Visualisations in healthcare

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Humane Visual AI: Telling the Stories Behind a Medical Condition

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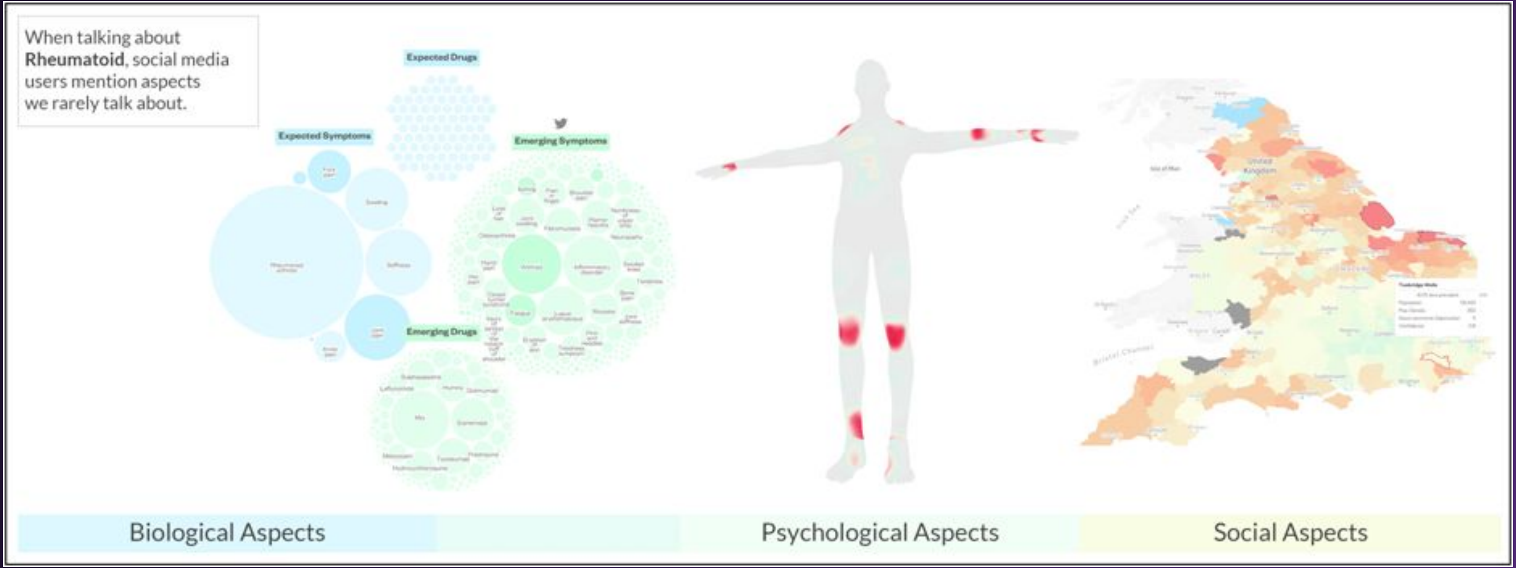
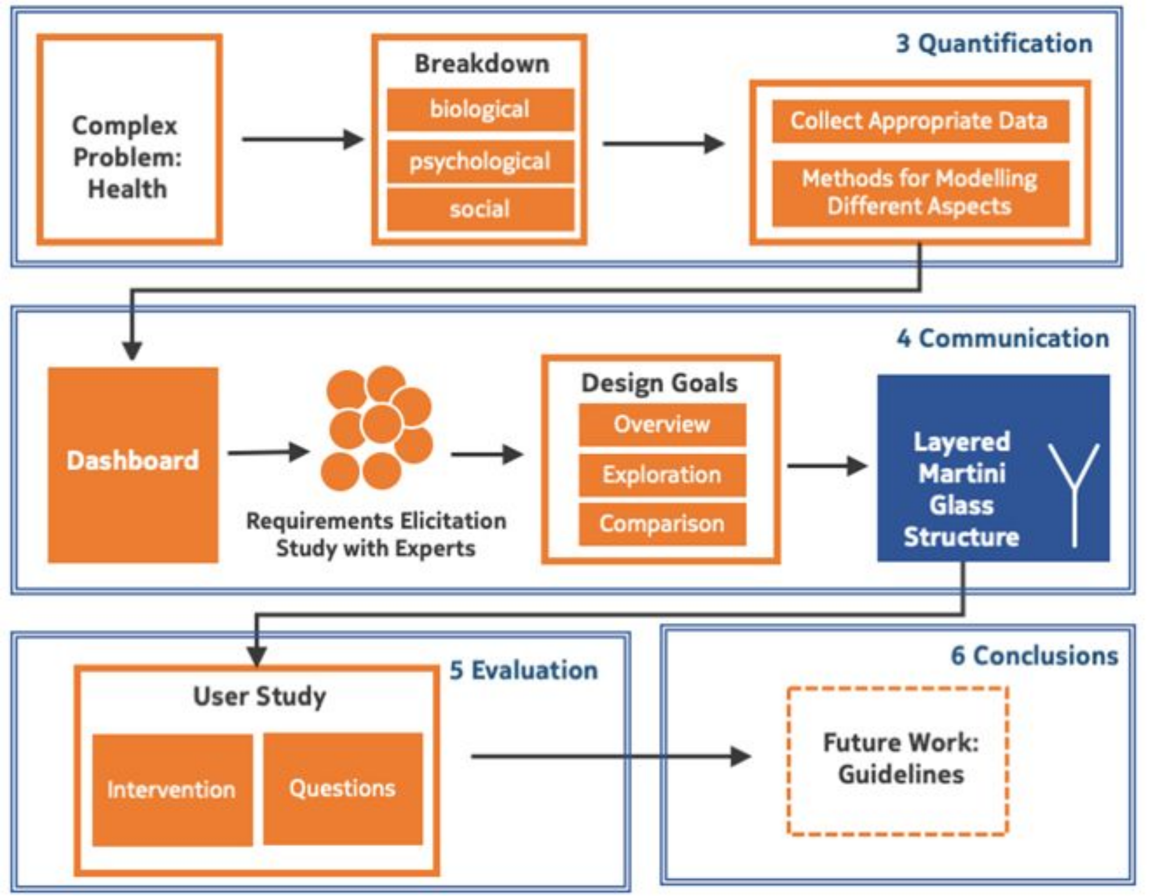


Presented by : Aimal Khan

Introduction

- This paper investigates various factors associated with medical conditions beyond the normal biological diagnoses
- These factors are:
  - Biological (current standard)
  - Psychological – related to emotional wellbeing, depression and anxiety
  - Social – related to economic affluency
- Medical conditions, when considering such multi-dimensional aspects are difficult to quantify and by extension, difficult to assess
- The authors propose a new visualization tool to build a complete picture behind a diagnosed medical condition through the use of the proposed Bio-Pyscho-Social model

