue" isFinalResult="false"> | n return 0. if not treated, then return 1n of SBP> | | | | |
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| | | ISBP"/> | | | |
| | | | | | |
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| isFinalResult="true"> | | | | | |
| <apply fucntion="-"></apply> | | al" dataType="boolean"> | | | |
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| <apply fucntion="pow"></apply> | | pe="integer">1 | | | |
| <constant>0.95012</constant> <fieldref field="hazard ratio"></fieldref> | | n return 0. if not treated, then return ln of SBP> | | | |
| | | SBP"/> | | | |
| | integer">0 | | | | |
| | | | | | |
| | | | | | |
| | | | | | |
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| <numericpredictor coefficient="1.20904" name="logTCL"></numericpredictor> <numericpredictor coefficient="-0.70833" name="logHDL"></numericpredictor> | | | | | |
| - CONTRACTOR CONTRACTOR | | | | | |

O-PMML scoring engine

- PMML defines the specifications of the algorithm,.
- The scoring engine applies the model on data.



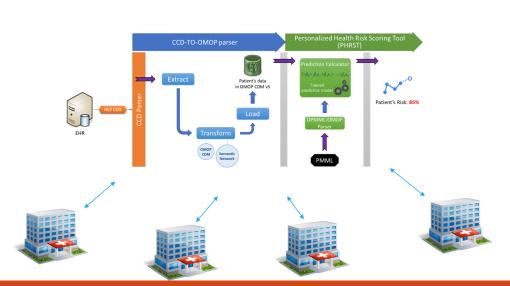
The timeline of estimated 10-year risk score of cardiovascular disease of 8 patients that had full set of required values to generate scores.

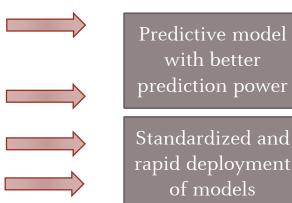


Conclusion

The developed cloud-based system:

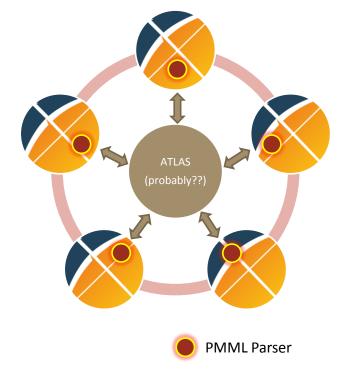
- Enables to collect and process patient medical records from disparate repositories with diverse coding systems in a real-time manner for population health research
- Enables to evaluate the performance of predictive models across multiple databases with no need to relocate data
- Enables to deploy predictive models as "plug-and-play" units
- Enables to deliver health risk estimation at the point-of-care





What does it mean for OHDSI?

- Share analytics across OHDSI collaborators/systems in real-time manner
 - The analytics request is submitted to the cloud (ATLAS??) in PMML, or specified through a GUI.
 - ATLAS passes over the uploaded or generated PMML to OHDSI entity.
 - Parsing engine (located in the OHDSI) entity mines the CDM and performs the requested analytics. So, data does not leave data owner's system.
 - The analytic results are sent back to ATLAS.
 - The PMML can be re-used for other entities.
 - The results can be archived for other collaborators' use.



Future work

PMML needs to be tested for

- Cohort selection
- Descriptive analysis
- Other statistical algorithms

Thank you!

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*This project was originally conducted at Indiana University.