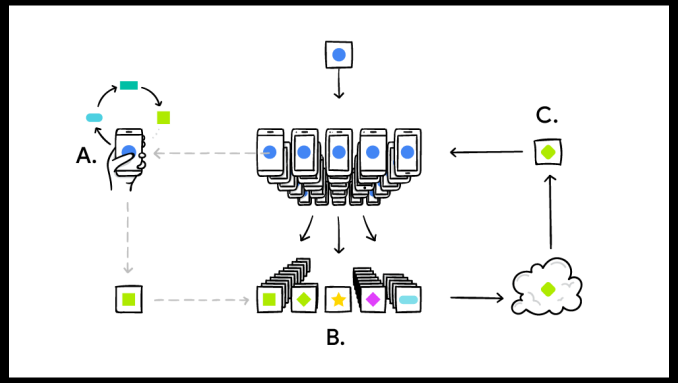
MORPH Guest Lecture

Implementing Machine Learning

Mentor: Eric Lin

Hi! I’m Eric


Done
SALE
Dragon Gate
Landmark · 43 mi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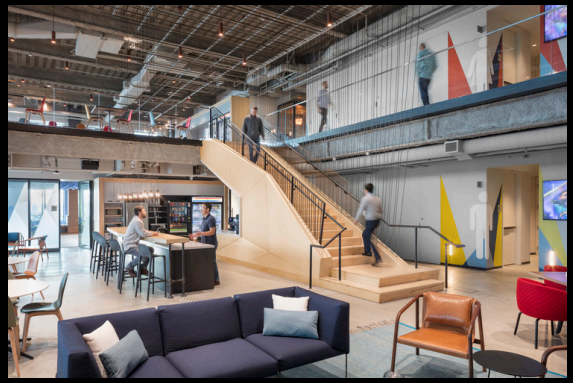
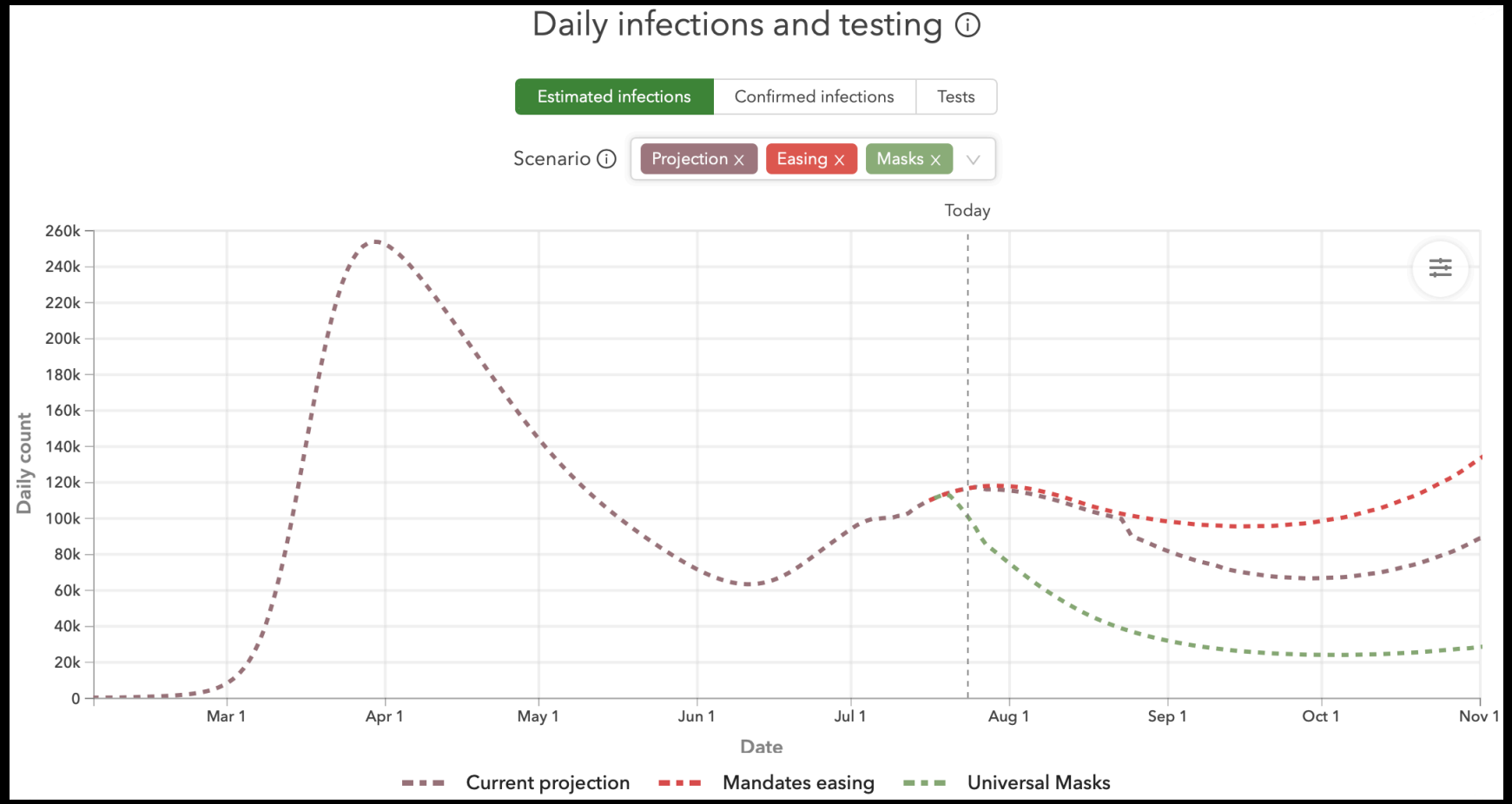