Bio-Psycho-Social Model



Quantifying Biological Aspects

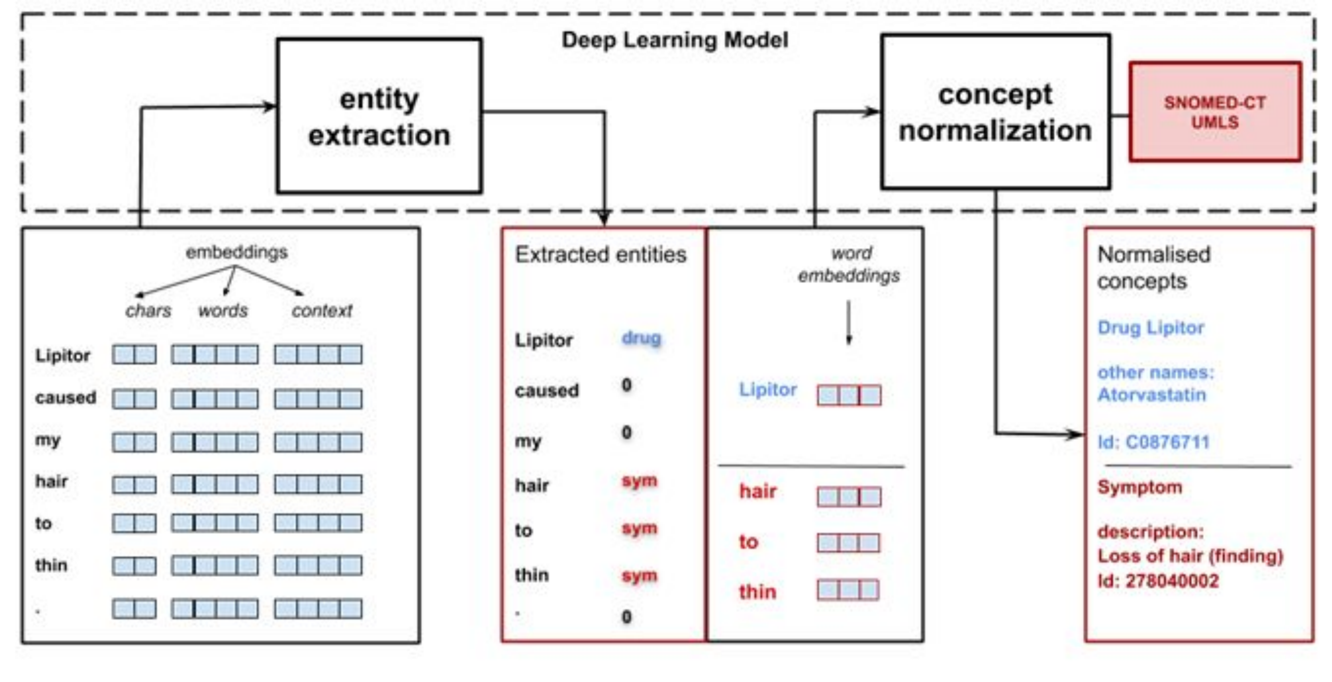
- ➢ In this paper 14 medical conditions are studied
- ➢ For biological aspects, a standardized naming convention, SNOMED-CT (Systematized Nomenclature of Medicine – Clinical Terms) is used
- ➢ With this, links between the symptoms/drugs with the entries in the SNOMED-CT database can be established
- ➢ For example, Rheumatoid Arthritis was associated with
  - Symptoms: stiffness, tenderness, swelling, and pain in joints
  - Drugs: Leflunomide and Celecoxib

Quantifying Psychological Aspects

- ➢ In order to quantify psychological aspects, two sets of experiences are explored that the patients mentioned:
  1. All the drugs and symptoms,
  2. Emotions, and
  3. body parts
- ➢ 1. is challenging as people use different terminologies for expressing the same symptom (e.g., *brain fog / clouded consciousness*), which also needs to be linked with the same SNOMED-CT entry
- ➢ This is formulated as a Natural Language Processing (NLP) problem and with the use of deep learning both of these problems are solved using the Reddit dataset
- ➢ For 2. the “EmoLex” word-emotion lexicon framework is used for classifying words into one of the eight basic emotions such as: anger, joy, disgust etc.
- ➢ These classifications are then linked via pointwise mutual information analysis to establish the association between a given condition and each emotion category
- ➢ For 3. a similar approach is used to link words to specific body parts (such as lips, tongue to mouth)

Quantifying Psychological Aspects

- Deep learning based model for medical mention extraction from social media and association with SNOMED-CT



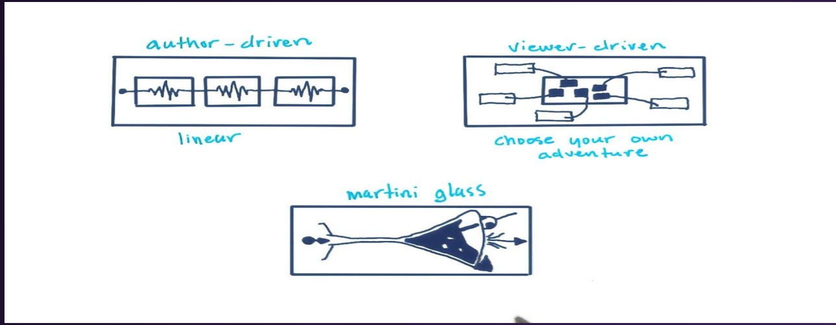
Quantifying Social Aspects

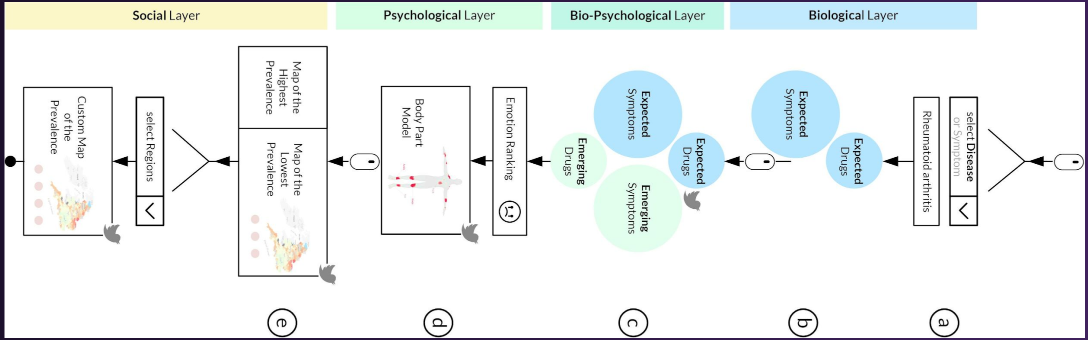
- Social aspects are explored to establish correlations between people’s economic status that has an influence on people’s well being which can then be linked with certain medical conditions
- On the other hand, certain medical conditions may impact people’s social life
- In this work, such socio-economic conditions are associated with disease prevalence
- This is achieved by associating census data with prescription data
- For linking drugs with medical conditions, another database (DrugBank) is used
- With this, for a given condition, a set of associated drugs are found in order to estimate the total number of prescriptions for this condition in a certain location

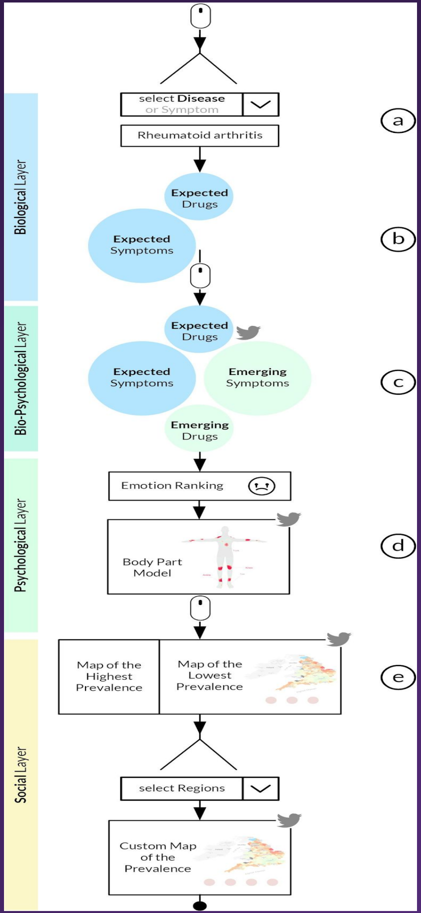
Communication - Layered Martini Glass Structure

