





Medical Big Data Analysis System to Discover Associations between Genetic Variants and Diseases

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Background

- Health Record Data
 - Used to record data on patients
 - Biological measurements
 - Disease Diagnoses
 - Medical procedures
- ► Genetic Data
 - Retrieved from DNA in blood samples



Name: Jane Doe Medical History #: 111111 DOB: 01/01/1950 Weight: 150 lbs Height: 5'5'' Address: 1000 N. Oak Street

Diagnosis & Procedure (ICD9 codes): 250 = Diabetes 493.1 = Intrinsic Asthma 474.00 = Chronic Tonsillitis 28.2 = Tonsillectomy

Prescriptions: Antibiotics Albuterol Metformin

Background-cont'd

- Marshfield Clinic Research Institute (MCRI)
- Genome-Wide Association Studies (GWASs)
 - ► Find genetic variants for certain diseases
 - Phenotype-to-genotype approach
- Phenome-Wide Association Studies (PheWASs)
 - Explore multiple diseases relevant to genetic variant
 - Genotype-to-phenotype approach
- Electronic Health Records (EHRs) and DNA genotype are the main resources used to discover individual differences
- We designed and implemented a Medical Big Data analysis system that retrieves results from a GWAS-by-PheWAS dataset

Motivations

- Our motivation
 - Longer times to search results; We made this system
- Goal 1: Finds the link between genetic variants and human diseases
 - Aim to help medical professionals more with data analysis with their patients
- Goal 2: Implement a web query system that finds the links between human disease and genetic variants with PheWAS and GWAS
 - GWAS study scans markers across DNA or genomes of many people to find variations associated with a disease
 - PheWAS study explores multiple diseases relevant to a genetic variant



Dataset

- Data of biobank in Marshfield Clinic Research Institute (MCRI)
- Consists of genotype DNA and EHR of 20,000 patients
 - ► Age range 18 to 98.5
 - ▶ 57.2%
 - PheWAS dataset searchable by RS ID or genetic position of SNP
 - GWAS dataset searchable by ICD-9 disease code or description

PheWAS Example	22,29854579 G,A,8613,0.19234,0. 0065506,-,0.935493,dx903, Type 1 (Juvenile Type) Diabetes Mellitus With Ketoacidosis Uncontrolled , 250.13
GWAS Example	22,17265124,17265124,A,C,exoni c,XKR3,NA nonsynonymous SNV,XKR3:NM_175878:exon4:c:T7 65G:p.F255L,0.694489,0.6282, rs5748623, 1,T,0.0,B,0.0,B,0.001,N,1.000,P,- 1.1,N,NA,,

System Architecture

- Each node runs on
 - Dell PowerEdge R710
 - 2U rack sever (144GB)
 - ► 2 Intel Xeon 5660
- Each node has
 - ► 2 TB SSD
- ► 8 TB for Spark cluster
- ▶ Ubuntu 18.04
- Standalone cluster manager



Software Architecture

- Web Query System architecture
 - ► Front-end user interface
 - ► R Shiny
 - Back-end server
 - ► GlusterFS
 - ► Spark
 - ► MongoDB
 - ► Java daemon



Control flow

- A user would type a request to find:
 - Diseases relevant to genomic data
 - Genomic data relevant to diseases
- Requests are sent to master through sparkR
- Partial results are sent to Shiny, the keys are saved temporarily in MongoDB and sends emails



New Search: Front-end

- New Search is used to find diseases
 - Inputs consist of RS# (location of the genome) and end positions
 - Inputs to find genotypes consist of disease codes or description
- ► UI consists of shiny widgets
 - selectInput (dropdown button)
 - ► textInput
 - actionButton
 - dataTable (showing results in table format)



New search user interface

New Search: Front-end - cont'd

Algorithm 1

- Processes new search requests to find diseases
- Given inputs (chromosomes, list of RS ids and end position) PheWAS and GWAS data for the chromosomes are loaded from CSV files



New Search: Back-end

- Requests that take a long time are processed in the background after partial results are returned to front-end UI.
- ► Spark cluster
 - The analysis application retrieves the list of key pairs of a chromosome
 - An end position from Mongo DB through Mongo DB Java driver
 - Processes the analysis in worker nodes
- The data frame returned from workers are converted and saved into Mongo DB for narrow search later
- The analysis application sends a notification email every time each job is processed

Narrow Search

- Enables a user to find exact results by reusing search results saved in Mongo DB
- Shiny application retrieves results from Mongo DB through mongolite R package
- Retrieve partial documents
 - ▶ First, prev, next and last
 - First and last buttons load the first and last block in a collection
- "plot" button used to visualize table formats using Manhattan plot
- To draw PheWAS data, we use scatter plot using plotly R graphing library which makes interactive graphs



Narrow search user interface

Evaluation Set Up

- SparkR (front-end), Spark-submit (back-end)
- Measured running time of:
 - Front-end & back-end operations
 - Averaged 5 times running the same request using 'sar' command
- ► Each executor: 2 CPU cores, 16 GB
- Varying the number of executors to 4, 8,16 and 32
- Equally distributed to four worker nodes
 - (e.g., 32 executors, each worker node runs 8 executors with 16 cores and 128 GB, resulting in 64 CPU cores and 512 GB in total for processing a user request)



Performance

- Running time for disease / genome data
 - Running time becomes faster with more executors on parallel processing
 - Running time of front-end is much less than back-end processing
 - Separating workloads between front-end and back-end is configurable
 - For all chromosomes, long time for front-end operation
 - Running time with 16 and 32 executors is similar, indicating the existence of upper bounds





Search genome

Overhead

- Figures show additional CPU/Memory usage
- CPU overhead
 - CPU per node increases with more executors
 - Workload is balanced to four nodes
- Memory overhead
 - Memory usage increases with more executors
- Underutilized CPU/Memory
 - ▶ For genome, CPU used 40 % out of 66% allocated
 - ▶ Memory used 25 % out of 90% allocated
 - Dynamically changing # of cores and memory size in an executor can increase performance while utilizing resources at maximum





Search disease



CPU usage





Search genome

Memory usage

Related Work

- SedImayr et al
 - Using Spark cluster along with SparkR increase better performance over message passing interface
- Hong et al
 - Shiny R package
 - Developing interactive Web applications in R
 - Graphical and interactive analysis
- Criscuolo & Angelini
 - StructuRly a shiny app: to produce interactive plots for population genetic analysis

Future Work & Conclusion

Medical big data analysis system is a prototype

- Check the application design and system architecture
- ► To handle more data
 - Large scale Spark cluster
 - More worker nodes
 - MCRI biobank: 20 petabytes
- ► Future
 - Dynamic resource allocation
 - A hybrid system

Thank you

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