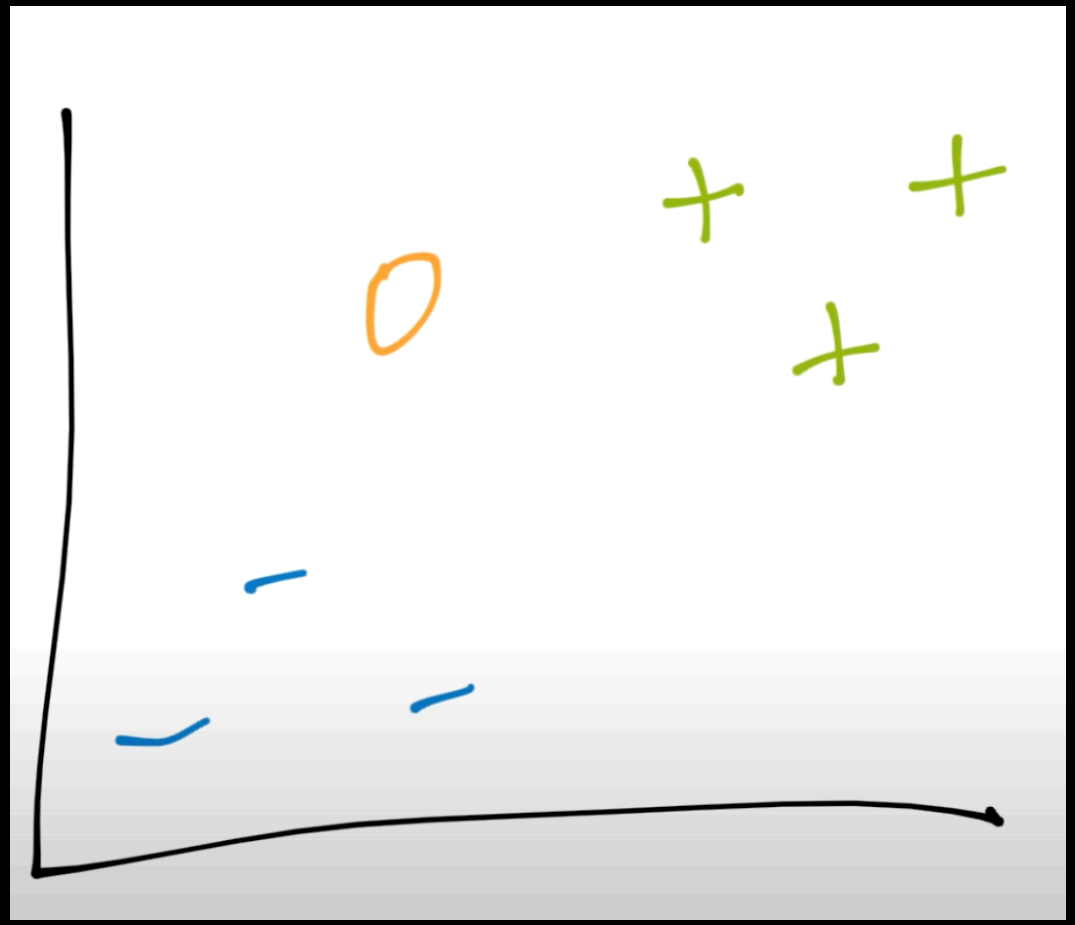
3 Archetypes of Machine Learning

1. Supervised
   - Given a dataset of points with correct output
2. Un-supervised
   - Input data without “correct” output
3. Reinforcement
   - Encouragement when actions align with positive behavior

