

A blue-tinted photograph of an operating room. In the center, a surgeon in blue scrubs and a surgical cap is looking at a monitor displaying a medical image. To the right, another surgeon in blue scrubs and a surgical cap is performing a procedure on a patient lying on an operating table. The room is filled with medical equipment, including monitors, IV stands, and surgical instruments. The overall atmosphere is clinical and focused.

# Quantifying Post-Operative Blood Loss

Team Surgience



## Meet Our Talented Team

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Neil Sundaram

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Sitara Rao

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Jeremy Yuan

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Alexandra Miekisz

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Cassie Hoppenrath

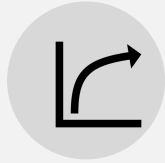
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Richa Bhujbal

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# Key Milestones

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A successful working prototype for vital signs plot



POC of UI design and development



Parsed ASAC dataset for a preliminary model



Contacted relevant physicians

# Logistic Regression Pros vs Cons

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## PROS:

- Easier to implement, interpret, and very efficient to train—training a model with this algorithm does not require high computation power
- Makes no assumptions about distributions of classes in feature space
- Easily extend to multiple classes and a natural probabilistic view of class predictions
- Not only provides a measure of how appropriate a predictor(coefficient size) is, but also its direction of association (positive or negative)--so we can use logistic regression to find out the relationship between the features
- Very fast at classifying unknown records
- Good accuracy for many simple data sets and it performs well when the dataset is linearly separable
- Can interpret model coefficients as indicators of feature importance

## CONS:

- If the number of observations is lesser than the number of features, it may lead to overfitting
- It constructs linear boundaries
- Major limitation is the assumption of linearity between the dependent variable and the independent variables
- It can only be used to predict discrete functions
- Non-linear problems can't be solved with logistic regression because it has a linear decision surface. Linearly separable data is rarely found in real-world scenarios
- Requires average or no multicollinearity between independent variables
- Tough to obtain complex relationships; more powerful and compact algorithms such as Neural Networks can easily outperform this algorithm

LR: After discussing with a number of professionals 9/10 times the regression model would be preferred over any other machine learning or artificial intelligence algorithm. Most of the time you are delivering a model to a client or need to act based on the output of the model and have to speak to the why. It is relatively easy to explain a linear model, its assumptions, and why the output is what it is. Trying to do that with a neural network would be not only exhausting but extremely confusing to those not involved in the development process

## Machine Learning Model Results

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### Log Regression

- Only two outcomes in our case: Fluids (1) and no fluids (0)
- Want to find the probability threshold of “Fluids” vs “No Fluids”
- Output is a number between 0 and 1, which is our predicted probability that output is 1. Our threshold is where we draw the line to decide probability.

### KNN

- KNN assumes that similar things will exist in close proximity based on variables, in our case patients needing fluids will be similar to other patients needing fluids and vice-versa
- KNN finds the “distance” between data points and classifies them as Fluids (1) or No Fluids (0)

# Neural Network Pros vs Cons

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## PROS:

- Neural networks are flexible and can be used for both regression and classification problems. Any data which can be made numeric can be used in the model, as a neural network is a mathematical model with approximation functions.
- Neural networks are good to model with nonlinear data with a large number of inputs; for example, images. It is reliable in an approach of tasks involving many features. It works by splitting the problem of classification into a layered network of simpler elements.
- Once trained, the predictions are pretty fast.
- Neural networks can be trained with any number of inputs and layers.
- Neural networks work best with more data points.

## CONS:

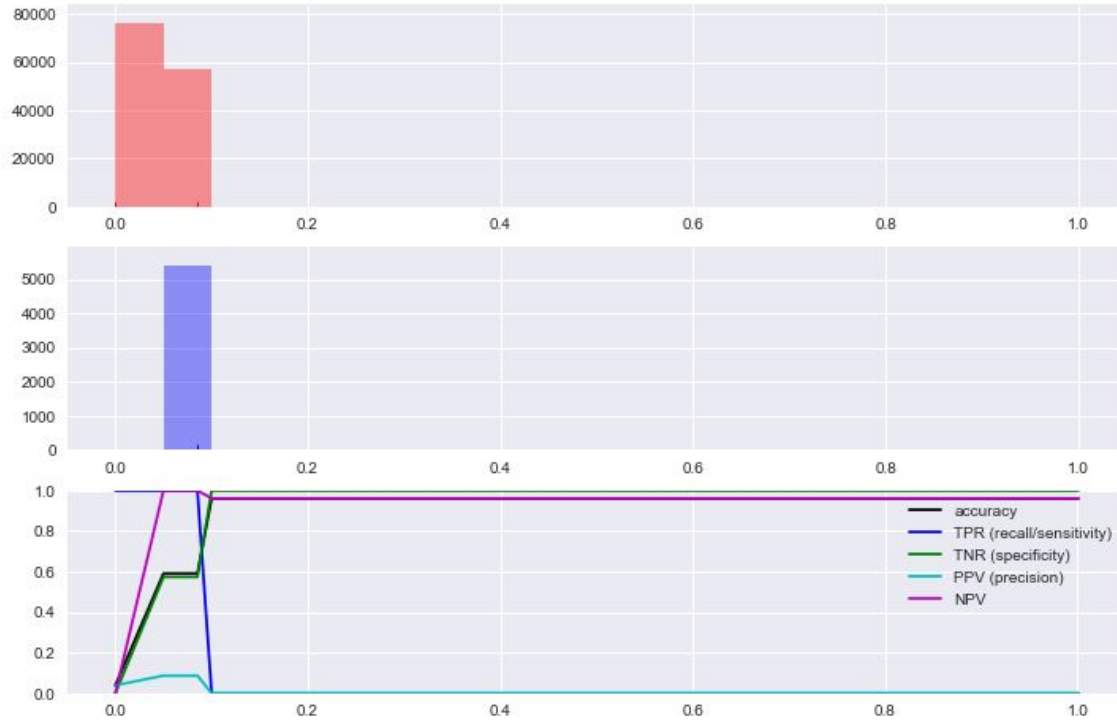
- Neural networks are black boxes, meaning we cannot know how much each independent variable is influencing the dependent variables.
- It is computationally very expensive and time consuming to train with traditional CPUs.
- Neural networks depend a lot on training data. This leads to the problem of overfitting and generalization. The model relies more on the training data and may be tuned to the data.