➢ Narrative Storyline of the Visualisation

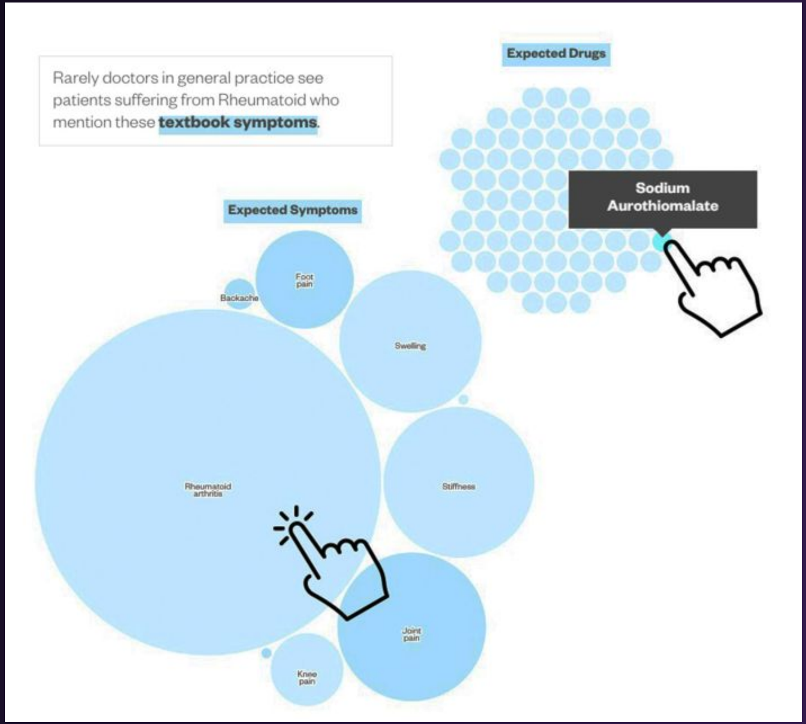
- From author driven to viewer driven



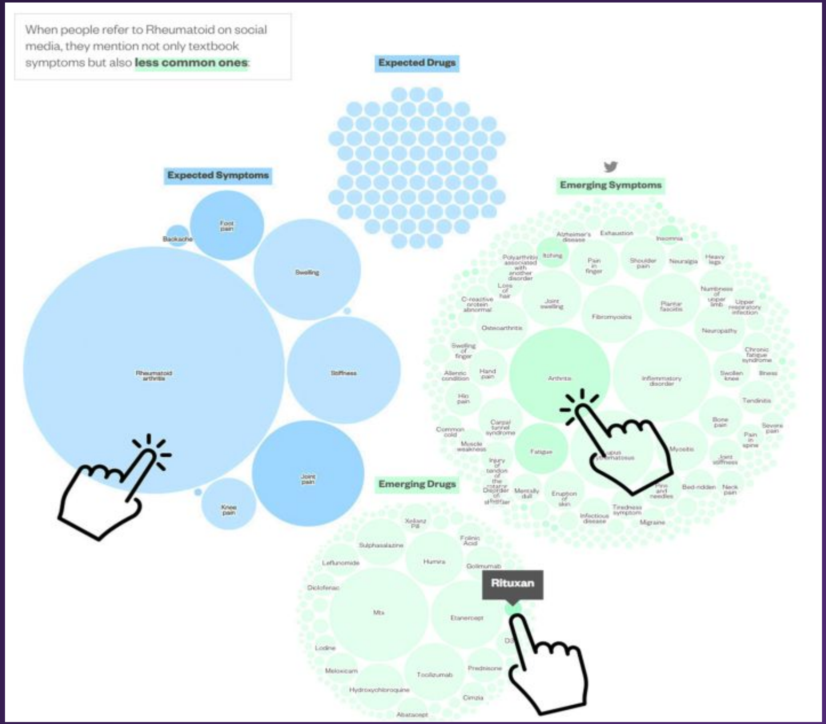




Visualising - Biological Aspect



Biological Aspect - Blue Bubbles

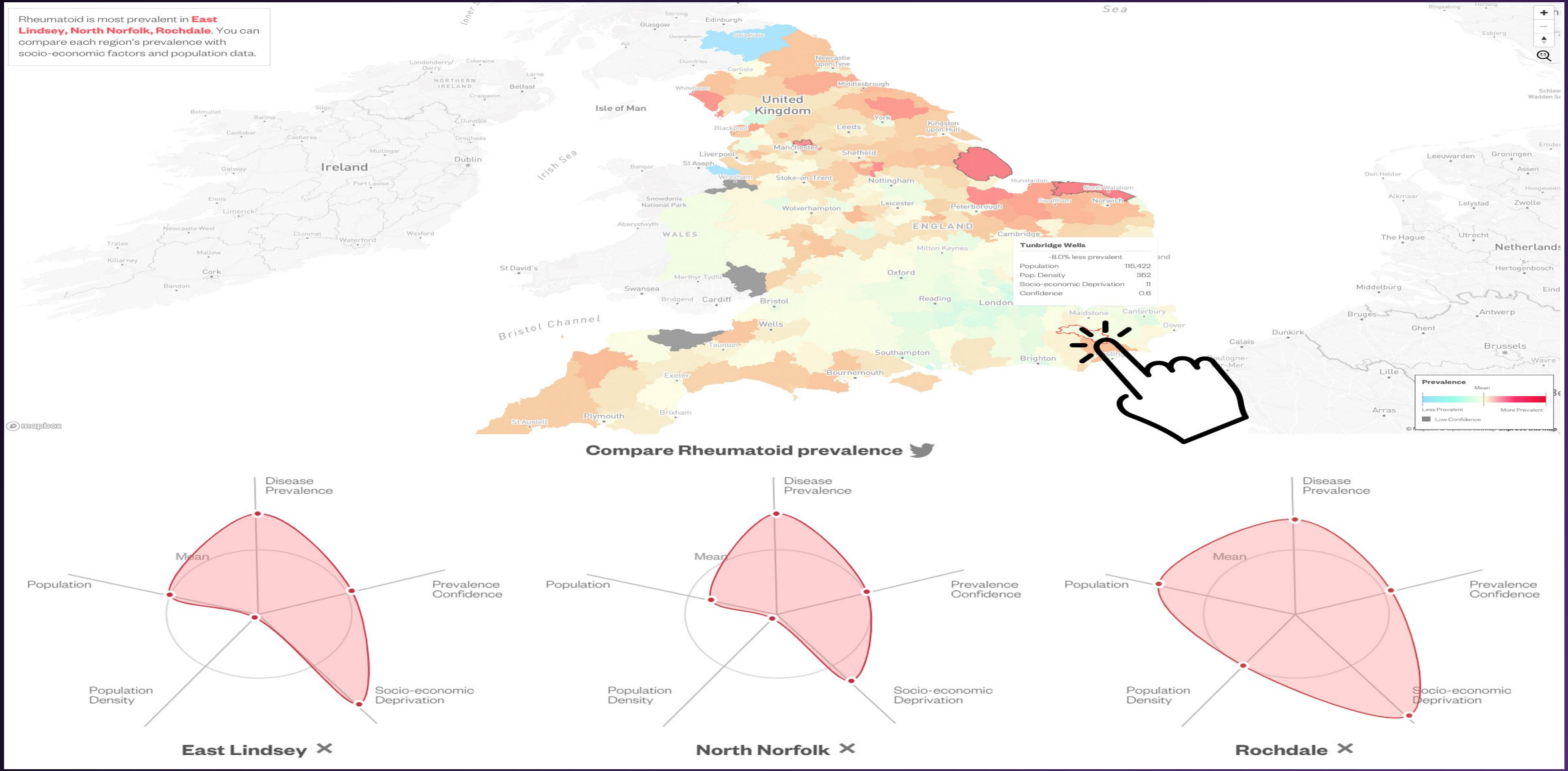


Bio-Psycho Layer - Blue Green Bubbles

Visualising - Psychological Aspect

Psychological Aspect - Body Part model

Visualising - Social Aspect



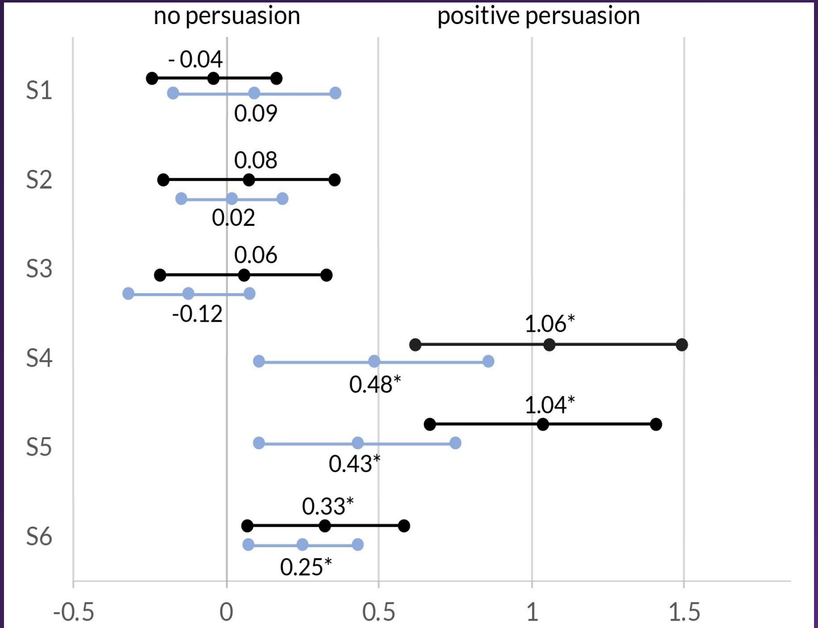
Social Aspect - Choropleth map

Evaluation and Conclusion

Persuasion Likelihood

#	Statement	NP	NWP	PP
	In treating medical conditions, doctors should:			
S1	treat only the corresponding symptoms	.00	**.04**	-.04
S2	consider also the emotional state of patients	.00	-.10	**.10**
S3	consider also the socio-economic background of patients	.06	-.12	.06
S4	analyse what their patients shared on social media	-.27	**.21**	.06
	In treating your medial conditions, your doctor should:			