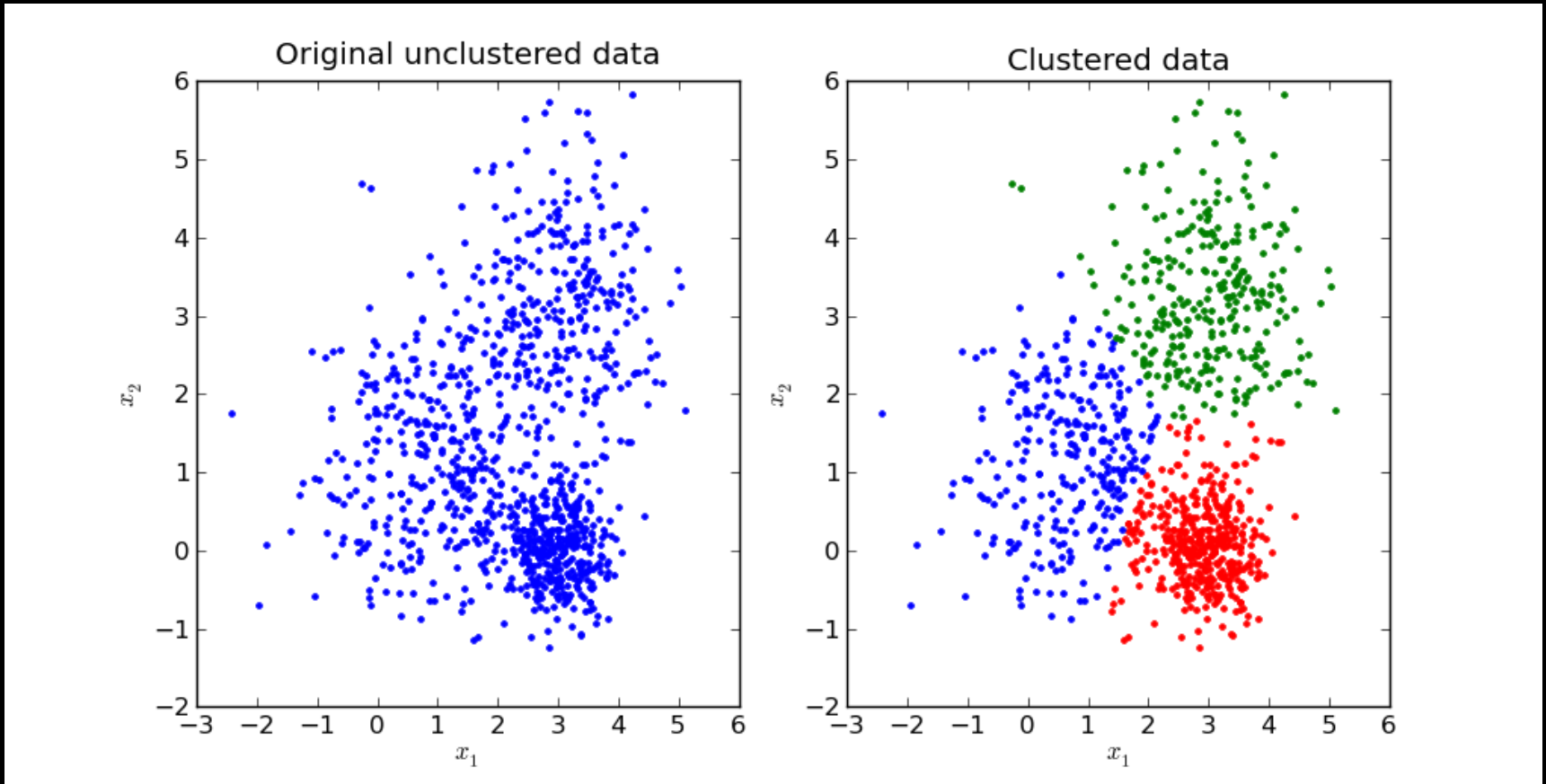
Supervised Learning: Regression



Supervised Learning: Classification



Unsupervised Learning: Clustering



Data Science Workflow

1. Formalizing problem statement and approach
2. Setting up / building data pipeline
3. Collecting data
4. Cleaning data
5. Preprocessing data
6. Exploring data
7. Conducting analysis
8. Validating results
9. Communicating findings

Data Science Workflow

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How do we implement ML?

