Predicting 1-year risk of Heart Failure for patients with Type 2 Diabetes

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Why?

• Patient-level prediction of the risk of HF in T2DM can potentially help to define the optimal therapeutic strategy and can improve healthcare outcome.

• For example, under current Diabetes Guidelines the use of Thiazolidinediones (TZDs) is cautioned in patients at risk of HF.

• No viable prediction models exist for this problem.

• There is a need for an effective, well calibrated, externally validated prediction model.
Among pharmaceutically treated T2DM patients (T), we aim to predict which patients at a defined moment in time (t=0) will experience Heart Failure (O) during a time-at-risk of 1 year. Prediction is done using only information about the patients in an observation window prior to that moment in time.
Pharmaceutically treated T2DM

- Initial Event Cohort
  - Metformin, DPP-4 inhibitors, GLP1s, SGLT2s, TZDs, Sulfonylureas, Insulin
- at least 1 occurrences of a condition occurrence of Type II Diabetes
  - starting between all days Before and 365 days After event index date

- 365 days continuous observation

- Inclusion Criteria #1: No Type I diabetes
- Inclusion Criteria #2: No Secondary Diabetes

- Limit qualifying cohort to: earliest event per person

Cohort Definition available at: http://www.ohdsi.org/web/atlas/#/cohortdefinition/1769345
Heart Failure

- A condition occurrence of Heart Failure
- Inpatient Visit (if available in database)

- Limit qualifying cohort to: all events per person.

Cohort Definitions available at:
Hospitalisation:
http://www.ohdsi.org/web/atlas/#/cohortdefinition/1769346

Non-Hospitalisation:
http://www.ohdsi.org/web/atlas/#/cohortdefinition/1769347
We developed models with multiple algorithms (Gradient Boosting Machines, Lasso Logistic Regression, Random Forest).

We used the following covariates for model development:
- Gender
- Age Group (5yr bands)
- Race
- Ethnicity
- Index Year and Month
- Condition Occurrence Long Term
- Drug Exposure Long Term
- Procedure Occurrence Long and Short Term
- Measurement Long and Short Term

Design and implementation of a standardized framework to generate and evaluate patient-level prediction models using observational healthcare data

Jenna M Reps, Martijn J Schuemie, Marc A Suchard, Patrick B Ryan, Peter R Rijnbeek

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**Abstract**

**Objective**

To develop a conceptual prediction model framework containing standardized steps and describe the corresponding open-source software developed to consistently implement the framework across computational environments and observational healthcare databases to enable model sharing and reproducibility.
## External Validation

### Train

- **Model**: Train

### Apply

- **2**: Apply
- **11**: Evaluate

### Evaluate

- **Auc2, Cal2**
- **Auc, Cal**
- **Auc11, Cal11**

### Database Details

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<th># of T2DM</th>
<th>Outcome</th>
<th># of HF</th>
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</table>
## Results

A Heatmap showing the AUROC values for different development and validation databases. The AUROC values range from 0.5 to 1.0.
Optum Panther Calibration

See poster 27 in the showcase for more on the smooth calibration.
Conclusions

• Very good model performance across diverse external validation sets with respect to discrimination and calibration.

• The study demonstrates the impact of the OHDSI Patient Level Prediction framework on prediction model generation and external validation. Creating capabilities to do this at a global scale.

If you are a data stakeholder you can validate this study using the package available at:
https://github.com/OHDSI/StudyProtocolSandbox/tree/master/HFinT2DMValidation