

SC1015 Mini-Project

# Robo-Medivisor

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Heart Disease Prediction

SC19 Team 7

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Insights &  
Solution



01

# Our Motivation

Introduction



## Heart Disease

- Leading cause of death worldwide → 32% of all deaths
- In Singapore, about 19 people die from it everyday





## **Problem Definition**

How can we assist doctors to speed up the diagnosis of heart disease to minimise further implications?



02

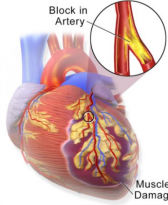
# Exploring Dataset

Exploratory Data Analysis &  
Data-driven Insights

# Data Preparation

## Dataset Used:

### HEART DISEASE DATASET (COMPREHENSIVE)



Block in Artery

Muscle Damage

★★★★★ 4 ratings - Please [login](#) to submit your rating.

Citation: Manu Siddhartha (Liverpool John Moore's University)

Submitted by: MANU SIDDHARTHA

Last updated: Fri, 11/06/2020 - 04:17

DOI: 10.21227/dz4t-cm36

Data Format: \*.csv

Links: A database for using machine learning and data mining techniques for coronary artery disease diagnosis

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16779 Views

Categories: Machine Learning, Health, Biomedical and Health Sciences

Keywords: Heart Disease, Coronary artery disease, Cardiovascular disease, heart disease dataset

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## Dataset Variables:

**Heart Disease Dataset Attribute Description**

S.No.	Attribute	Code given	Unit	Data type
1	age	Age	in years	Numeric
2	sex	Sex	1, 0	Binary
3	chest pain type	chest pain type	1,2,3,4	Nominal
4	resting blood pressure	resting bp s	in mm Hg	Numeric
5	serum cholesterol	cholesterol	in mg/dl	Numeric
6	fasting blood sugar	fasting blood sugar	1,0 > 120 mg/dl	Binary
7	resting electrocardiogram results	resting ecg	0,1,2	Nominal
8	maximum heart rate achieved	max heart rate	71–202	Numeric
9	exercise induced angina	exercise angina	0,1	Binary
10	oldpeak =ST	oldpeak	depression	Numeric
11	the slope of the peak exercise ST segment	ST slope	0,1,2	Nominal
12	class	target	0,1	Binary

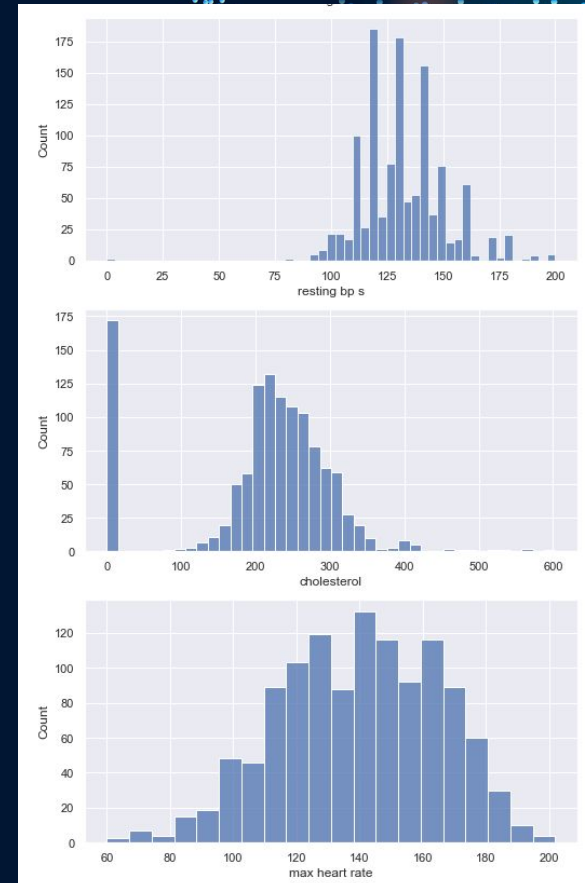
# Data Preparation

## Data Cleaning:

- Separated numerical and categorical variables
- Renamed variable (sex) for exploratory data analysis
- Removed anomalies for numerical data
- Ensured dataset is balanced

## Data Visualisation:

Importing pandas and NumPy to analyse data,  
seaborn to analyse relationship and several  
scikit-learn tools for regression and classification