Data Science Workflow

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Learning Frameworks

```
import torchvision.transforms as transforms
from torch.utils.data.sampler import SubsetRandomSampler
import matplotlib.pyplot as plt

#Using MNIST
#dataset = datasets.MNIST(root='./data')
#idx = dataset.train_labels==1
#dataset.train_labels = dataset.train_labels[idx]
#dataset.train_data = dataset.train_data[idx]

# Using CIFAR-10
# Load training data
transform_train = transforms.Compose([
    transforms.RandomCrop(32, padding=4),
    transforms.RandomHorizontalFlip(),
    transforms.ToTensor(),
    transforms.Normalize((0.4914, 0.4822, 0.4465), (0.2023, 0.1994, 0.2010)),
])
trainset = torchvision.datasets.CIFAR10(root='./data', train=True,
                                        download=True,
                                        transform=transform_train)
#Edit and Load validation data
validset = torchvision.datasets.CIFAR10(root='./data', train=True,
                                        download=True,
                                        transform=transform_train)
valid_size = 0.2
indices = list(range(len(trainset)))
split = int(np.floor(valid_size * len(trainset)))

if True:
    np.random.shuffle(indices)

train_idx, valid_idx = indices[split:], indices[:split]
train_sampler = SubsetRandomSampler(train_idx)
valid_sampler = SubsetRandomSampler(valid_idx)

trainloader = torch.utils.data.DataLoader(trainset, batch_size=128,
                                          sampler=valid_sampler, shuffle=False,
```

ML Services and Tools

IBM Cloud

Microsoft Azure

amazon web services

Google Cloud Platform

Real world use case…

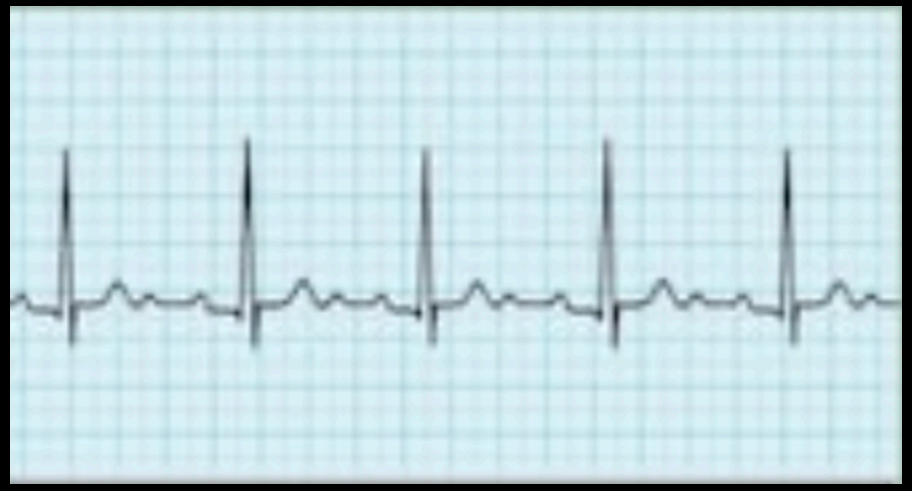
Predicting heart attacks

- Need
  - Predict if person is at risk of heart attack
- Given
  - ECG rhythm (electric signals)

A ML Solution at a High Level

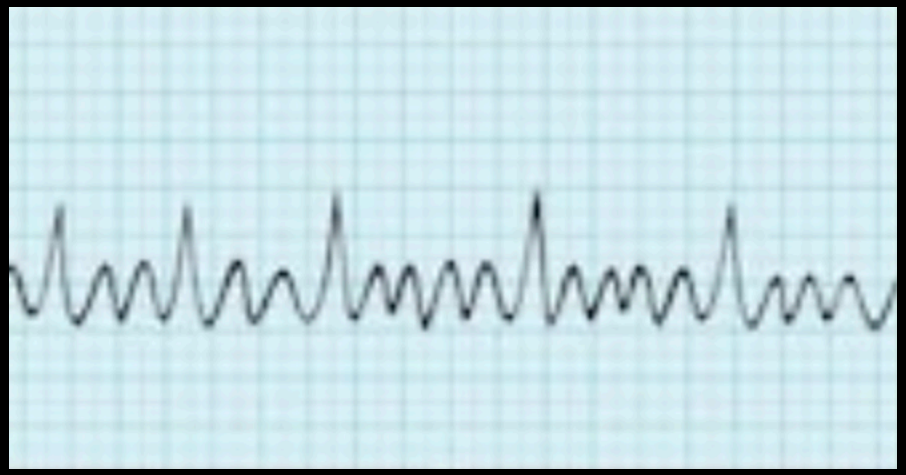
- ML model to classify ECGs as either “at risk” or “healthy”
  - E.g. AdaBoost or Convolutional neural network
- High level solution overview
  - Collects ECGs, labeled with either “at risk” or “healthy”
  - Looks at a piece of data: ECG + label
  - Finds patterns between ECGs
  - Trains model based on this data
  - Updates model
  - Repeat