S5	analyse what you shared on social media	-.27	**.21**	.06
	Artificial Intelligence can:			
S6	improve healthcare	-.04	-.06	**.10**

Average Opinion change



Hiwot Girma Lassa

Big Data Analysis and Services: Visualization of Smart Data to Support Healthcare Analytics

What is big data?

- Big Data is a high volumes of a wide variety of valuable data can be easily generated or collected at a high velocity.
- Big Data is creating significant new opportunities for organizations to derive new value and create competitive advantage from their most valuable asset.

Big Data Characteristics

- Volume
- Variety
- Velocity
- Visibility

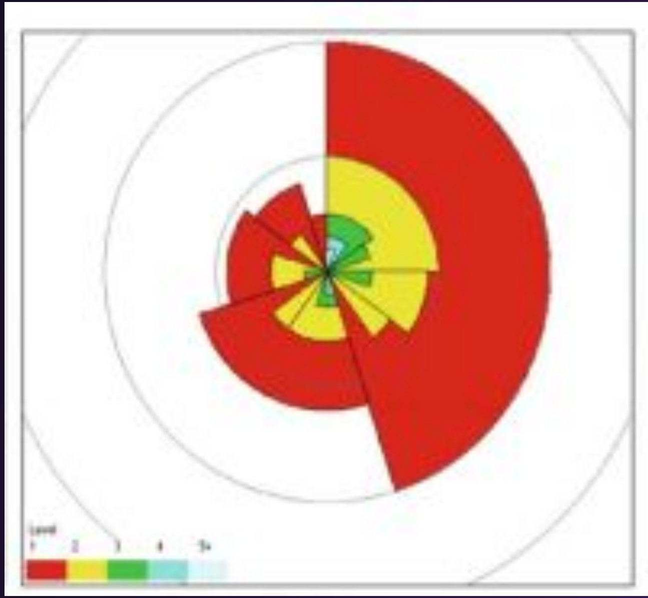
Big Data applicable areas

- Healthcare services
- Shopping market
- Bank Industry

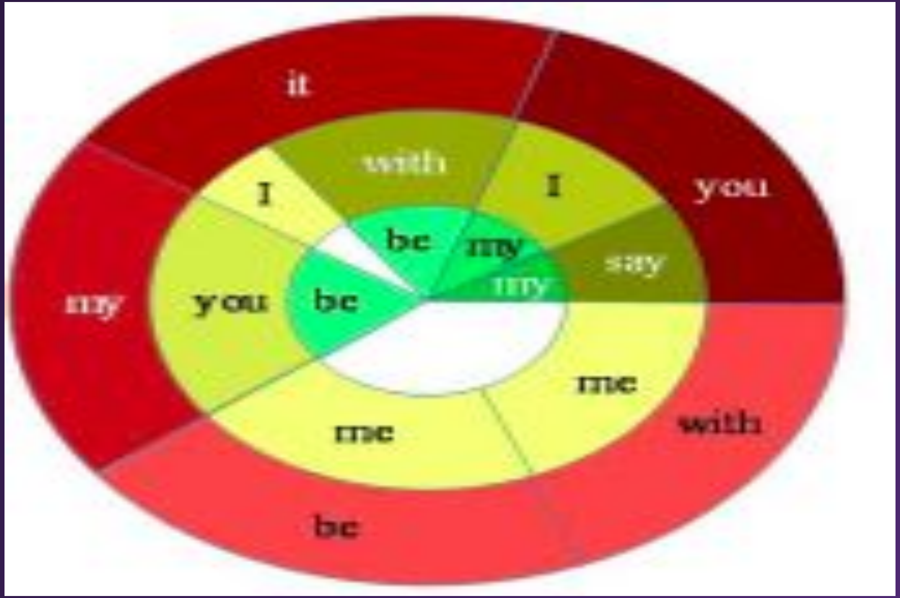
Smart Data

- Smart data is new tool for real-life application.
- Big data gets turned into Smart Data
- Smart data in healthcare sector to help them work smarter, rather than harder