NN: Regression is a method dealing with linear dependencies, neural networks can deal with nonlinearities. So for data with some nonlinear dependencies, neural networks should perform better than regression.

In some applications, neural networks fits better than another model such as linear regression. And it usually occurs when there are nonlinearities involved. Though, it is important to evaluate before other aspects. For example: a linear regression model will have less parameters to estimate than a neural networks for the same set of input variables. Then, neural networks will require a larger dataset for its optimization in order to get its benefit of generalization and nonlinear mapping. So, if we do not have enough data, despite existing nonlinearities involved, a linear regression model may be better adjusted.

# Machine Learning Model Results

## Log Regression

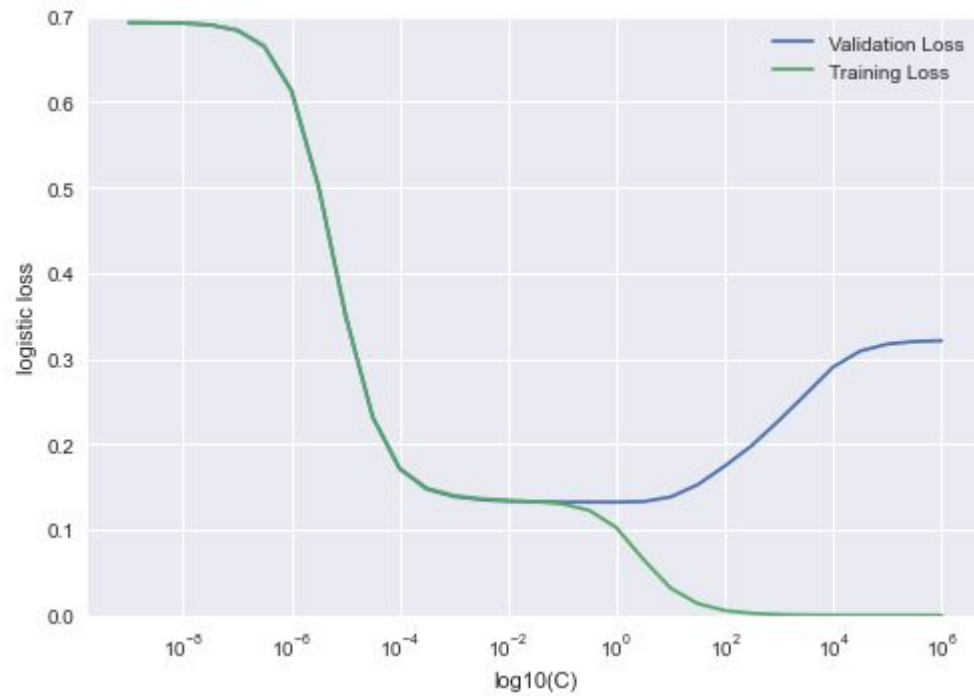


## KNN

# Machine Learning Model Results

## Log Regression

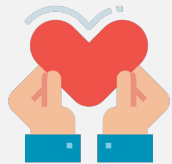
## KNN



# Summary & Next Steps

A better way for surgeons to utilize real time hemodynamic status to minimize postoperative complications

Traditional methods of quantifying blood loss are **inaccurate**



- ✓ UI Health has moved towards monitoring hemodynamic status instead of measuring blood loss

Current alternatives of hemodynamic monitoring are **lacking**



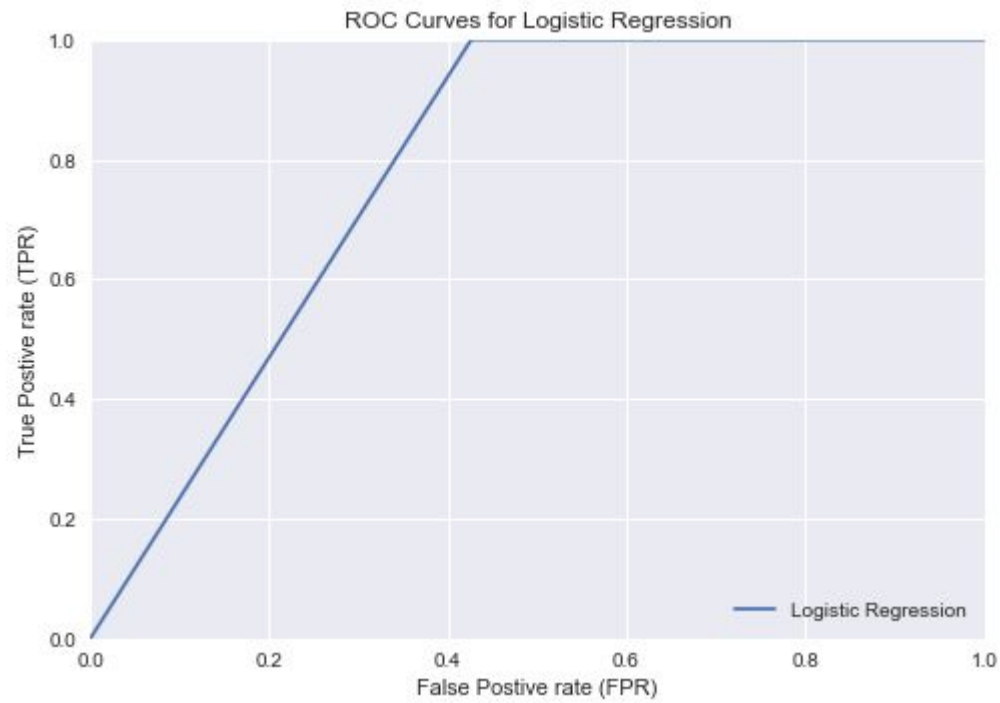
- ✓ ML models are accurate but are underutilized
- ✓ Massimo provides supplemental data to the surgeon but is not comprehensive

## For next semester...

- Visit Operating Room to develop a pseudo dataset from model training
- Develop a working POC to prove that ML learning can be applied
- Consult various surgeons on UI and interface preferences

# Machine Learning Model Results

## Log Regression



## KNN

# Current Practices



## Visual Estimation

Estimation of blood volume from visual inspection of pads, sponges, and suction containers.