Variables: Beats per minute



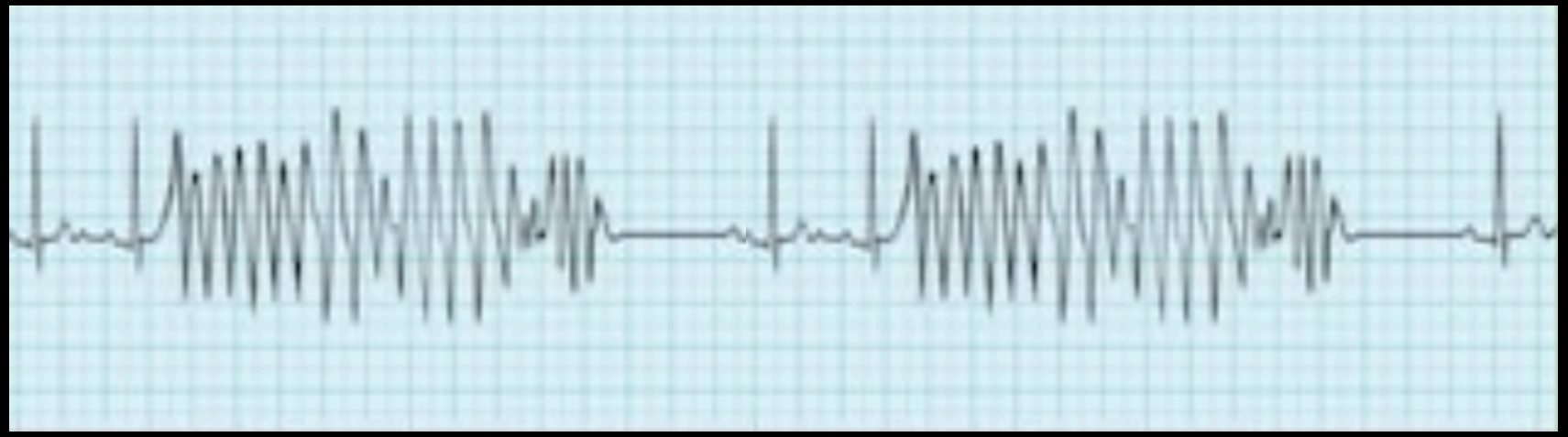
Normal

Variables: Beats per minute, seconds between beats



At risk
(atrial fibrillation)

Variables: Beats per minute, spacing between beats, irregularities per minute



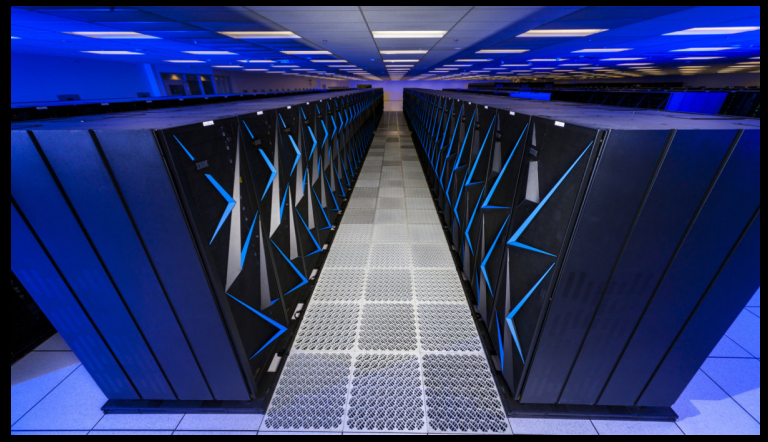
At risk
(ventricular tachycardia)

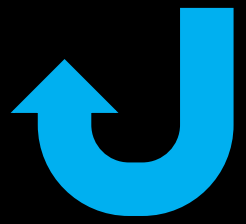
Variables: Beats per minute, seconds between beats, irregularities per minute

Normal
(ventricular tachycardia)