Smart data Visualization models



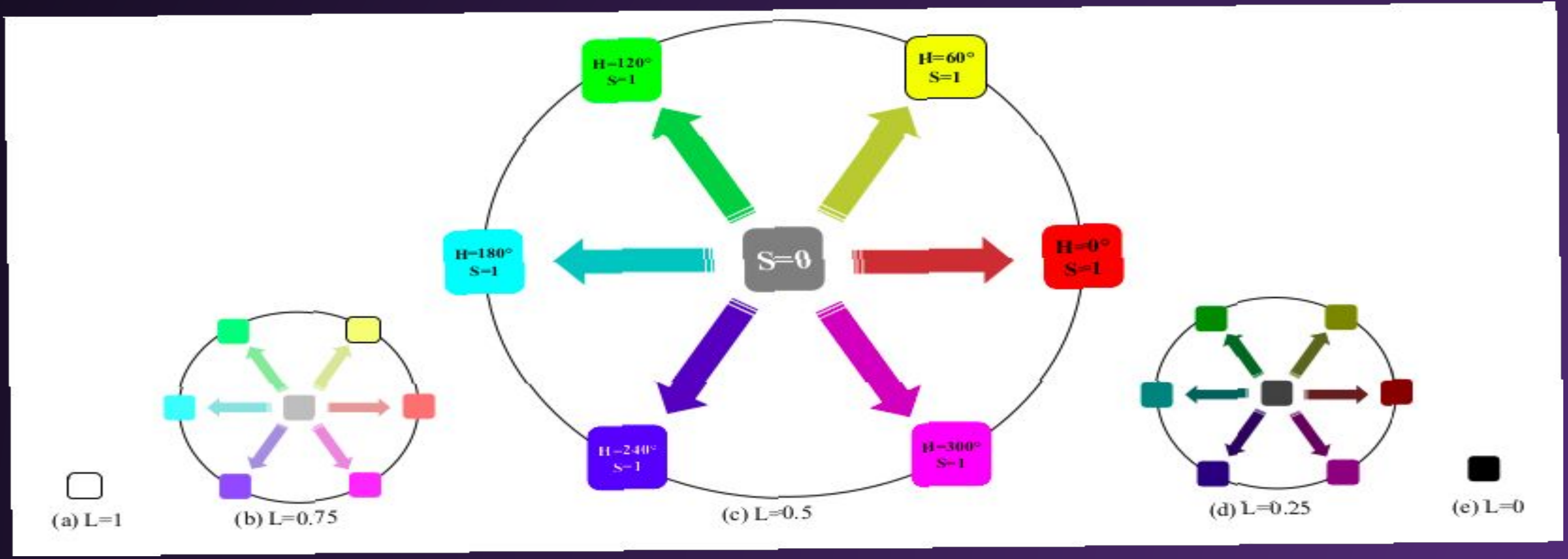
Radial Viz



HSVis Model

Frequent patterns represent in the HSL colour model

Hue saturation and Lightness (HSLviz) uses hue to represent the cardinality of frequent patterns, it uses a combination of saturation and lightness to represent frequency.



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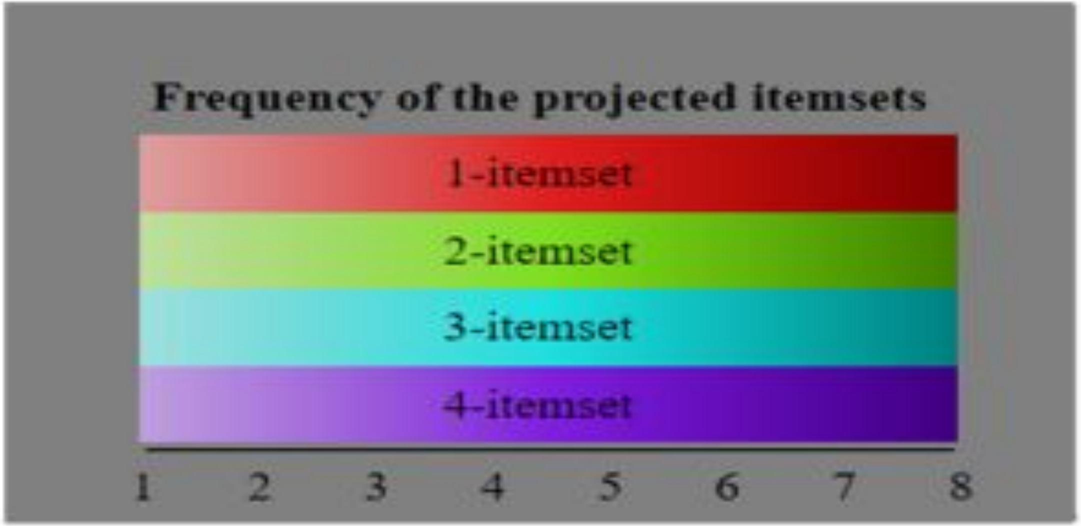
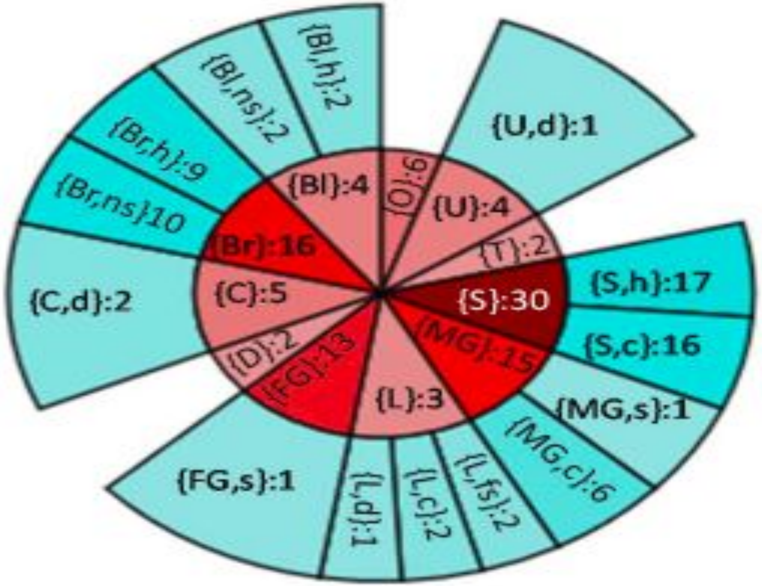
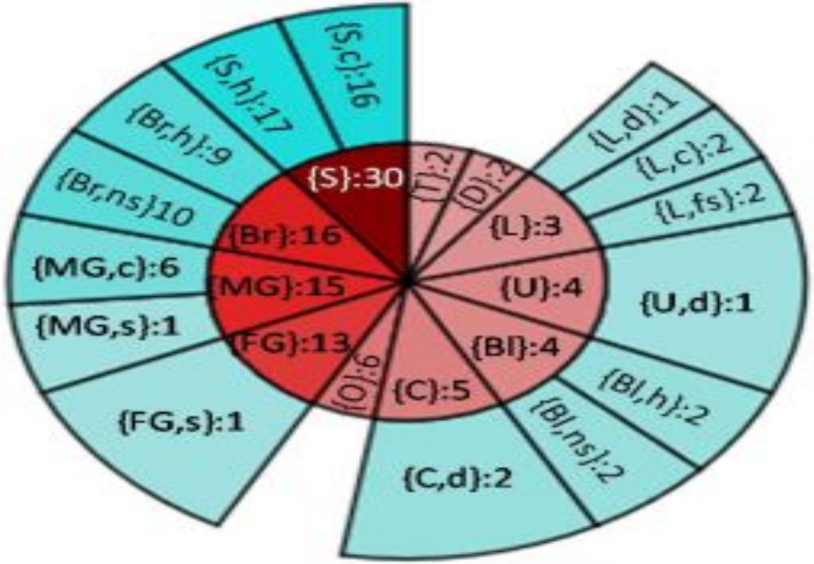


Cardinality and frequency of frequent *k*-itemset in HSLviz

Visualization of smart data tosupport healthcare



(a) Alphabetical order



(b) Descending frequency order

Conclusions

- The HSV model not support the program but,many programs support the HSL colour model, no extra conversion is needed.
- HSLviz Model for the visualization of smart data to support healthcare analytics.
- HSLviz can efficiently represent useful information and discovered knowledge.