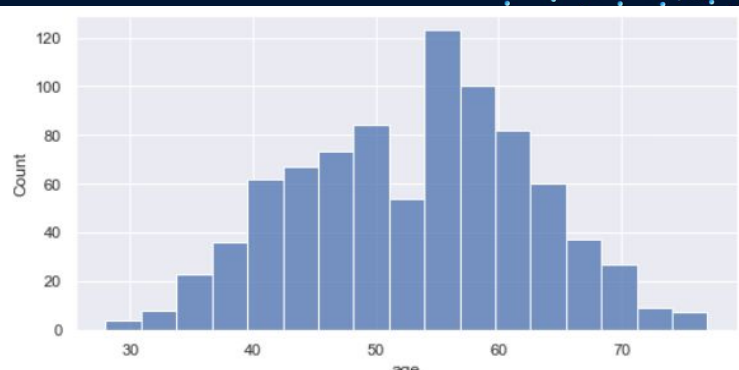
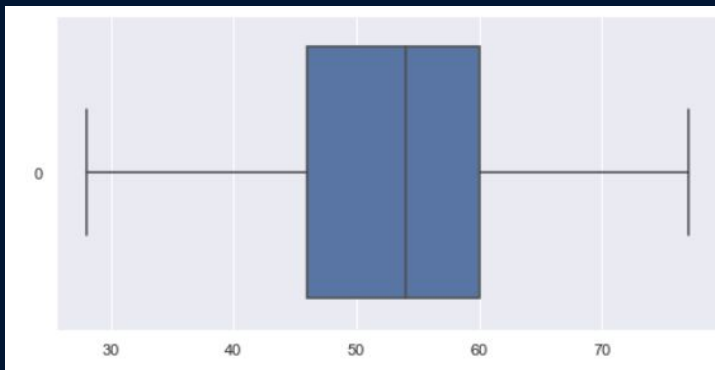


# Exploratory Data Analysis

## Numeric Variables (Uni-variate)

- Box Plot
- Histogram

	age	resting bp s	cholesterol	max heart rate	oldpeak
count	856.00	856.00	856.00	856.00	856.00
mean	53.10	130.99	243.72	137.97	0.99
std	9.47	15.67	56.13	22.40	1.09
min	28.00	92.00	85.00	69.00	-0.10
25%	46.00	120.00	208.00	122.00	0.00
50%	54.00	130.00	237.00	140.00	0.80
75%	60.00	140.00	274.00	155.00	1.70
max	77.00	170.00	603.00	185.00	6.20



# Exploratory Data Analysis

## Numeric Variables (Multi-variate)

- Correlation Table and Heatmap

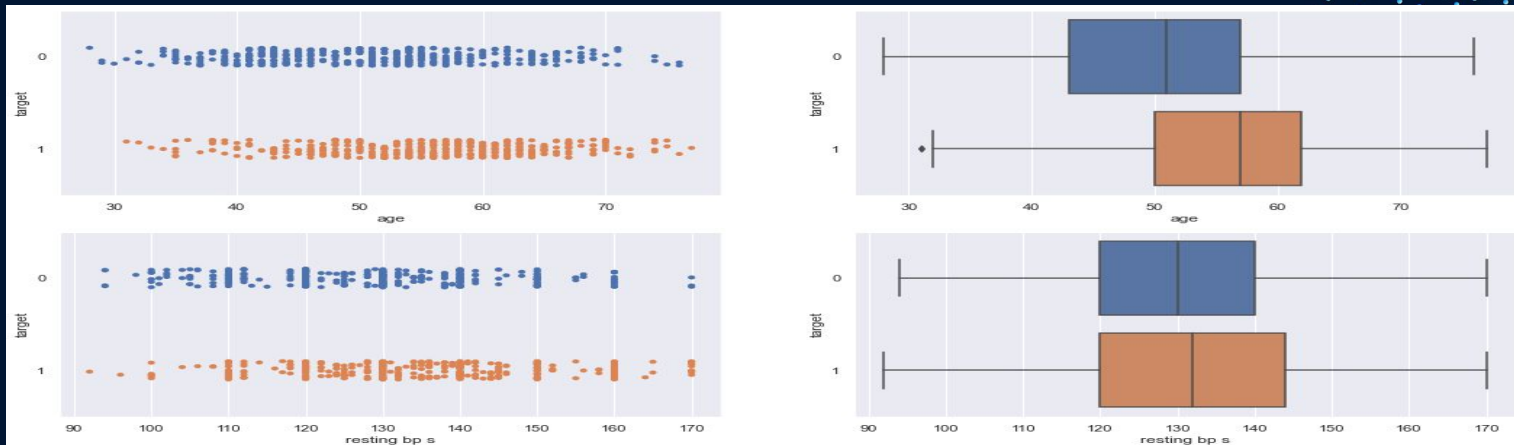
	age	resting bp s	cholesterol	max heart rate	oldpeak
age	1.000000	0.280102	0.047276	-0.443281	0.298883
resting bp s	0.280102	1.000000	0.099058	-0.155518	0.230970
cholesterol	0.047276	0.099058	1.000000	-0.020512	0.042241
max heart rate	-0.443281	-0.155518	-0.020512	1.000000	-0.233011
oldpeak	0.298883	0.230970	0.042241	-0.233011	1.000000



