Use of unstructured text data in electronic health records to improve patient-level prediction models

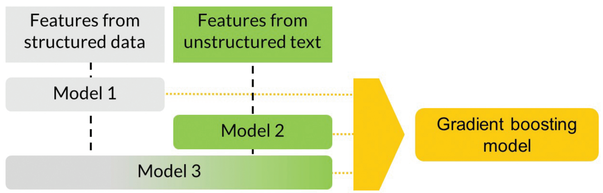
PRESENTER: **Tom M. Seinen**

INTRO:

- Lots of unstructured text available in OMOP cdm databases.
- Clinical text possibly contains additional/other information compared to structured/coded data.
- Use this information in PLP models.
- **Contributions**:
  - Customizable language independent NLP pipeline for within the OHDSI framework
  - Example study on a Dutch OMOP cdm database
- **Objective**:
  - Explore the contribution of features extracted from clinical text to the development of patient-level prediction models.

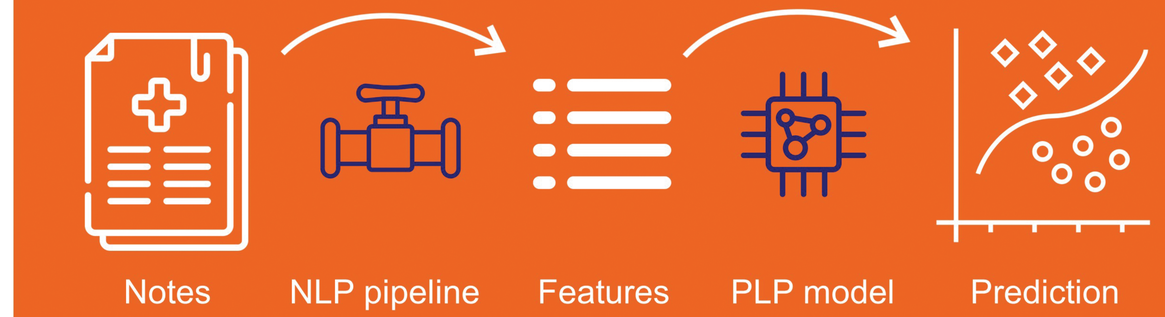
METHODS

- **Natural language processing pipeline**
  1. Retrieve cohort notes from CDM
  2. Pre-process note text
  3. Tokenize note text
  4. Vectorize text: Numeric representation
- **Proof of concept study**
  - Database: ***Integrated Primary Care Information (IPCI)***
  - Target: ***Type 2 diabetes adult patients (16,437)***
  - Outcome: ***30-day risk of heart failure (92)***
- **Features/Covariates:**
  - Observation time: ***1 year***
  - Structured data:
    - ***All FeatureExtraction covariates*** (30d/365d)
  - Unstructured text:
    - ***1 and/or 2 ngrams, bag-of-words(TFIDF)*** (365d)
- **Experimental setup**



RESULTS

Model	AUC (CI)	AUPRC
1 Structured	0.67 (0.56-0.79)	0.012
2a Text n=1	0.68 (0.56-0.97)	0.011
2b Text n=1,2	0.69 (0.58-0.80)	0.012
3a Struct. + Text n=1	0.80 (0.73-0.88)	0.022
3b Struct. + Text n=1,2	0.71 (0.59-0.82)	0.017



Feature extraction from unstructured **clinical text** for **patient-level prediction**

TRITON: Text Represented In Terms Of Numeric-features
https://github.com/mi-erasmusmc/Triton

Model settings

Split:	75% training, 25% test.
Gradient boosting:	maxDepth: 17; minRows=2; ntrees:100; learnRate:0.1
Hyperparameter tuning:	3-fold cross-validation

NLP pipeline settings:

Preprocessing:	Lowercase; digit and symbol removal
Tokenization:	Word tokenization (stringi)
Stopword removal:	Dutch stopwords (SnowballC)
Word ngrams	Uni and bigram (n=1,2)
Min. term frequency:	50
Min. percentage of documents with a term:	0.1%
Max. percentage of documents with a term:	40%

Preprocessing additional options:

- Dictionary/CDM vocabulary search
- Specific regex rules

Text representations:

- Bag-of-words
- TFIDF
- To be implemented:
  - *Topic Models (LDA)*
  - *Embeddings*
    - *Word (GloVe)*
    - *Document (GloVe aggregated, Doc2vec)*
  - *Transformers (BERT, BioBERT)*

Discussion: Information in Coded data vs Clinical text

- Depends on:
  - Database: EHR (lot of text) vs claims (mainly coded)
  - Problem settings with much text and few coded data:
    - Psychology/Depression
    - Family situations
    - Lifestyle
- If structured data is well-coded (high quality), the clinical text will not provide additional information.

Tom M. Seinen, Jan A. Kors, Erik M. van Mulligen, Peter R. Rijnbeek

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