An interactive web based platform for healthcare data analysis and visualization

Muhammad Usama Shehzad

Abstract

The Health Vision platform providing us advanced and multi-scaling data analysis and visualization to overcome a challenge for reaching robust conclusions of exponentially increasing volumes of health data of different types.

In user defined workflow, we distinct into four layers: 1. Raw Data 2. Data Analysis 3. Decision support 4. Data Visualization

By using raw data layer we collect data from different platforms that can be considered, while data analytics layer provides data analysis services for data mining. Then decision support layer facilitates the selection of appropriate visualization methods taking into consideration the specification of raw data and the output of the data analysis.

Finally, the Data visualization layer provides intelligent visualization methodology in order for the user to interact with the data and gain meaningful results.

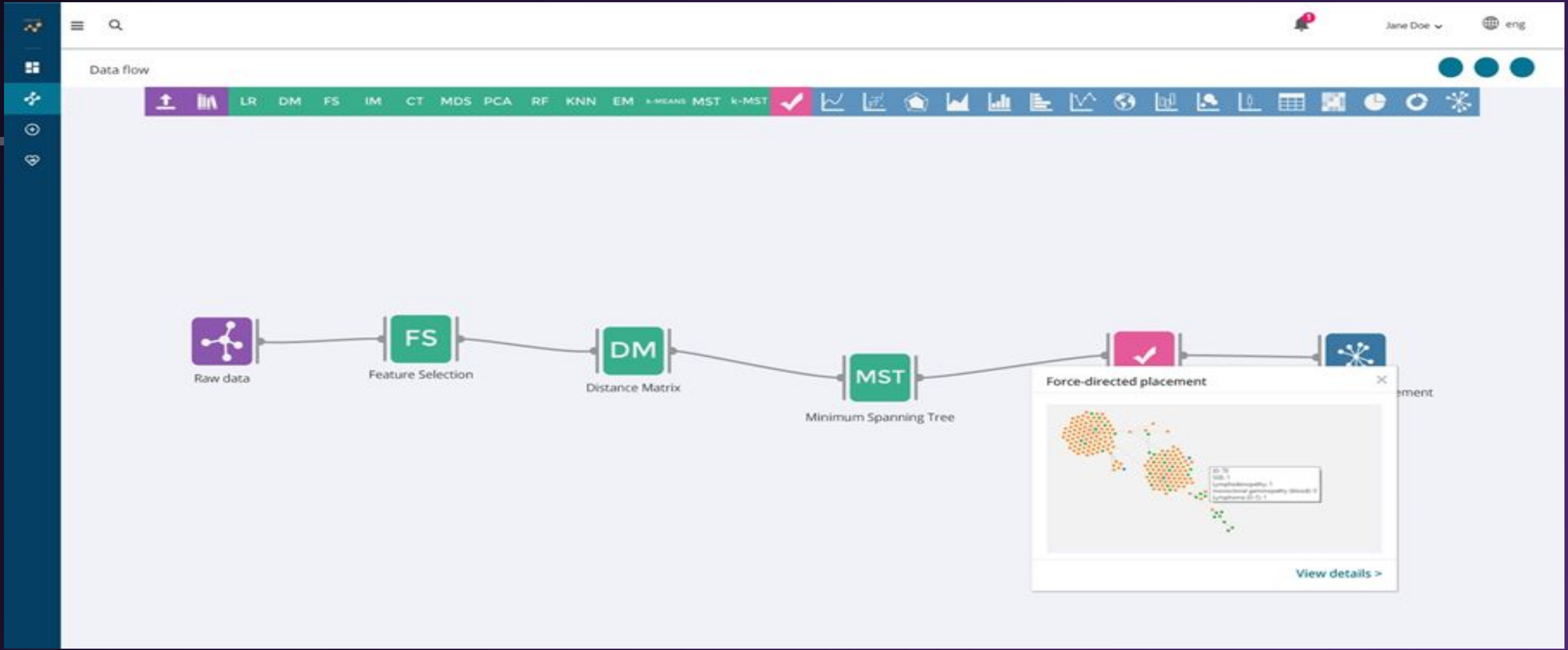
Visualization is supported by a reactive workflow mechanism, allowing the composition of analysis and visualization services in a custom application-specific data flow.

Introduction

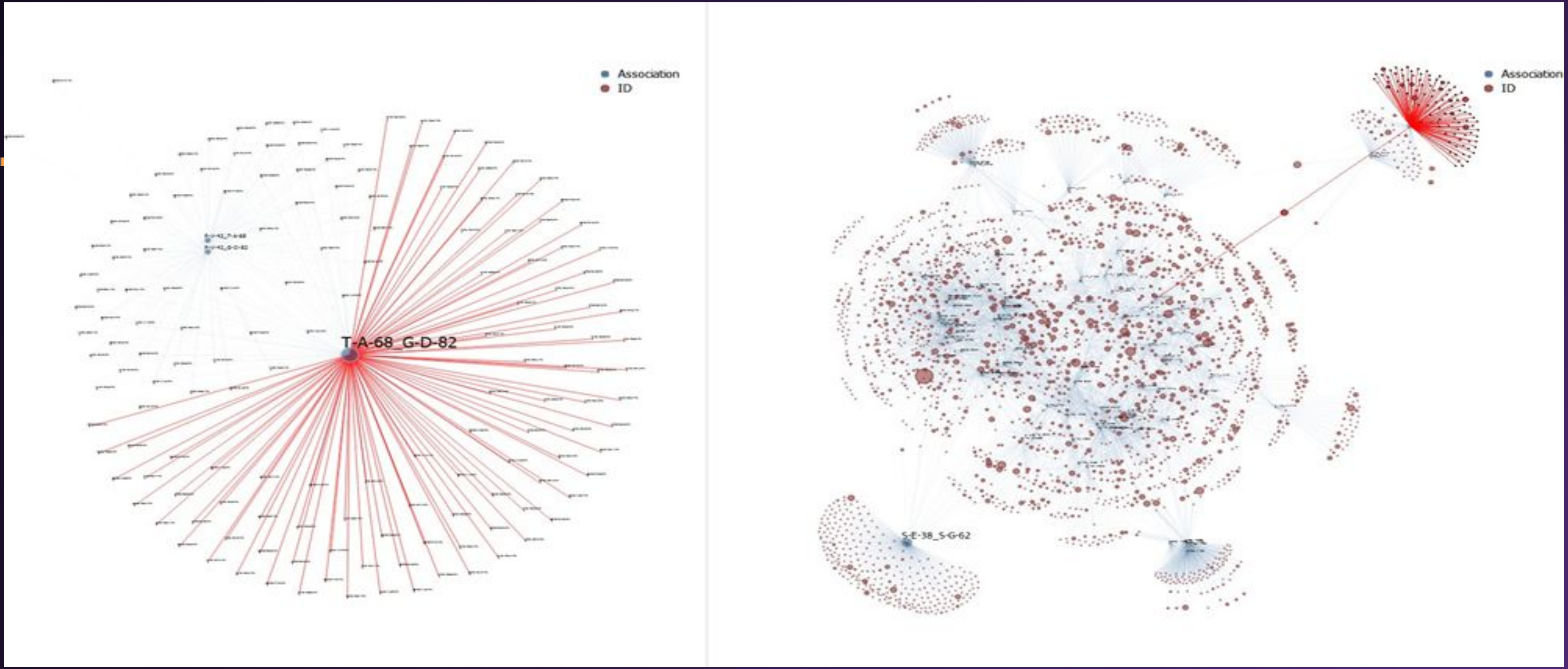
Information visualization (IV) and visual analytics (VA) hold a key role as they provide an interactive environment to analyse large scale, multi-source, variable-type, and time-varying data and assist towards effective decision making.