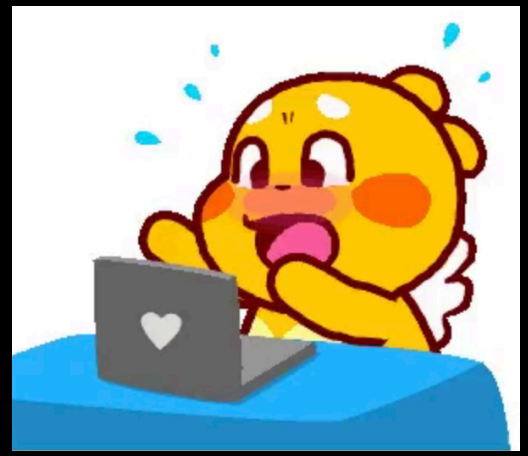
Central Server Model

Data





Model Training



Programmer


10:09
Back
ECG Detail
0s
1s
2s
Sinus Rhythm
88 BPM Average
This ECG does not show signs of atrial fibrillation.
Export a PDF for Your Doctor
If you believe you're having a heart attack or a medical emergency, call emergency services.
SAMPLE DETAILS
Start Time
Sep 12, 2018 at 10:08:31 AM
End Time
Sep 12, 2018 at 10:09:01 AM
Source
ECG
Today
Health Data
Sources
Medical ID
76 BPM
10:09
24sec
It helps to rest your arms on a table or your legs.

Predicting heart attacks

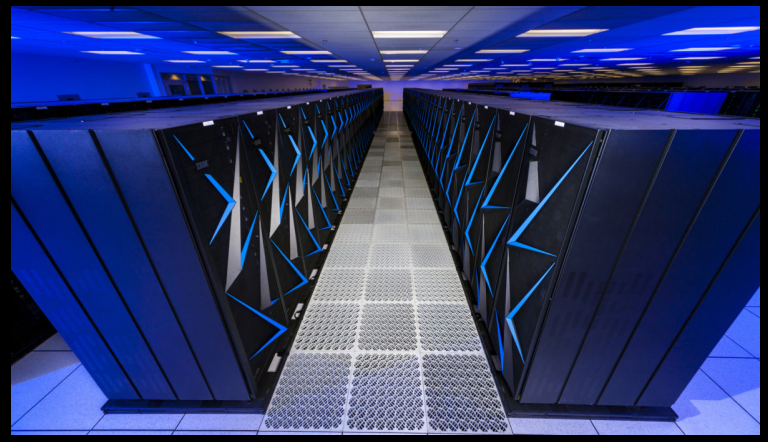
- Need
  - Predict if person is at risk of heart attack
- Given
  - ECG rhythm (electric signals)

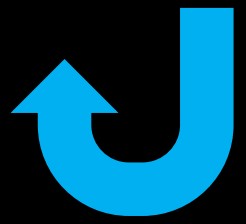
Predicting heart attacks

- Need
  - Predict if person is at risk of heart attack
- Given
  - ECG rhythm (electric signals)
- Obstacle
  - As a patient, I don’t want my data to be stored on Apple’s servers.

Central Server Model

Data





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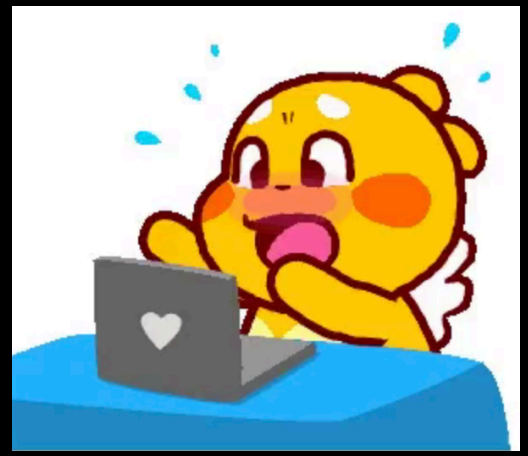

