NYU Langone Health

PROJECT 1: PREGNANCY PILL BOX MOBILE APP STORYBOARD

PROJECT 2: CLASSIFICATION OF SLEEP APNEA PHENOTYPES TO AID PERSONALIZED MEDICINE

Group 4: Jennifer Blakemore, Erica Chio, Lea Lough, Brianna Roseberry

PROJECT 1: PREGNANCY PILL BOX

- BACKGROUND
  - Pregnancy is a unique time in a woman's life where taking the correct medications, at the appropriate time, affects the health outcomes of not one but two patients.
  - Despite the best of intentions of both physician and pharmacist, medications that are inappropriate or contraindicated are often dispensed.[1]
  - Despite the best of intentions of the patient, compliance with medications is often suboptimal.
  - A mobile app offers a unique opportunity to arm patients to optimize their healthcare, and that of their fetus, with minimal effort.
  - There are several mobile health apps aimed at medication administration, but none that are optimized for use during pregnancy or with "changing timing."[2]
- DATA
  - Drug Data:
  - Patient Data: due date

1. Raebel MA, Carroll NM, Kelleher JA, et al. Randomized Trial to Improve Prescribing Safety During Pregnancy. J Am Med Inform Assoc. 2007;14:440-450.
2. Bailey SC, Belter LT, Pandit AU, et al. The availability, functionality, and quality of mobile health applications supporting medication self management. J Am Med Inform Assoc. 2013;21(3):542-546.

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PROJECT 1: PREGNANCY PILL BOX

- METHODS
  - First Goal Mobile health app
  - Patient Data as above = INPUT 1
  - Drug data from lexicomp as above = INPUT 2
  - Combining the data to enhance pregnancy specifics
    - One example: certain antibiotics are unsafe by mouth but okay inhaled or applied topically on the skin
- Outcomes:
  - How many Drugs get warnings to check with a physician
  - How many current drugs are stopped
  - How many drug-drug interactions are missed
  - How many pill box alerts / how many medications missed or delayed.

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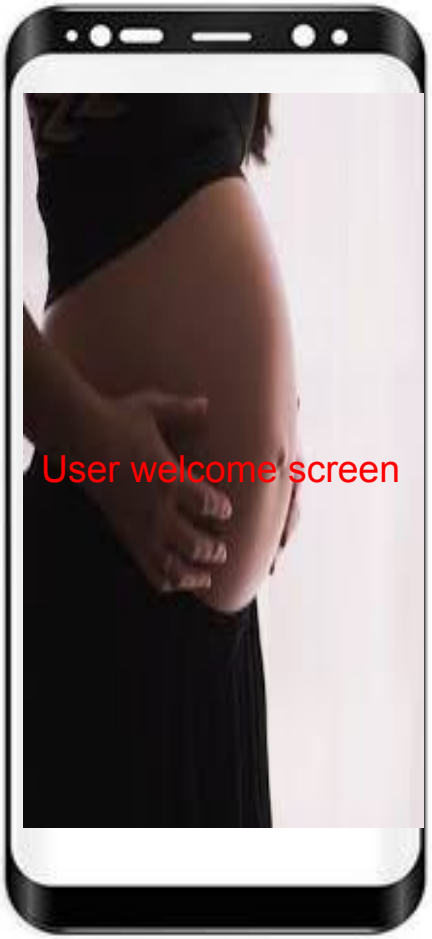
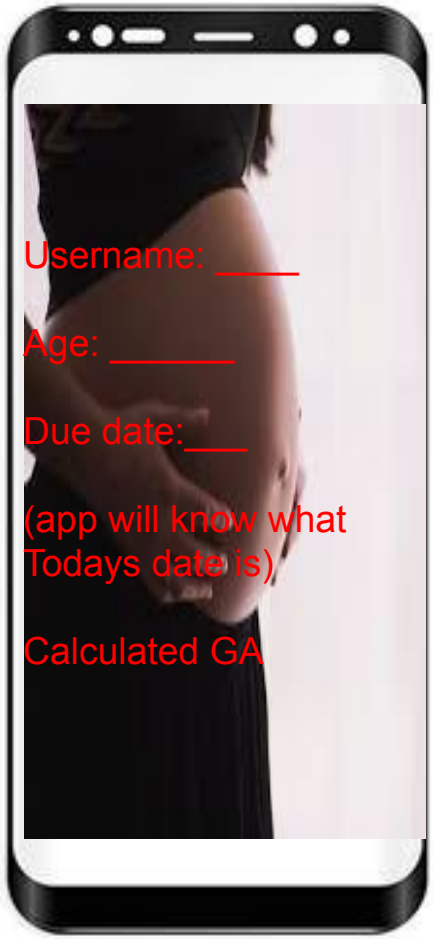
PROJECT 1: APP STORYBOARD