Health Vision performs data exploration, analysis and visualization, in the context of various scenarios:

- Design data-driven visual analytics methodologies;
- Analysis of heterogeneous datasets;
- Establishment of information visualization methodologies in different types of diseases



Visualization of Sjogren's syndrome patients based on their Salivary gland enlargement (SGE), Lymphadenopathy and monoclonal gammopathy



Relation between SHM associations and CLL patients

Evaluation

The proposed HV platform has been evaluated in the context of several health-oriented projects for the exploration of data in domains such as Sjogren's syndrome (SS), Parkinson's ¨ disease, chronic lymphocytic leukemia, asthma and frailty. Different use cases may involve different types of raw data and analysis, leading to the usage of different workflows and components.

CONCLUSIONS

In this paper, the Health Vision platform for the visualization of healthcare data is presented. The platform supports several data types, analytics methods, decision support rules and visualization.

Directions for future work include the evaluation of the platform in other types of clinical data, e.g. data from self management platforms or in combination with interoperability and data harmonization approaches, in order to support large-scale studies.

DPVis visual analytics with hidden Markov models for disease progression pathways

Welemhret Welay Baraki

Introduction

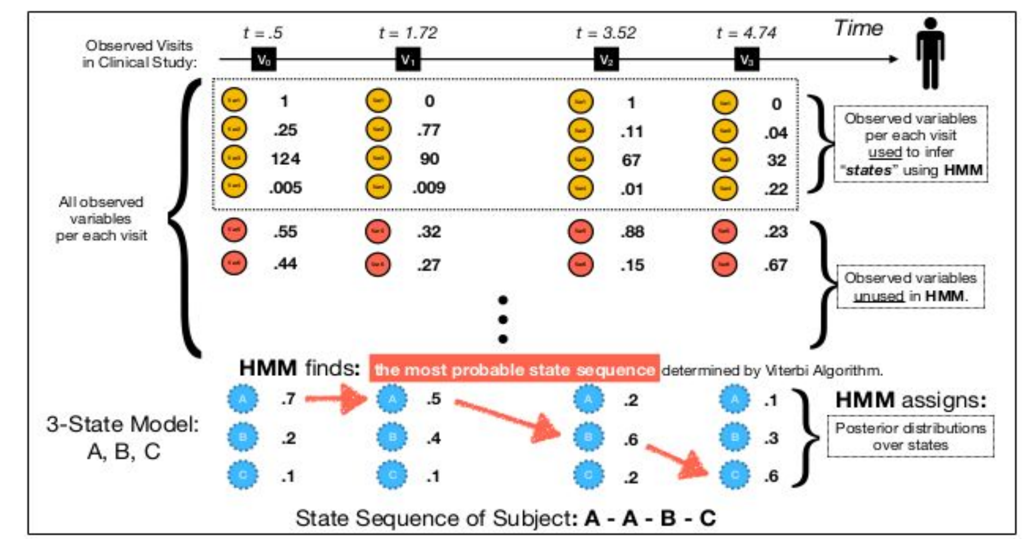
- Investigate disease progression patterns in observational data collected from clinical studies.
- Participants: Clinical researchers who conduct and investigate observational data through iterative discussions.
- The Goal of Clinical researchers:
  - develop optimal treatments tailored for individuals by estimating their disease progression patterns precisely.
  - Discover distinct states of patients
  - Early and accurate detection of presymptomatic progression signals can lead to early intervention and precision medicine.
- To achieve these goals they use: Bio markers, lab tests, and others

Identified Goals and Tasks

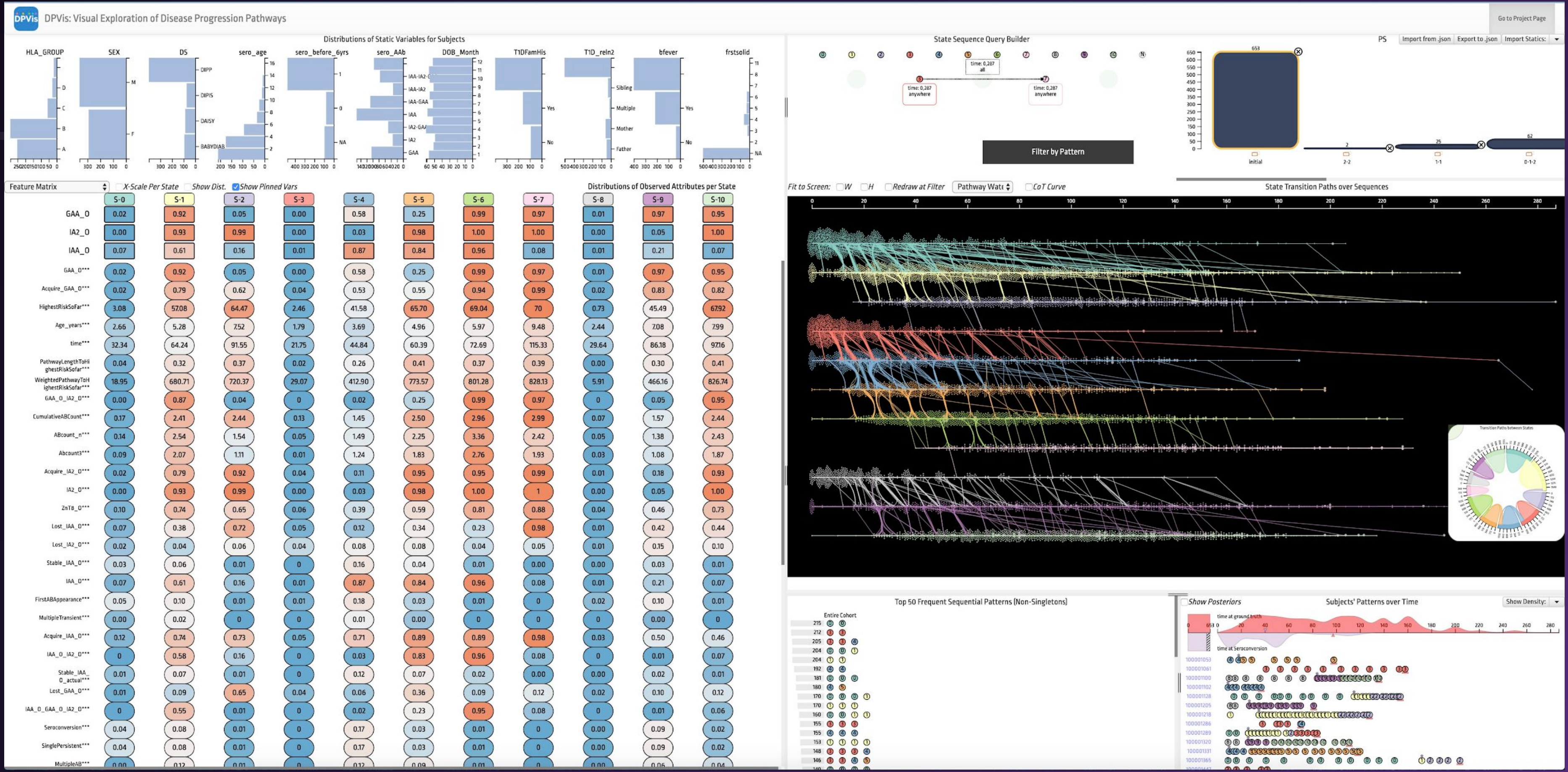
- Three goals identified:
  - G1-Explain disease progression -discovery of distinct states
  - G2-Discover heterogeneous trajectory groups
  - G3- Find associations between trajectory groups and variables
- Visual disease progression analysis tasks
  - T1- Characteristics of states
  - T2- State transition patterns
  - T3- Relationships between trajectories and variables
  - T4- Subject details
  - T5-Subgroup management