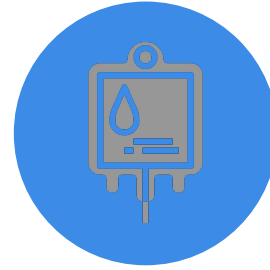
- Huge influence from factors such as professional experience, gender, and age. <sup>[10]</sup>
- Inaccuracies have a median of around 30% of true blood volume. <sup>[11]</sup>



## Gravimetric

Indirect measurement, weighing blood-contaminated surgical material and comparing with dry material weight.

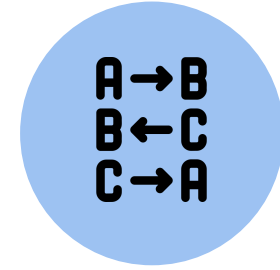
- Dilution and rinsing are two main factors that lead to large inaccuracies. <sup>[11]</sup>
- Measurement is also extremely time-consuming.



## Direct Measurement

Mainly used in obstetrics, use of calibrated blood collection bag during vaginal delivery

- Improved accuracy when used in combination with visual estimation, but studies still show serious deviations from true blood loss. <sup>[11]</sup>



## Calculated Blood Loss

Estimation using mathematical formulas, takes into account hemodynamic factors and gender, age, height, etc.

- Studies show that mathematical formulas show a tendency to overestimate blood loss. <sup>[11]</sup>

**Under or late transfusion: increased mortality rates in high blood loss surgeries<sup>[1]</sup> and poorer neurological outcomes. <sup>[2]</sup>**

**Over transfusion (too much blood): higher risk of postoperative bacterial infection<sup>[5]</sup>**

# Concept Solution: Data Collection



**Dependent Variable: Volume of blood that a physician would administer at that moment in time**

# User Needs

User Need Item	User Need	Rationale
1	Device must be sanitizable	Device will be used in operating room and must be sanitized prior
2	Device must be used for multiple days at a time	Patient recovery time may vary and we want to monitor hemodynamic status continuously
3	Device must be used by medical staff	Device interface must be easy and quick to use as wasting surgical time may be expensive
4	Device must rapidly give hemodynamic status of the patient when necessary	During critical procedures constant knowledge of patient status is necessary to ensure safety
5	Device must be portable for post-operative monitoring	Device should function outside OR to help prevent post-op complications

# Design Requirements

Item	Design Criteria Item	Quantifiable Requirement	Units	Rationale	Verification Method
A	2	Device must have be powered by a rechargeable battery with 9V to power Arduino	V	Device battery must be rechargeable for continued used and must be strong enough to power Arduino microcontroller	Multimeter
B	2	Device must have 8GB of memory	GB	Device must have enough memory to store and analyze patient data	Purchase of 8GB SD card
C	1	Device must meet at least an SAL of $10^{-6}$ prior to operating room entry	SAL (sterility assurance level)	Device must be sterile prior to entering operating room	Once the number of microbes killed is determined, double the log reduction of this number and this gives you the SAL
D	4	Model must have a runtime of less than 30 seconds	seconds	Knowledge of hemodynamic status must be quickly retrievable during surgery	Time
E	1	Device must be able to connect to network	Latency	Patient data should be backed up on network	ping

# What have we done so far?



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## Regulatory Standards

We have conducted research on regulatory standards relevant to our device and its implementation.

### Leading us to:

**IEC 62304:** This standard defines the lifecycle for software as a medical device (SaMD)  
and

**ISO 24291:** This standard governs the use cases for machine learning in medicine that is used for clinical practice

### Why is this important?

These standards have allowed us to determine certain design requirements and processes necessary for model development

# What have we done so far?



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## Data Availability

**Our major focus so far has been finding data that allows for us to build and validate our model**

## Leading us to:

**The Anaesthetic Shoulder Arthroscopy Cases (ASAC) Dataset, this dataset includes patient data and time-stamped medical events and interventions including drug, vapour administration, repositioning of the patient etc for a total of 20 cases.**