User personal info input

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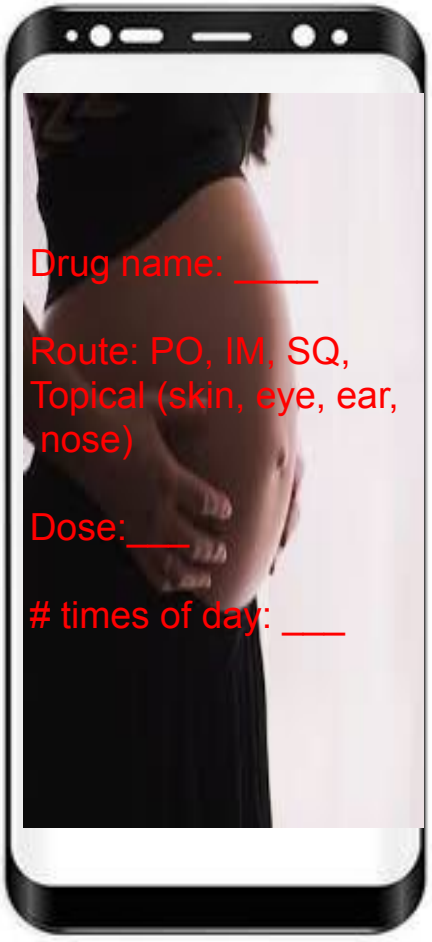

Specific Medicine input

Safety / Warning output screen

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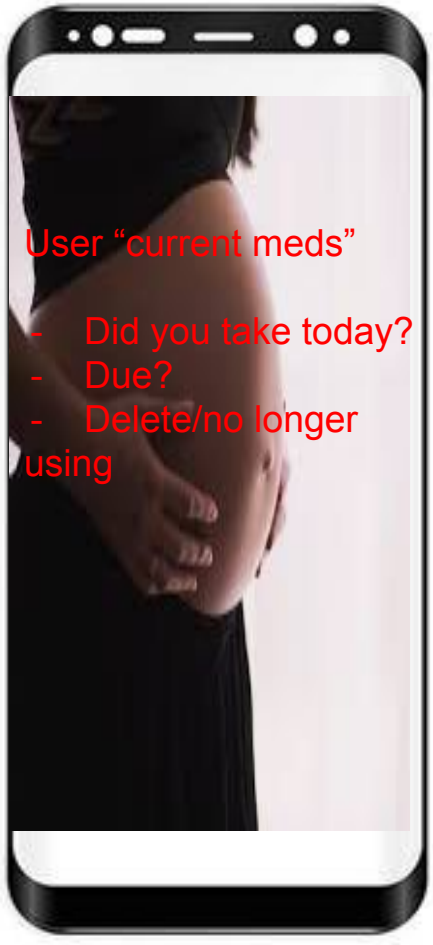
Overall Medicine data base



Pillbox for compliance

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PROJECT 1: PREGNANCY PILL BOX