# Exploratory Data Analysis

## Numeric Variables (Predictors vs Target)

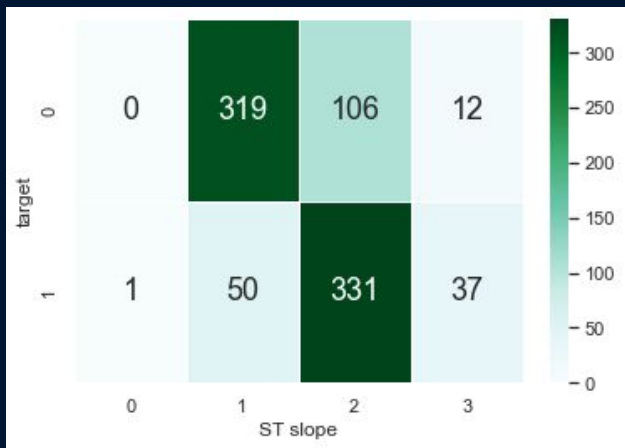
- Strip Plot
- Box Plot



# Exploratory Data Analysis

## Categorical Variables (Predictors vs Target)

- Heatmap





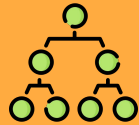


**03**

# **Core Analysis**

Machine Learning Models

# Machine Learning Models



Decision Tree



Random Forest

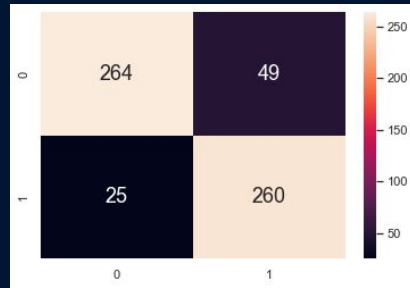


Logistic Regression

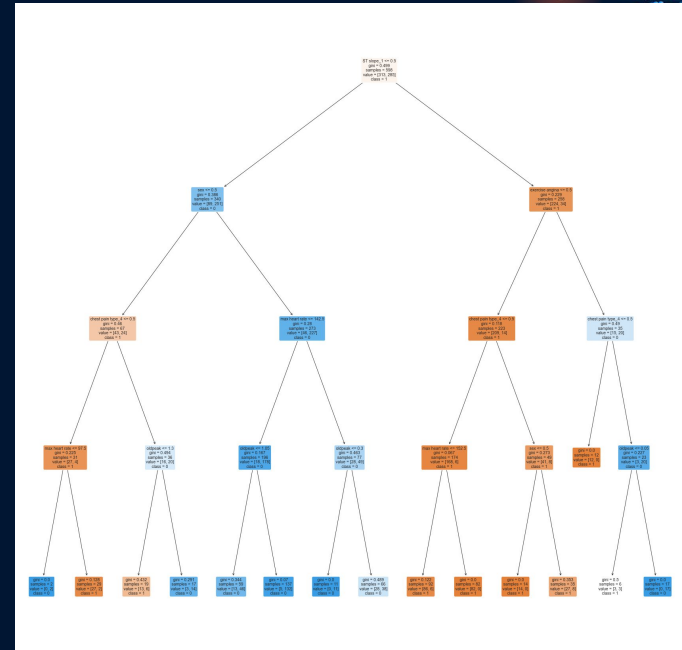
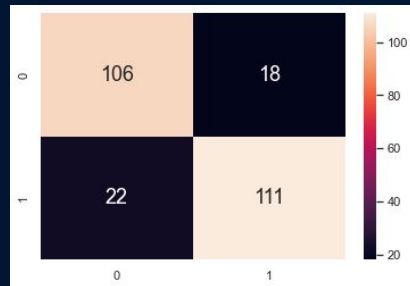
# Decision Tree