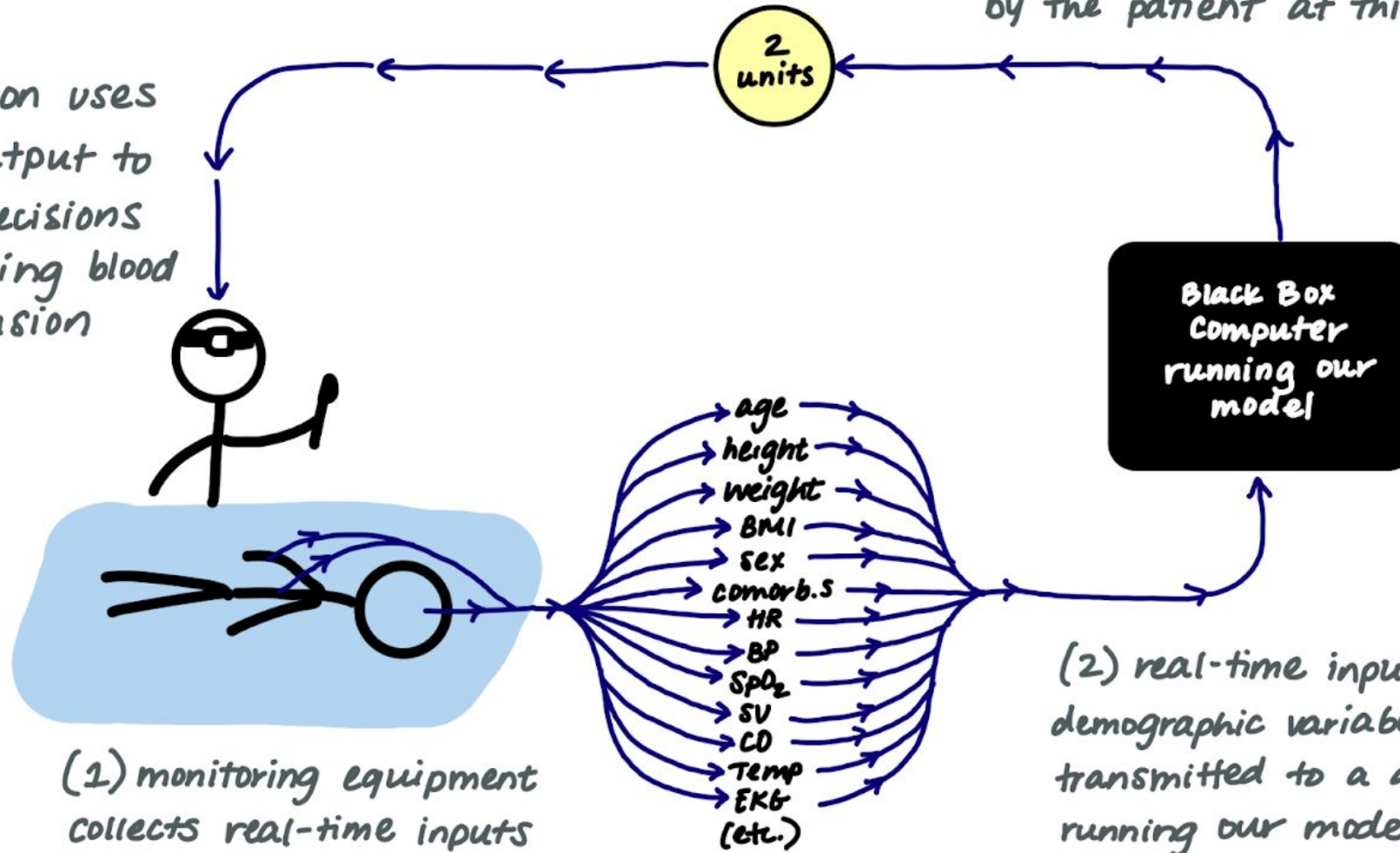
## What have we done?

**So far we have worked towards parsing data from the XML format to allow us to utilize this data for model development**

→ information flow

(3) model outputs a prediction of blood transfusion volume needed by the patient at this time

(4) surgeon uses model output to inform decisions surrounding blood transfusion



(2) real-time inputs & demographic variables are transmitted to a device running our model.

(1) monitoring equipment collects real-time inputs

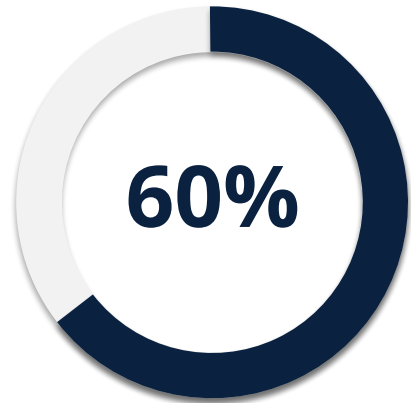
## Understanding the Problem

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- Adverse outcomes from excessive perioperative bleeding and blood loss **underestimation** have been extensively documented.<sup>[1][2][3][4][5][6][7]</sup>
  - Heart attack
  - Stroke
  - Renal Failure
  - Sepsis
  - Longer ICU and hospital stays
  - Death
- **Overestimation of perioperative blood loss can also be a problem.** Increased fluid retention can lead to adverse outcomes post-operation as well.
- **Currently there is no method to accurately measure and monitor patient perioperative hemodynamic status**

WIP

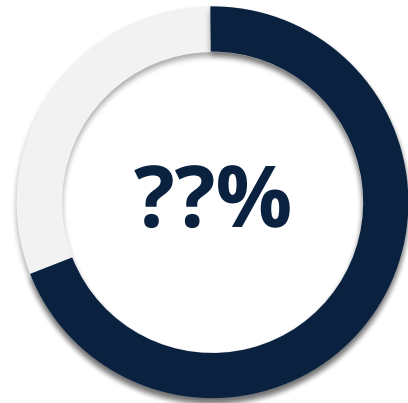
# Model Performance & Comparison



## Logistic Regression

Typical classification model used in datasets with linear data. Easy to implement, interpret, and very efficient to train.

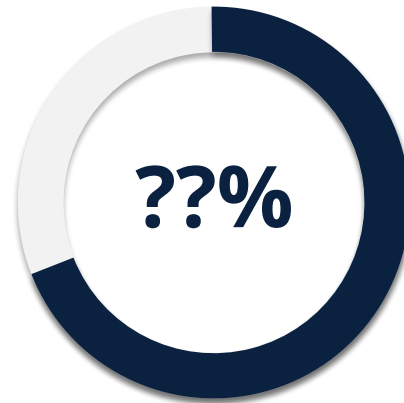
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## Neural Network

Intelligent model that is capable of handling non-linear data. Can form complex interaction between variables and discover hidden patterns.

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## Support Vector Machines

Classification algorithm that finds the distance between the query and nearest (k) examples in data to find the most frequent label

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### Outcome Focus

A linear model will be more interpretable while a non-linear model will be more powerful.



### Future Applications

A NN cannot give descriptive statistics about how an independent variable affects the dependent variable. It is black box.



### Training data

LR will perform better with simpler datasets while NN will perform better with larger / more complex datasets.



### Flexibility

NN are more flexible and can be used for both regression and classification problems. Can also handle continuous data.



### Computational Power

NN are **significantly** more computationally expensive when compared to LR.