FIRST PITFALL: accessible data - so we made a dummy data set

sample data - Sheet1

name	route	first	second	third
Nitrofurantoin	PO (mouth)	Caution:Only when no other alternative exists	Safe for use	Safe until 37 weeks, then contraindicated
Ibuprofen	PO (mouth)	NOT SAFE	NOT SAFE	NOT SAFE
Acetaminophen	PO (mouth)	Safe for use	Safe for use	Safe for use
Trimethoprim-Sulfamethoxazole	PO (mouth)	NOT SAFE	NOT SAFE	NOT SAFE
Levofloxacin	PO (mouth)	Caution:Only when no other alternative exists	Caution:Only when no other alternative exists	Caution:Only when no other alternative exists
Levofloxacin	Opthalmic (eye drops)	Safe at lowest dose possible	Safe at lowest dose possible	Safe at lowest dose possible
Tretinoin	Ointment (skin cream)	NOT SAFE	NOT SAFE	NOT SAFE
Inactive Flu vaccine	IM (injection)	Safe for use	Safe for use	Safe for use
Activated Flu Vaccine	IM (injection)	NOT SAFE	NOT SAFE	NOT SAFE
Prednisone	PO (mouth)	Caution:Only when no other alternative exists	Caution:Only when no other alternative exists	Caution:Only when no other alternative exists
Tdap Vaccine	IM (injection)	Caution:Only when no other alternative exists	Caution:Only when no other alternative exists	Safe for use
Aspirin (salicylates)	PO (mouth)	NOT SAFE	Safe at lowest dose possible	Safe at lowest dose possible

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PROJECT 1: PREGNANCY PILL BOX

- **OTHER PITFALLS/VARIABLES:**
  - User
  - Integration with NYU myChart
  - Availability of data
  - Time constraints

- Ultimately we made a website prototype

- **NEXT STEPS**
  - Flush out the website and/or app capabilities
  - Get access to a full data set
  - Test with pregnant subjects
  - Consider integration with myChart

PROJECT 2: SLEEP APNEA PHENOTYPES

- SIGNIFICANCE: **Sleep apnea and cardiovascular disease (CVD).**
  - Sleep apnea increases the risk of CVD due to the effects that a lack of oxygen has on the body.
  - When oxygen levels drop, carbon dioxide levels increase resulting in a release of adrenaline-like molecules into the bloodstream.
  - These substances damage the lining of the body's blood vessels and result in CVD.
  - Interestingly, some patients are more severely affected by sleep apnea than others even though they have the same drop in oxygen.
  - A better classification of high-risk patients is needed in order to better treat/prevent their CVD.

- **AIM: To use publicly available data from sleep apnea patients/participants to identify different sleep apnea phenotypes that are correlated with severity of CVD.**
- DATA
  - Sleep Heart Health Study (SHHS) dataset
    - 5802 patients
    - 1527 patients with CVD event

