In a Nutshell

A League of Disease Models/Consumers Report

Population Characteristics:
- Age, Male, Race, SBP, DBP, A1c, Smoke, BMI, HDL, LDL, Trig, TC, ACR, Lipid Ratio
- Age At Diagnosis Of Diabetes, AF, Survive Stroke, Survive MI, MicroAlbuminuria, Macroalbuminuria, Diabetes Type 2, Treated for Hypertension, Family History CHD, Rheumatoid Arthritis, Townsend Index, A1c Change, BMI Change, DBP Change, SBP Change, HDL Change, LDL Change, Trig Change, TC Change, Smoke Change, Year

Ranking Models per populations

Disease modelers who develop risk equations should add a temporal correction term within biomarker change introduced in the first year.

LDL Change, Trig Change, Townsend Index, A1c Change, CHD, Rheumatoid Arthritis, Type 2, Treated for MicroAlbuminuria

\[
\text{Method_A1c} = NDR_{35} + KP_{Total} + 34 + 2.19 \times 10^{-3} \times \text{Age} + 0.49 \times \text{Sex} - 0.0001 \times \text{BMI}\]

Best Model

\[
\text{ASPEN} = 32.4 + 49.4 + 18.6 + 4.4 + 12.3 + 0.1 \times \text{Age} + 0.05 \times \text{Sex} - 0.001 \times \text{BMI}\]

Inputs are based on secondary data:
- Published Risk Equations
- Published Clinical Trials: i.e. no real individual data
- Other publications

Outputs:
1. Clinical outcomes / Deaths
2. Costs / Quality of Life
3. Population / Equation / Hypothesis fitness

ABSTRACT

OBJECTIVES:
To figure out what disease models/equations/hypothesis work best on what populations.

METHODS:
1) Extraction of multiple published disease models/risk equations for cardiovascular disease and multiple diabetic population distributions and outcomes. The populations used were UKPDS, ASPEN, ADVANCE, ACCORD, NDR, KP.
2) Implementation of these components and systematic cross validation of models against populations using micro-simulation and relying on computing power.
3) Defining a fitness score to convert multiple outcome differences into a single number.
4) Defining different queries with weights to rank model / population fitness.

The methods avoid using individual data and rely on more accessible summary data.

RESULTS:
The fitness score matrix uses color coding and ranking to visually demonstrate the fitness between G24 populations/subsets and 64 combinations of published risk equations and hypotheses. The results show that different combinations of risk equations behave differently on different population cohorts. For each query, the system ranks the models. Models that implement the following two corrections generally behaved better:
1) Temporal correction for treatment improvement
2) Biomarker change introduced in the first year.

CONCLUSIONS:
1) Modelers should talk in terms of best fitting model rather than best model since in many cases, the best model changes according to specifics of the query.
2) Disease modelers who develop risk equations should add a temporal correction term within their risk equations to prevent model outdated.
3) The fitness score function allows comparing behavior of different populations using a similar metric and provides a visual explanation of current understanding of disease progression.

MODEL

**FITNESS: LOW SCORE = GOOD FITNESS**

**OVERALL MODEL RANKING RESULTS**

**Best Model**

Temporal treatment correction is a good idea! It accounts for model outdated

**References:**

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