# Post Operative Monitoring: A New Scenario

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## Fluid Estimation

Fluid resuscitation is an inexact science – which can be focused on restoring normal perfusions rather than replacing an estimated volume deficit. Visual estimation does not account for occult bleeding. [16]



## Delayed Action

Visual symptoms of bleeding are a late manifestation and typically occur after the blood loss has already exceeded 15 percent of the patient's total volume (class 1 haemorrhage). [16]

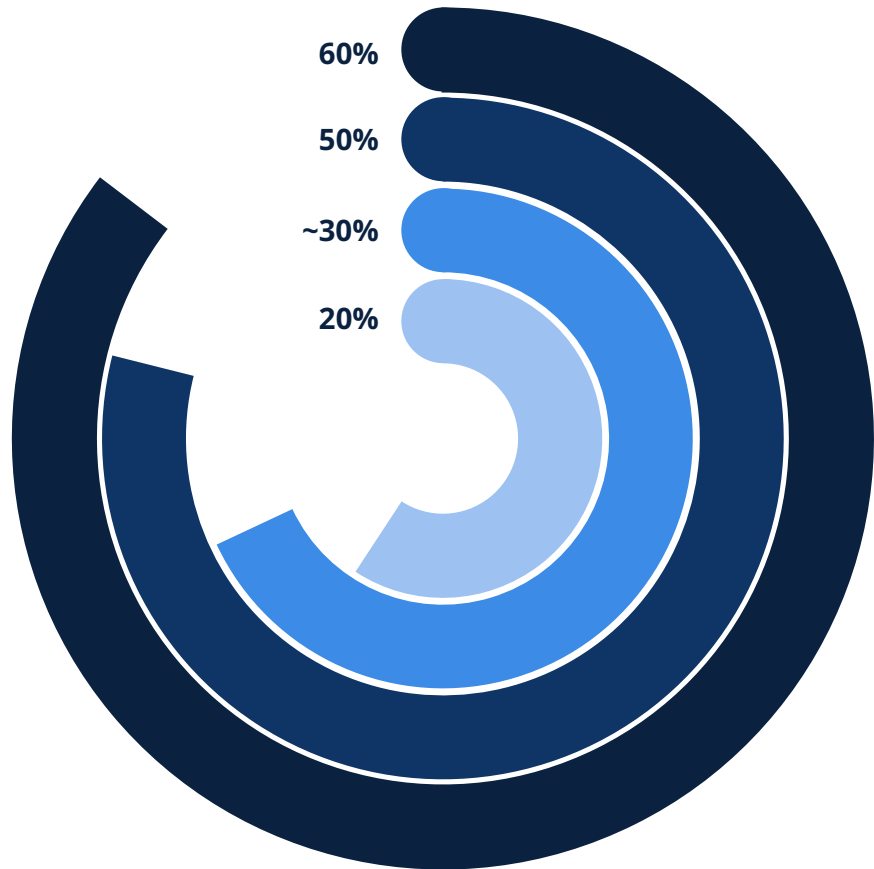


## Return to Operating Room

In most cases, a return to the operating room will be necessary to control the bleeding, therefore there is a need for a device that primarily functions in the post operative setting but contains design requirements that satisfy an intraoperative space. [16]

What are some issues with today's current practices?

# Wards require only intermittent "snapshots" of vital sign measurement (4-6 hours)



Hypoxemia occurred in 20% of all patients recovering from non-cardiac surgery. 90% of these hypoxemic cases in which O2 saturation <90% for at least 1 hour [17]



15-45% of patients suffer from postoperative complications – with an overall mortality rate of 1-2% within a month after surgery [17]



Hypotension (<65mm Hg) was missed with 50% of postoperative monitoring routine "spot checks" when compared to continuous monitoring [17]



At least 60% of patients have one abnormal vital sign 1-4 hours before an acute cardiorespiratory arrest [17]

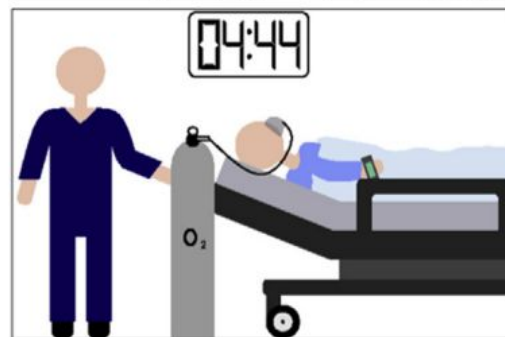
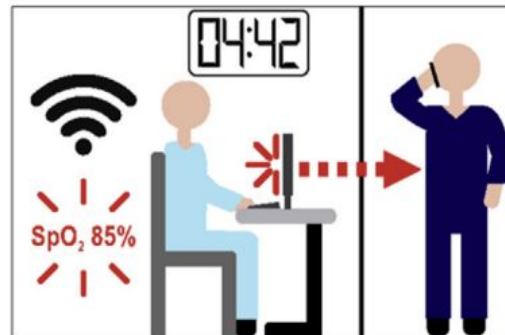
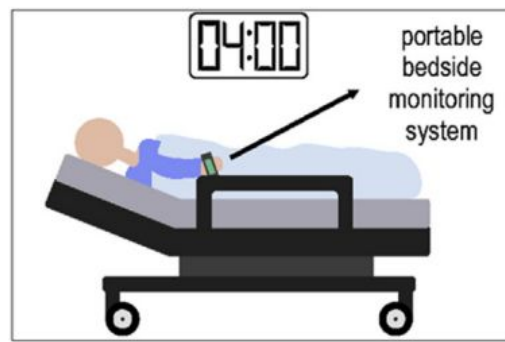
An inherent problem with the current periodic monitoring of vital signs in the ward is the lack of interpretation of **subtle** changes in vital signs or a pattern detection that may occur during early deterioration

Periodic monitoring



Late recognition of deterioration

Continuous ward monitoring



Early recognition of deterioration

## "4 a.m. phenomenon"

Unplanned and potentially preventable ICU admissions as a result of lack of timely intervention in the absence of continuous ward monitoring [17]



Usage of current vital signs as proxy to status  
Vital signs may be "late" in the hypovolemic setting due to compensatory mechanisms (increased peripheral constriction)



Invisible changes  
Perturbations in patient status may go undetected in traditional spot checks

# What must our solution accomplish?

## User Needs

### UI and Interface Design

Important hematological factors are at the forefront for viewing by surgical teams



### Portability

Interface is dynamic and can show necessary information on a smaller device that can follow the patient throughout the hospital



### Interpretability

Transfusion volume as an output better helps surgeons gauge transfusion volume than a risk metric would



## Design Requirements



### Multi-functional Data

Data can be easily transformed to fulfill latent needs or other upcoming projects.