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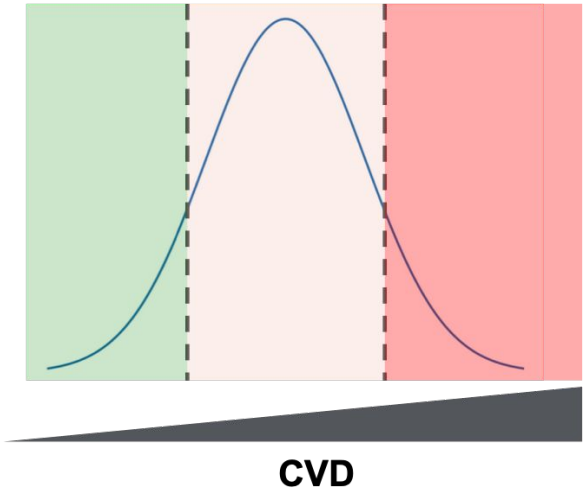
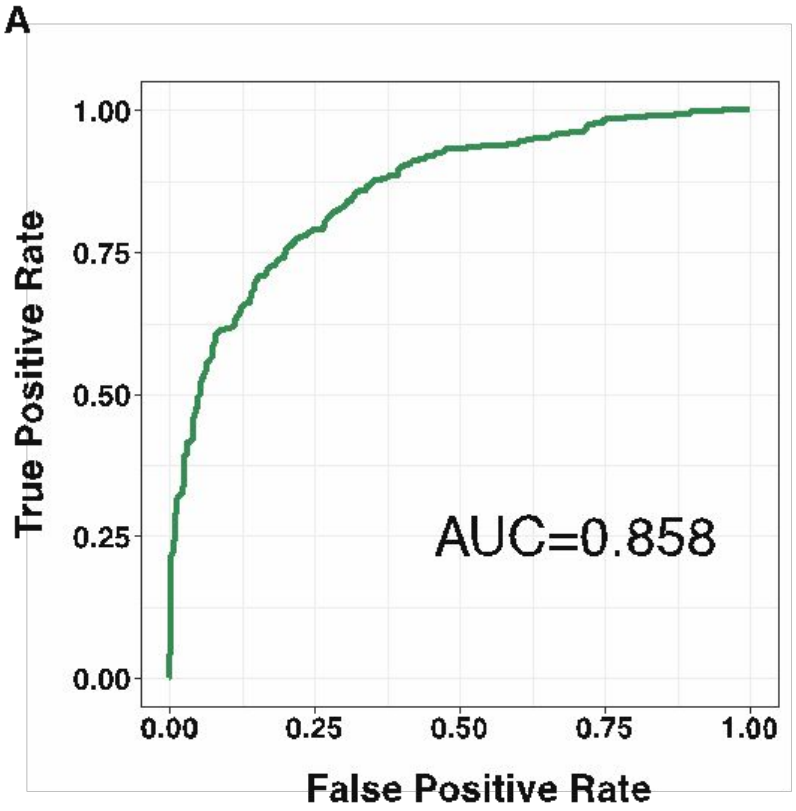
PROJECT 2: SLEEP APNEA PHENOTYPES

- METHODS / STRATEGY
  - Method:
    - Split data into training and test sets
      - 80/20
    - Random forests to pull significant features and predict if patient will have a CVD event
      - 3 times repeated 5 fold cross validation
    - Random forests to predict the individual cardiovascular events from a selected list
      - 3 times repeated 5 fold cross validation