Visualization Used

- Tools: Flask,Jinja , Django, D3.js, jQuery, and lodash
- Programming: Python and Java Script
- Model tested on type-1 diabetes
- Disease progression patterns of 559 subjects from birth cohort studies using the 11-state HHM model
- Evaluation: Cross Validation



Visualization Used

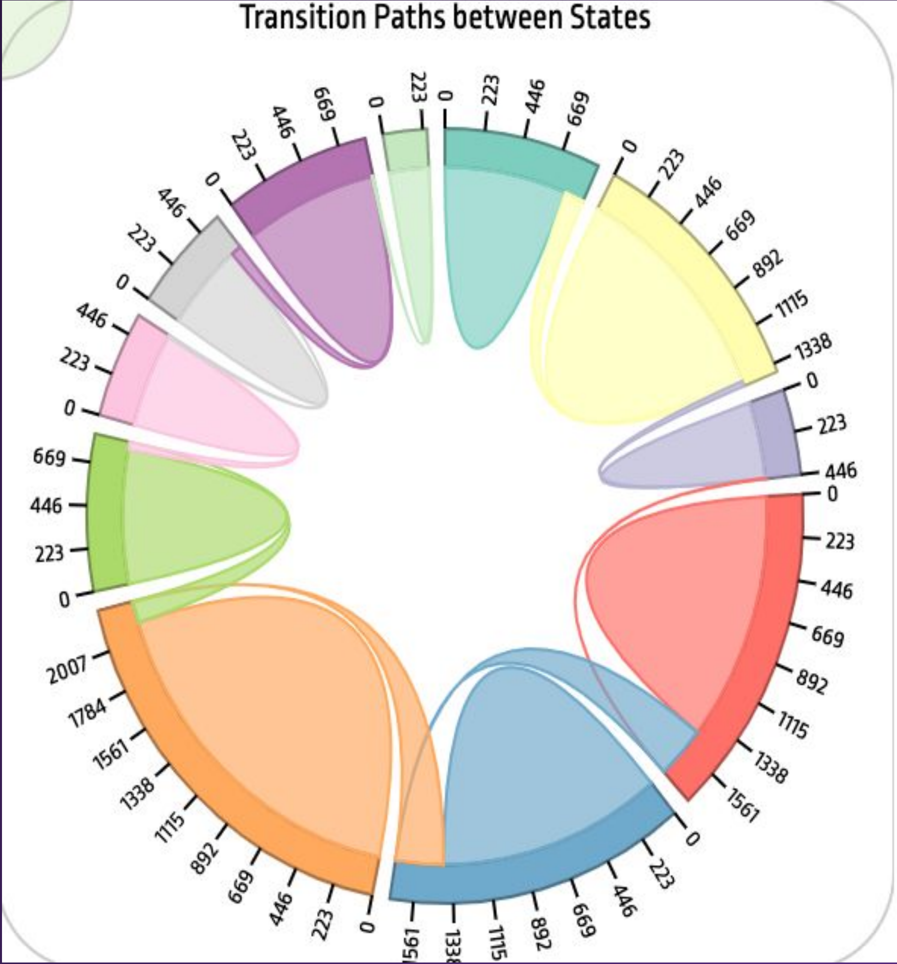


Visualization Used: State Summary Panel

- State Summary Panel
  - Contains
    - Feature matrix - Button Like Approach
    - Feature distribution -Histogram
- State Transition Panel
  - Pathway waterfall
    - using parallel beeswarm
  - Pathway over Observation
    - Sankey diagram approach
  - Pathway by time unit
    - Stacked bars

Visualization Used....

- State transition chord diagram
  - Summarizes transition Patterns.
  - Radial network diagram



Visualization Used: State Summary Panel

- State transition pattern List
  - Uses BIDE pattern mining algorithm
  - Extracts patterns like the most frequently occuring state sequence patterns.

Visualization Used

- **Panel for Patterns and Outcomes**
  - **Dual Kernel Densities View** - shows density diagrams each with increasing y-axis(density), in the opposite direction
  - **Subject List View -**Users can inspect details at the patient level.
- **Static Variables View** -Summary of subjects in terms of static measures
- **Subgroup Builder**
  - Subgroup List
  - State Sequence Finder

C LINICAL S TUDIES OF T YPE 1 D IABETES

- **Usage Scenario**
  - Observational data from three clinical studies:
    - DiPiS -Method to screen newborn infants
    - DAISY - Diabetes Autoimmunity in the Young Study (DAISY)
    - DIPP -Diabetes Prediction and Prevention (DIPP)
  - 559 subjects who were diagnosed with T1D
  - Model the subjects' progression data using Continuous time HMM (CT-HMM)
  - Three Groups: glutamate decarboxylase autoantibody(GADA), insulin autoantibody (IAA), and islet autoantigen-2 autoantibody (IA2A)

CLINICAL STUDIES OF TYPE 1 DIABETES

- **User Experiences on DPVis**
  - Reduces the effort required to analyze observational data
  - Helps users understand HMMs
  - Multiple views gives flexibility users to summarize
  - Users want to provide feedback to the HMM learning process

Limitations

- State sequence Jumps are not modeled.
- Subjects may represent an endotype that are not captured
- Interpretations of HMM model result is not intuitive
- Uncertainties in state assignments
- Data collection matters for outcome interpretation
- Unknown model configurations
- It takes time to learn and interpret(Complex)
- Didn’t modify states to formulate new states
- Lack of automatic detection of outliers in the pathway

Conclusions

- Develop visual analytics application for exploring disease progression pathways and their interaction with various measures.
- Integrates HMMs and provides views and interactive features that facilitate users to formulate and test hypotheses
- T1D case demonstrate the usefulness of the application to gain a summary of disease progression trajectories.

Discussion from all papers

- Dashboards or narrative visualization?
- Does HMM works for other Disease progression pathways?
- How to manage Heterogeneity of data challenges in big data analysis in healthcare?