### Uses outside of OR

Model can be scaled to catch undetected bleeds and postoperative hematological complications



### Open-Source Algorithm

The final algorithm will be open to the public for additional applications, further refinements and research purposes

## Problem Statement

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A continuous, smarter, and portable platform for surgical teams to monitor vital signs using **machine learning-based pattern detection solutions** to improve safety for post operative patients.



# Prototype Demo

# Sample Data Entry

INDEX	HADM_ID	AGE	EVENTS	FLUIDS
0	2400096	35	[ '2115-03-06 01:26:00', 'Heparin', 'Administered'], [ '2115-03-06 03:14:00', 'Acetaminophen IV', 'Administered'], [ '2115-03-06 03:14:00', 'Ketorolac', 'Administered'], [ '2115-03-06 05:23:00', 'EKG']	1

## Data Cleaning Process

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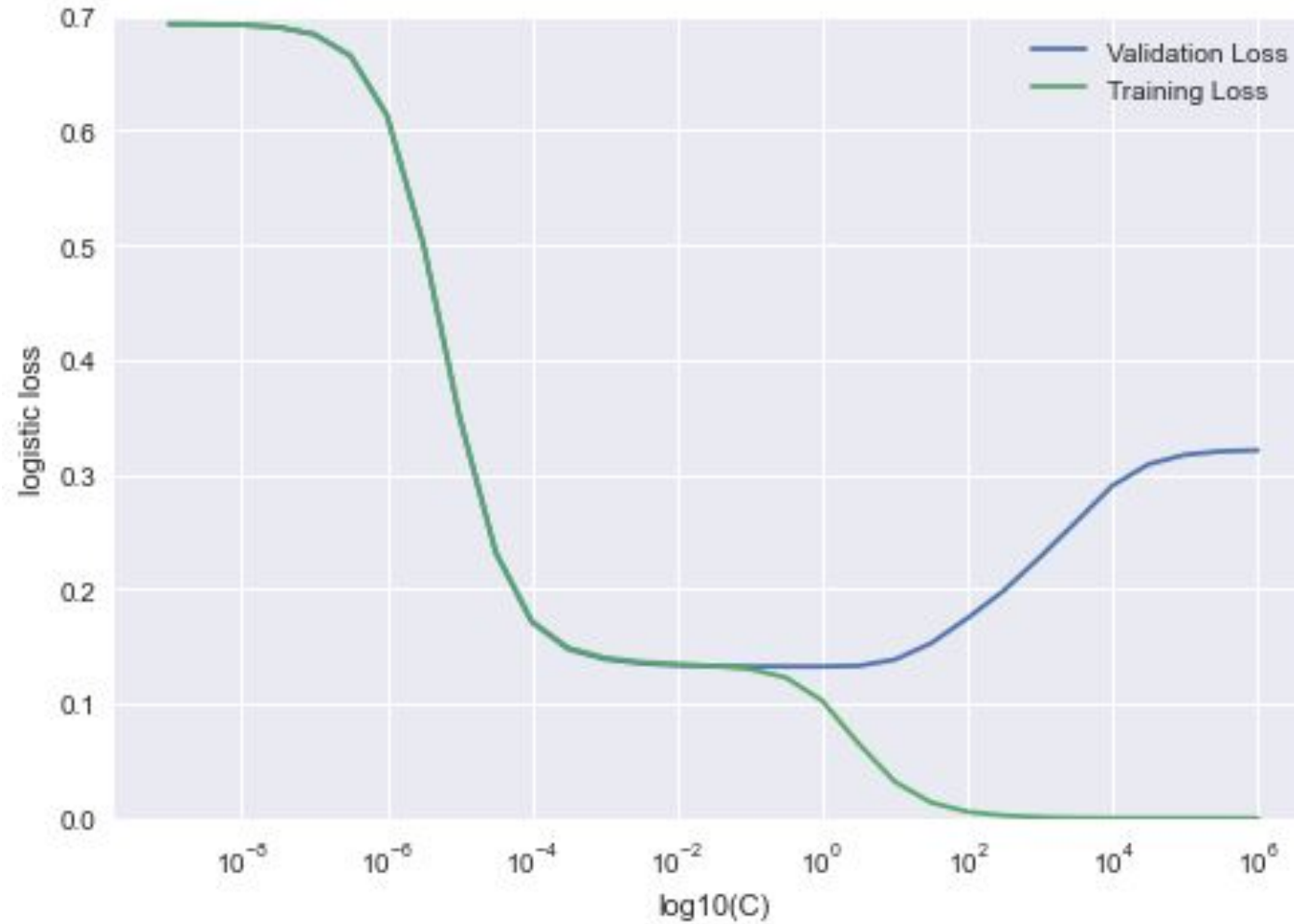
1. Load data from tables into data frames.
2. Calculate age from anchor\_year and anchor\_age utilizing MIMIC formula.
3. Remove any null values and unneeded columns from data frames.
4. Transform data frames to dictionaries, with the hadm\_id as the key.
5. Merge output events, procedure events, and emar dictionaries into events array
6. Utilizing the input events dataframe, we find all instances where blood was transfused and create a dictionary with hadm\_id as the key. Create final dictionary.
7. If blood was transfused to the patient, then Fluids is set to 'True'. Merge into final dictionary.
8. Write final dictionary to a CSV.