## Classification Accuracy

Train: ~87.63%



Test: ~84.44%



# Random Forest

## Classification Accuracy

Train: ~88.80%

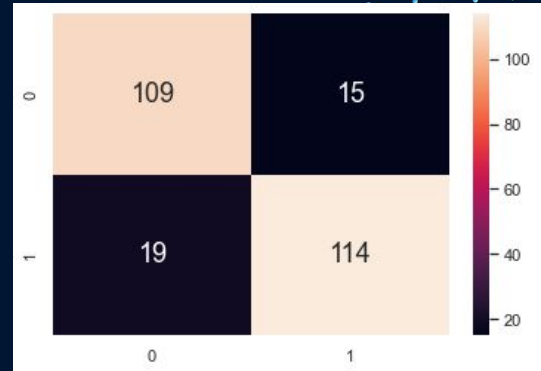
Test: ~86.77%

Number of decision trees used: 100

Maximum depth of each tree: 4



Train



Test



# Random Forest

## Classification Accuracy

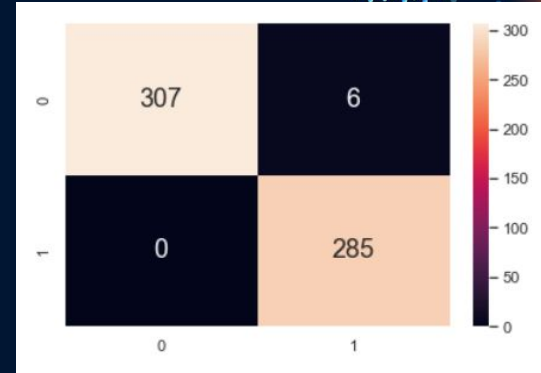
Train: ~99.00%

Test: ~93.00%

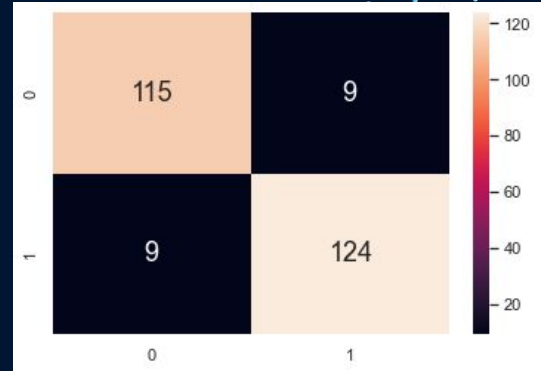
### After adjusting 2 major hyper-parameters:

Number of decision trees used: 1000

Maximum depth of each tree: 10



Train



Test

# Logistic Regression

Optimization terminated successfully.  
Current function value: 0.366927  
Iterations 7

Table 2:

Results: Logit

```
=====
Model:                Logit                Pseudo R-squared: 0.470
Dependent Variable:   target                AIC:          460.8447
Date:                2022-04-23 01:54      BIC:          509.1742
No. Observations:    598                  Log-Likelihood: -219.42
Df Model:            10                   LL-Null:       -413.85
Df Residuals:        587                  LLR p-value:    2.2210e-77
Converged:           1.0000               Scale:         1.0000
No. Iterations:      7.0000
=====
```

```
=====
                Coef.  Std.Err.  z  P>|z|  [0.025  0.975]
-----
age             -0.0218   0.0137  -1.5942  0.1109  -0.0486   0.0050
sex              1.6003   0.3071   5.2103  0.0000   0.9983   2.2022
chest pain type  0.4838   0.1330   3.6376  0.0003   0.2231   0.7445
resting bp s    -0.0054   0.0075  -0.7298  0.4655  -0.0201   0.0092
cholesterol      0.0019   0.0022   0.8373  0.4024  -0.0025   0.0063
fasting blood sugar 0.2432   0.3392   0.7170  0.4734  -0.4217   0.9081
resting ecg      0.1319   0.1376   0.9583  0.3379  -0.1378   0.4016
max heart rate   -0.0330   0.0049  -6.7075  0.0000  -0.0426  -0.0234
exercise angina  1.0641   0.2682   3.9682  0.0001   0.5385   1.5897
oldpeak          0.6580   0.1459   4.5094  0.0000   0.3720   0.9439
ST slope         1.1627   0.2506   4.6389  0.0000   0.6714   1.6539
=====
```