Programmer

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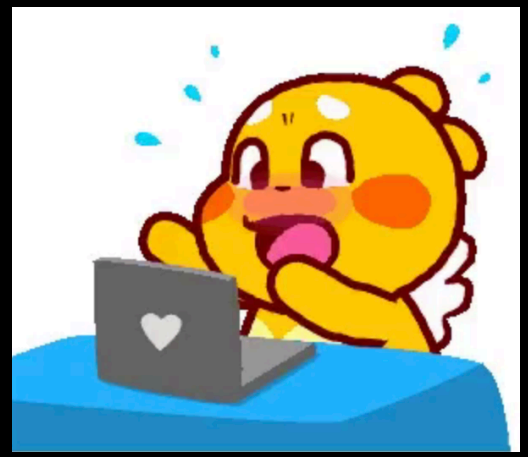
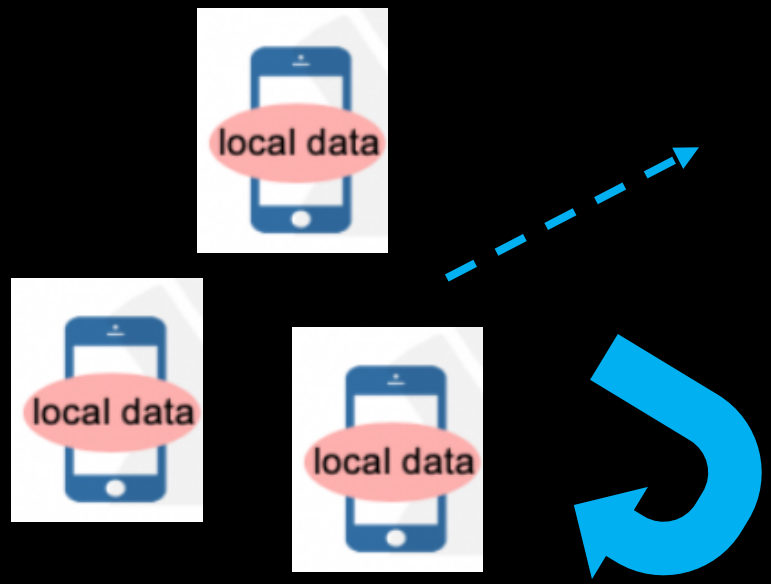
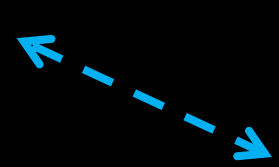
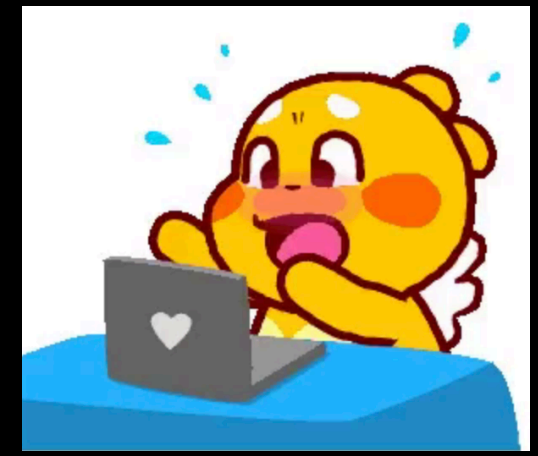