## Log Regression Intro

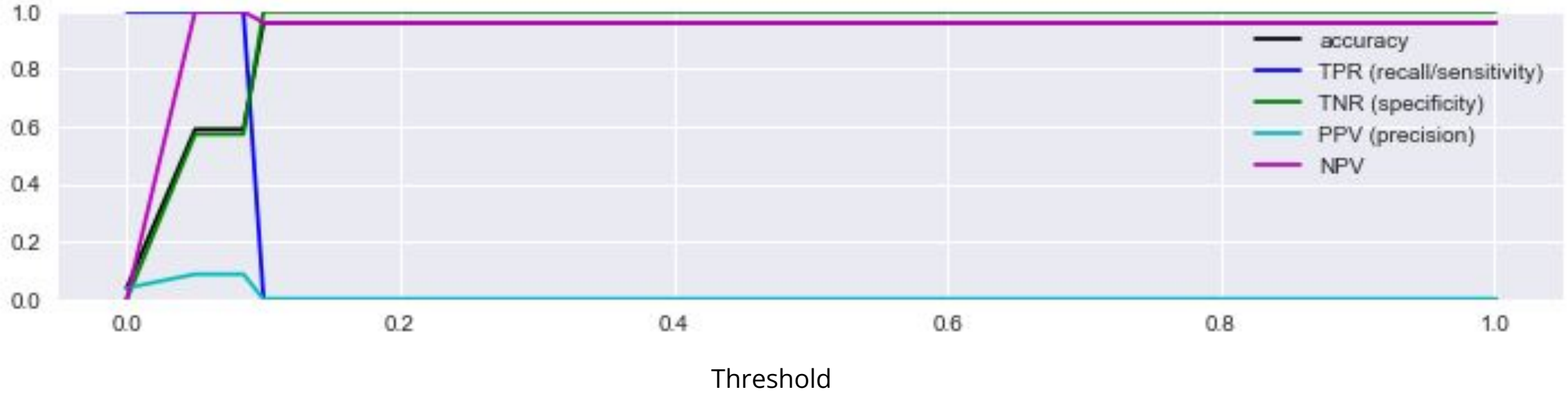
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- Only two outcomes in our case: Fluids (1) and no fluids (0)
- Want to find the probability threshold of “Fluids” vs “No Fluids”
- Output is a number between 0 and 1, which is our predicted probability that output is 1. Our threshold is where we draw the line to decide probability.

# Machine Learning Model Results

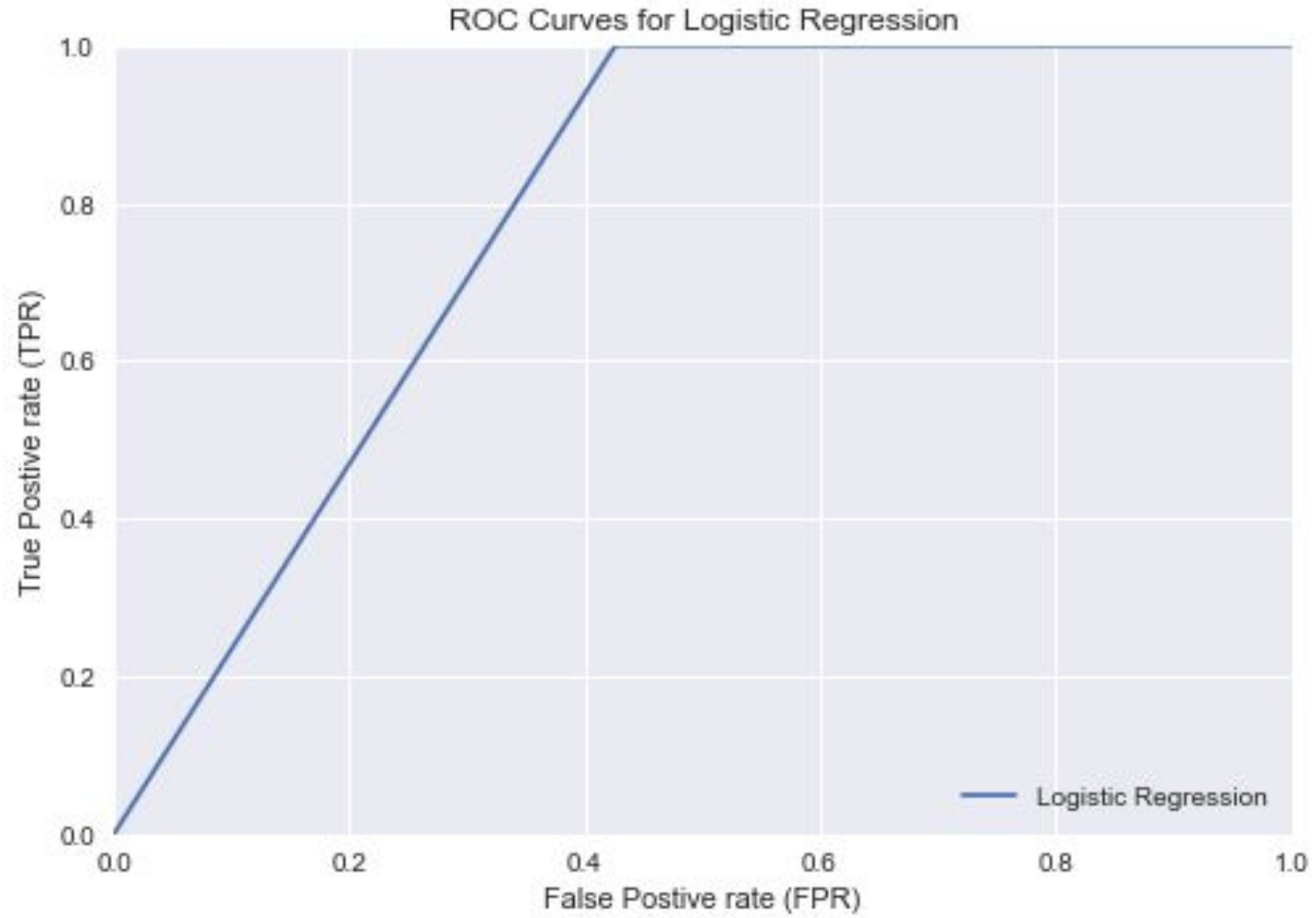


# Machine Learning Model Results



# Machine Learning Model Results

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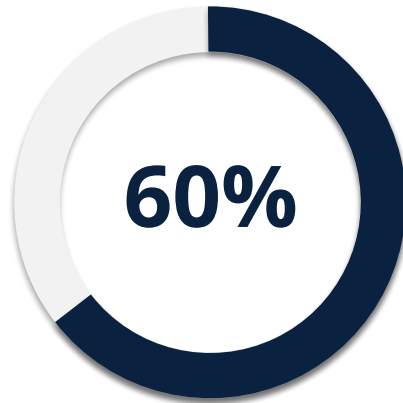


## ML Model Recap

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- Classification problem
- Normalize the data
- Perform feature engineering to enhance the model
- One-hot encode the categorical variables
- Remove or correct the outliers
- Perform visualisations for numerical variables

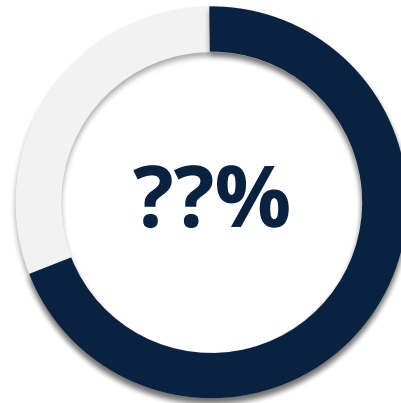
# Model Performance & Comparison



## Logistic Regression

Typical classification model used in datasets with linear data. Easy to implement, interpret, and very efficient to train.