PROPOSAL 2: SLEEP APNEA PHENOTYPES



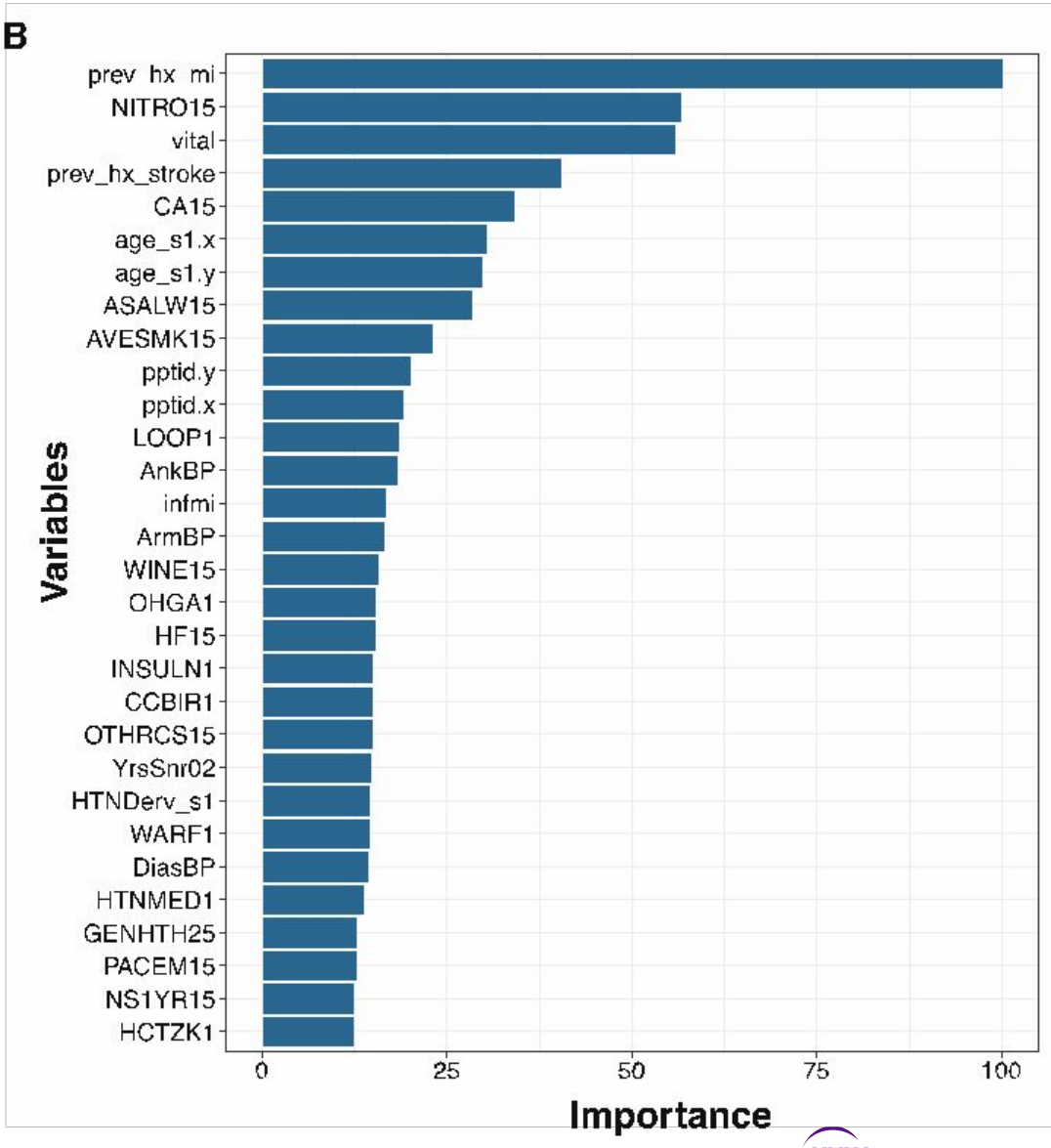


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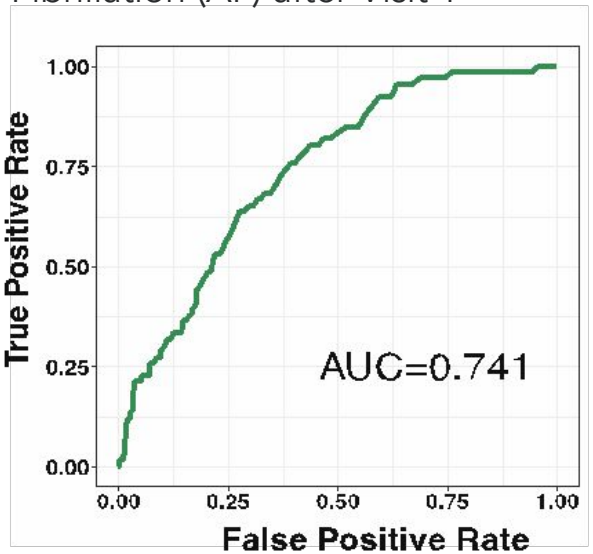
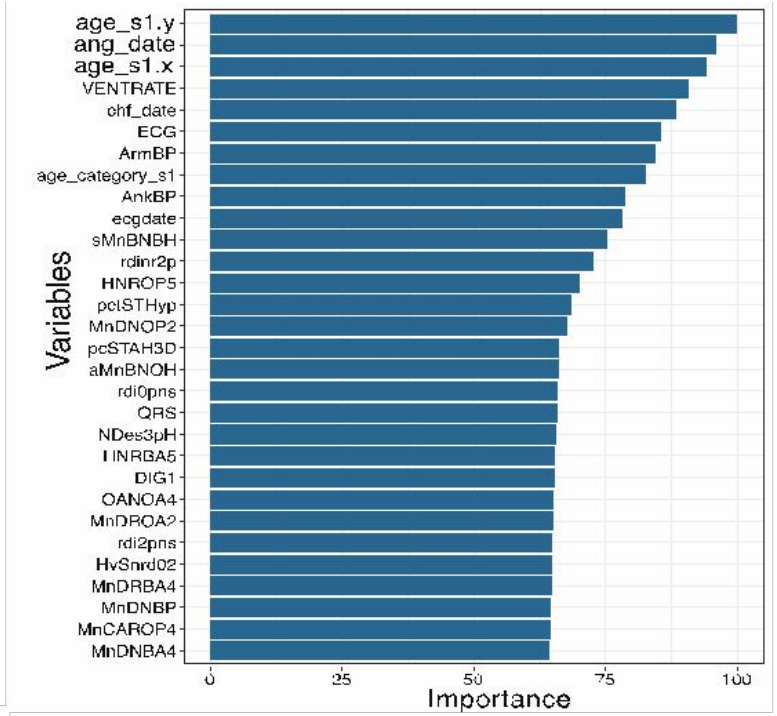
Table 1: Selected CVD outcomes used for predetermined CVD phenotypes