Model 1

Optimization terminated successfully.  
Current function value: 0.334024  
Iterations 7

Table 1:

Results: Logit

```
=====
Model:                Logit                Pseudo R-squared: 0.517
Dependent Variable:   target                AIC:          421.4930
Date:                2022-04-23 01:54      BIC:          469.8225
No. Observations:    598                  Log-Likelihood: -199.75
Df Model:            10                   LL-Null:       -413.85
Df Residuals:        587                  LLR p-value:    9.2910e-86
Converged:           1.0000               Scale:         1.0000
No. Iterations:      7.0000
=====
```

```
=====
                Coef.  Std.Err.  z  P>|z|  [0.025  0.975]
-----
age              0.0248   0.0162   1.5324  0.1254  -0.0069   0.0565
max heart rate  -0.0086   0.0071  -1.2103  0.2262  -0.0225   0.0053
oldpeak         0.5110   0.1510   3.3832  0.0007   0.2150   0.8070
sex              2.0473   0.3401   6.0190  0.0000   1.3806   2.7139
exercise angina  0.9549   0.2844   3.3576  0.0008   0.3975   1.5124
chest pain type_2 -0.3124   0.6158  -0.5073  0.6119  -1.5193   0.8946
chest pain type_3  0.0718   0.5495   0.1306  0.8961  -1.0052   1.1487
chest pain type_4  1.4195   0.5295   2.6807  0.0073   0.3816   2.4574
ST slope_1      -4.7011   1.7692  -2.6571  0.0079  -8.1687  -1.2335
ST slope_2      -2.6127   1.7210  -1.5182  0.1290  -5.9858   0.7603
ST slope_3      -3.6212   1.8168  -1.9931  0.0462  -7.1821  -0.0603
=====
```

Model 2

# Logistic Regression

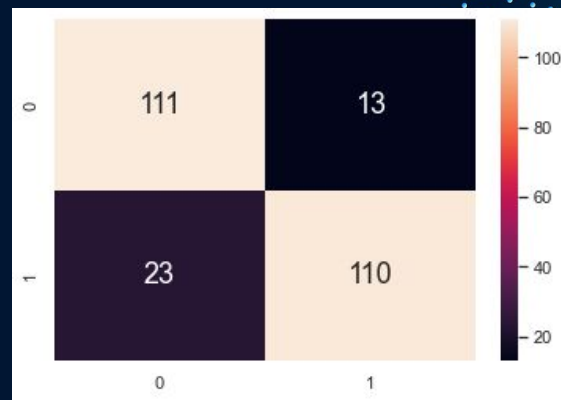
## Classification Accuracy (Model 1)

Train: ~86.79%

Test: ~85.99%



Train



Test

# Learning Points

## **Random Forest**

Handles numeric variables (regression) and  
categorical variables (classification)

---

## **Logistic Regression**

Binary classification  
Categorical target





04

# Our Outcome

Insights & Solution

# Evaluation



## Decision Tree

Pros:

Faster computation time  
compared to Random Forest

Cons:

Relatively less accurate since only  
one tree is used in the prediction,  
overfitting without control



## Random Forest

Pros:

Constructs multiple decision trees  
to improve predictions, making it  
more stable and accurate

Cons:

Slower computation time as  
compared to Decision Tree



**Random Forest returns a  
higher accuracy for our  
dataset**

# Evaluation



## Random Forest

Pros:

Offers higher accuracy than  
Logistic Regression

Cons:

Slower computation time and  
harder to interpret as compared  
to Logistic Regression



## Logistic Regression

Pros:

Easier to interpret and shorter  
computation time as compared  
to Random Forest

Cons:

Lower accuracy

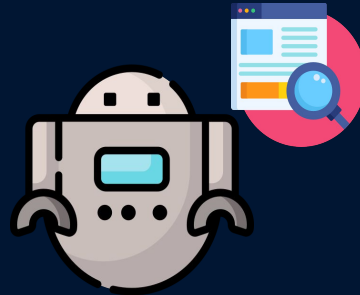
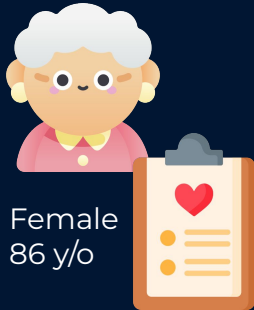


**Random Forest returns the  
highest accuracy for our  
dataset**

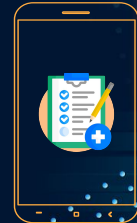
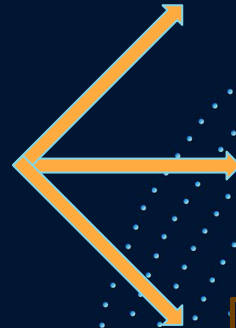
# Solution: *Robo-Medivisor*

Chosen model: **Random Forest**

Aim: lighten the workload of doctors and increase doctors' efficiency in detecting potential heart disease patients early



Robo-medivisor



Patient's phone





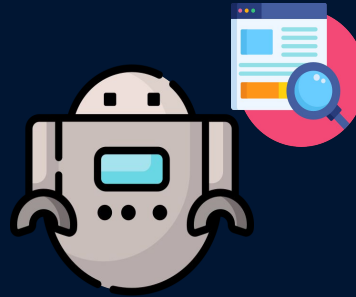
# Solution: *Robo-Medivisor*

Chosen model: **Random Forest**

Aim: lighten the workload of doctors and increase doctors' efficiency in detecting potential heart disease patients early



Male  
30 y/o

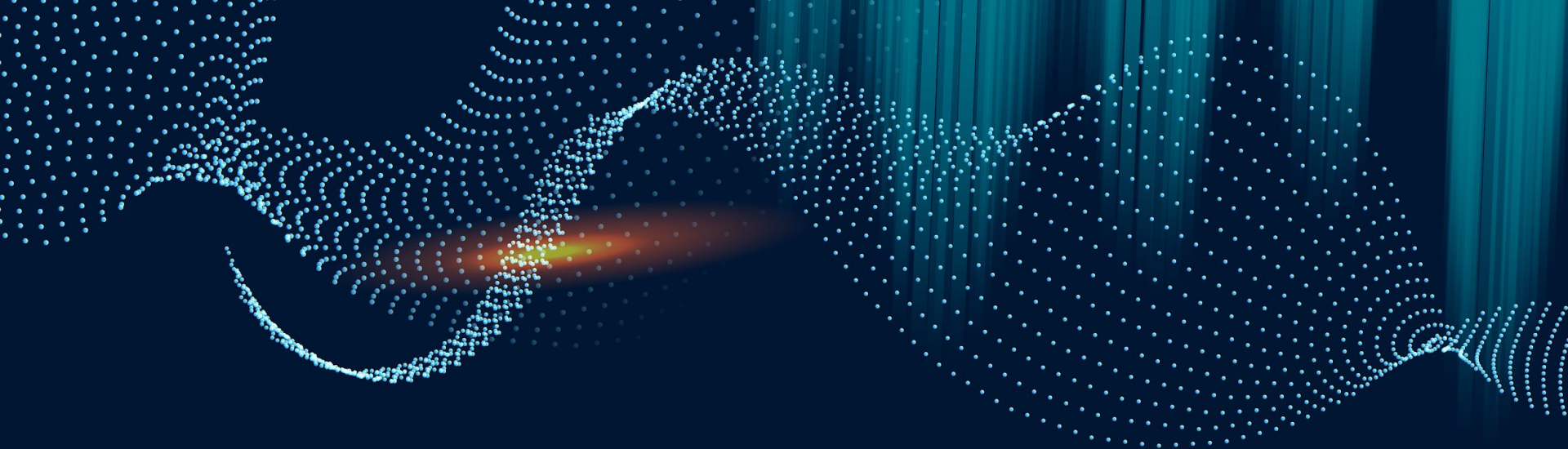


Robo-medivisor



Patient's phone





**THANK YOU**

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