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## Neural Network

Intelligent model that is capable of handling non-linear data. Can form complex interaction between variables and discover hidden patterns.

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### Outcome Focus

A linear model will be more interpretable while a non-linear model will be more powerful.



### Future Applications

A NN cannot give descriptive statistics about how an independent variable affects the dependent variable. It is black box.



### Training data

LR will perform better with simpler datasets while NN will perform better with larger / more complex datasets.



### Flexibility

NN are more flexible and can be used for both regression and classification problems. Can also handle continuous data.



### Computational Power

NN are **significantly** more computationally expensive when compared to LR.

# Tools for Business Value Analysis

Variable	Neural Network	Logistic Regression
Model Accuracy	<input type="checkbox"/>	? <input type="checkbox"/>
Model Intelligence	<input checked="" type="checkbox"/>	<input type="checkbox"/>
Computing Power	<input type="checkbox"/>	<input checked="" type="checkbox"/>
Interpretability	<input type="checkbox"/>	<input checked="" type="checkbox"/>
Complexity	<input checked="" type="checkbox"/>	<input type="checkbox"/>

## List of considerations & assumptions

### Model Focus

- Model accuracy
- Intelligence of model
- Run time and computing power

### Outcome Focus

- Additional time in hospital (~\$2k)
- Reentry to ICU (~\$6k)
- Average cost of malpractice claim (\$225k)

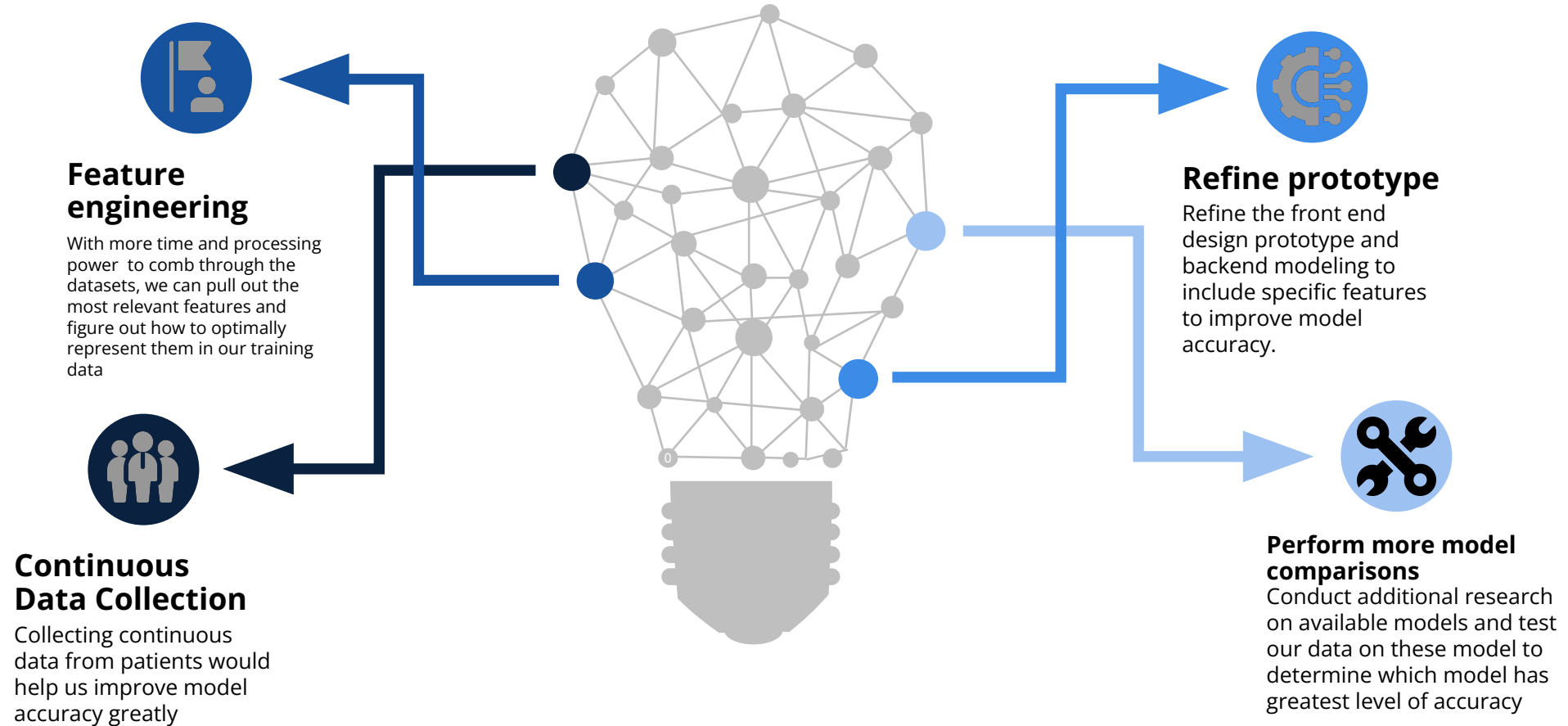


\$225k



\$6k

# Next Steps and Future Vision



**Our proposed solution is a machine learning model that allows for surgeons and other clinicians to accurately monitor and assess a patients' perioperative and postoperative hemodynamic status.**



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