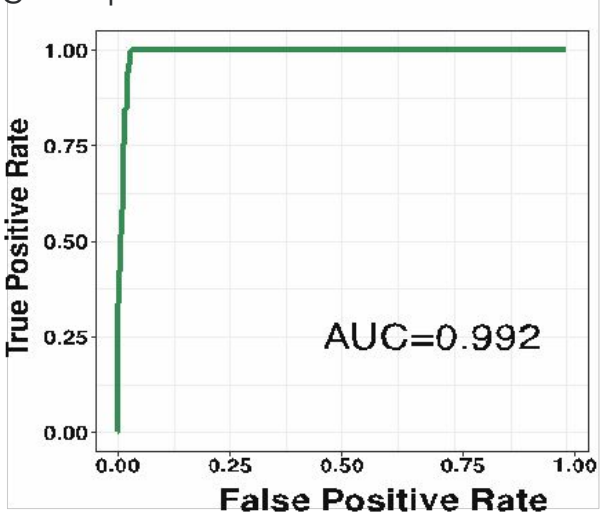
Name	Label
afibincident	Incident Atrial Fibrillation (AF) after SHHS Visit 1
angina	Number of Angina Episodes Since Baseline
any_chd	Any Coronary Heart Disease (CHD) Since Baseline
any_cvd	Any Cardiovascular Disease (CVD) Since Baseline
cabg	Number of coronary artery bypass graft surgeries (CABGs) Since Baseline
chd_death	Fatal Coronary Heart Disease (CHD) Since Baseline
cvd_death	Fatal Cardiovascular Disease (CVD) Since Baseline
mi	Number of myocardial infarctions (MIs) Since Baseline
mi_fatal	Fatal Heart Attack Since Baseline
stk_fatal	Fatal Stroke Since Baseline
stroke	Number of Strokes Since Baseline

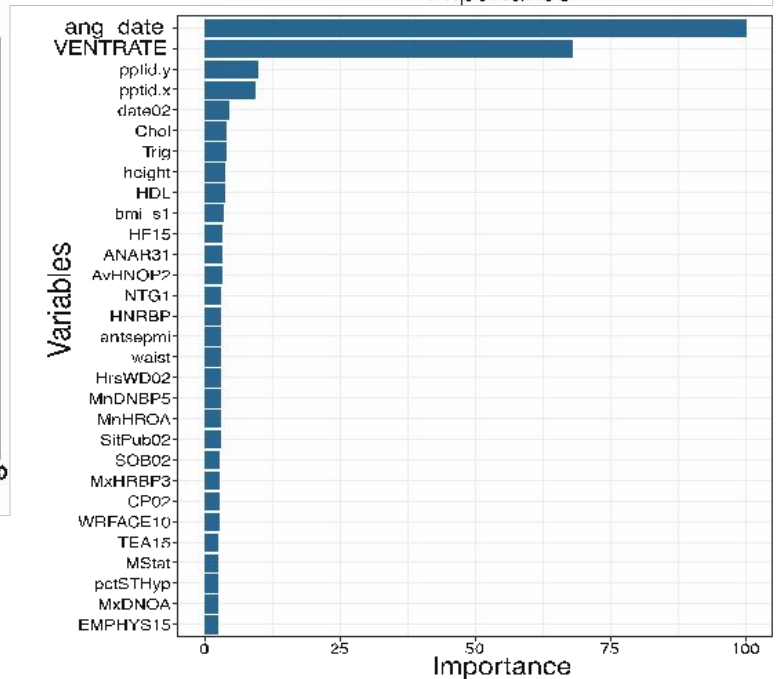
Incident Atrial Fibrillation (AF) after Visit 1





Number of Angina Episodes Since Baseline





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Name	Label	AUC	Important variable
afibincident	Incident Atrial Fibrillation (AF) after Visit 1	0.741	Age at visit one Days to First Angina Episodes Since Baseline
angina	Number of Angina Episodes Since Baseline	0.992	Days to First Angina Episodes Since Baseline Ventricular rate
any_chd	Any Coronary Heart Disease (CHD) Since Baseline	0.986	Days to First myocardial infarction (MI) Since Baseline Days to First Revascularization Procedure Since Baseline
any_cvd	Any Cardiovascular Disease (CVD) Since Baseline	0.994	Days to First Revascularization Procedure Since Baseline Days to First Congestive Heart Failure (CHF) Since Baseline Days to First myocardial infarction (MI) Since Baseline
cabg	Number of coronary artery bypass graft surgeries (CABGs) Since Baseline	1	Days to First coronary artery bypass graft surgery (CABG) Since Baseline
chd_death	Fatal Coronary Heart Disease (CHD) Since Baseline	0.951	Vital status at last contact Days to First myocardial infarction (MI) Since Baseline
cvd_death	Fatal Cardiovascular Disease (CVD) Since Baseline	0.961	Vital status at last contact
mi	Number of myocardial infarctions (MIs) Since Baseline	1	Days to First myocardial infarction (MI) Since Baseline
mi_fatal	Fatal Heart Attack Since Baseline	0.779	Overall Respiratory Disturbance Index (RDI) at >=4% oxygen desaturation or arousal Hypopnea per hour with >=2% oxygen desaturation or arousal (Rapid eye movement sleep (REM), Non-supine) Days to First myocardial infarction (MI) Since Baseline
stk_fatal	Fatal Stroke Since Baseline	0.853	Days to First Stroke Since Baseline Average oxygen desaturation w/ arousals (Non-rapid eye movement sleep (NREM), Supine, >=4% oxygen desaturation) Percent of sleep time in Hypopnea
stroke	Number of Strokes Since Baseline	1	Days to First Stroke Since Baseline

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stroke	Number of Strokes Since Baseline	1	Days to First Stroke Since Baseline

PROJECT 2: SLEEP APNEA PHENOTYPES

- Future directions
  - To verify the important variables for the CVD outcomes, more specialized and selective models should be used.
  - Decreasing the patient population and variables could lead to a more accurate phenotypic clustering.
    - For ex: it is known that insufficient sleep in black minorities leads to higher rates of CVD.
      - The dataset can be used to identify specific sleep apnea phenotypes due to race.
  - Finally, phenotypic clustering analysis of all the variables would be ideal in categorizing the sleep apnea phenotypes.

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THANK YOU

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