Programmer

Federated Learning Model





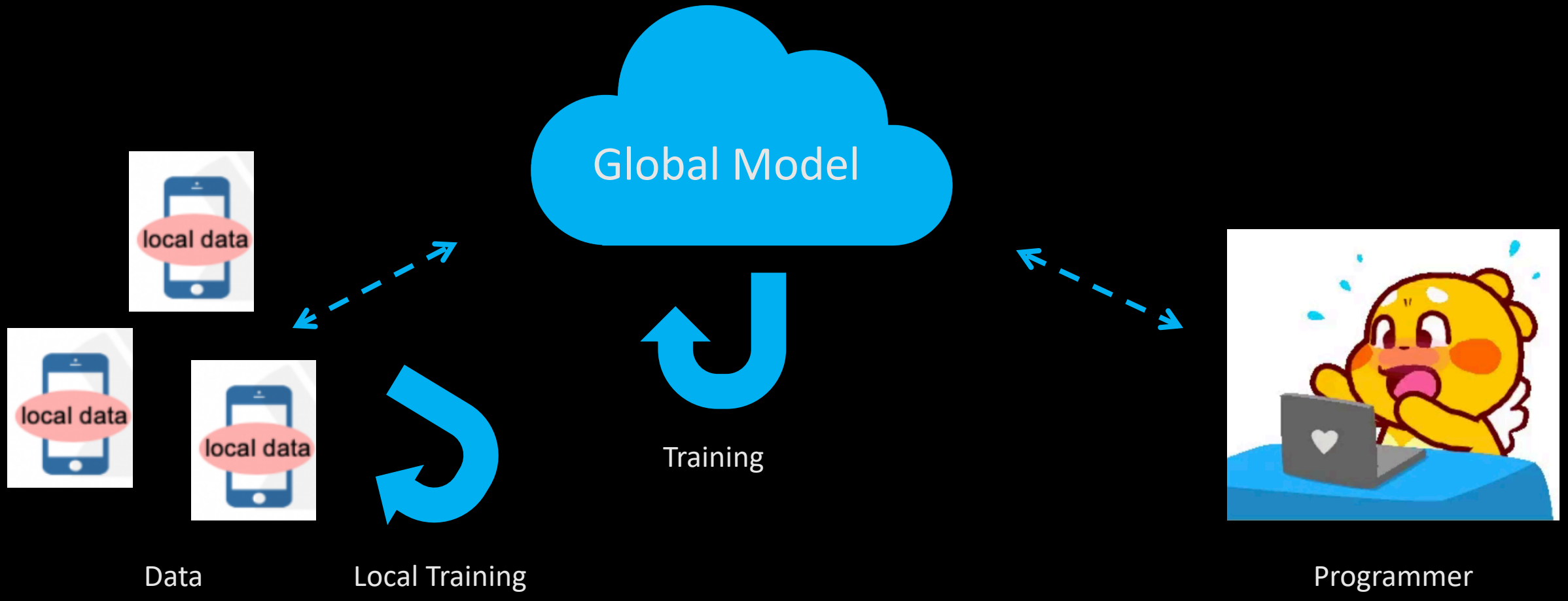


Data

Model Training

Programmer

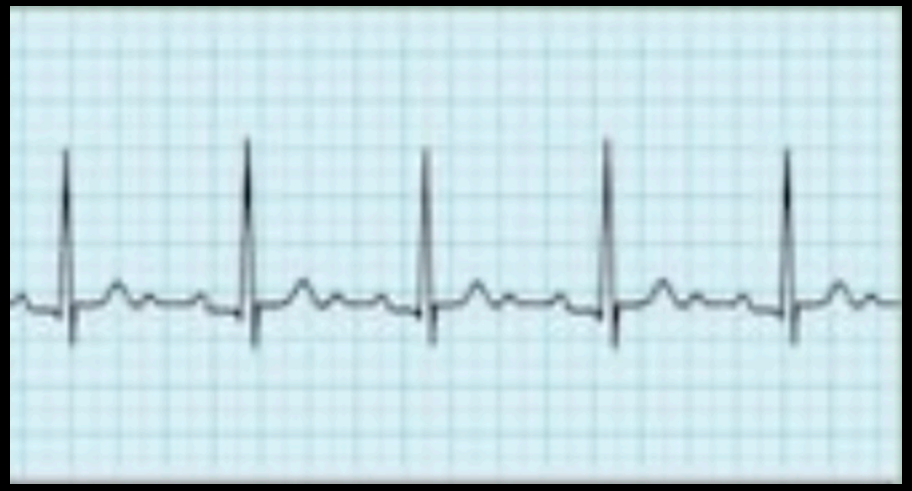
Federated Learning Model



Federated Learning

- Data stays on edge devices (e.g. phones)
- Maintain a global model shared among edge devices
- Training occurs on edge devices
- Edge devices send updates to global model
- Global model sends the total updated model to all edge devices
  - All devices benefit from the learnings from all data

Variables: Beats per minute



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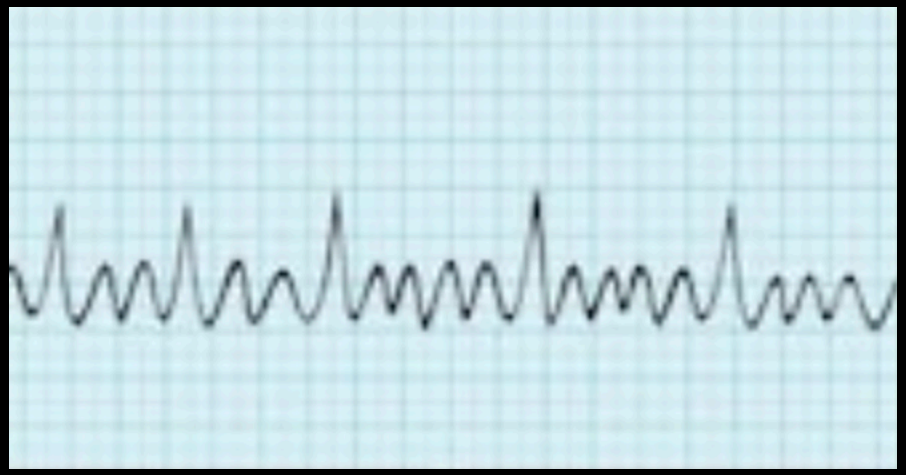

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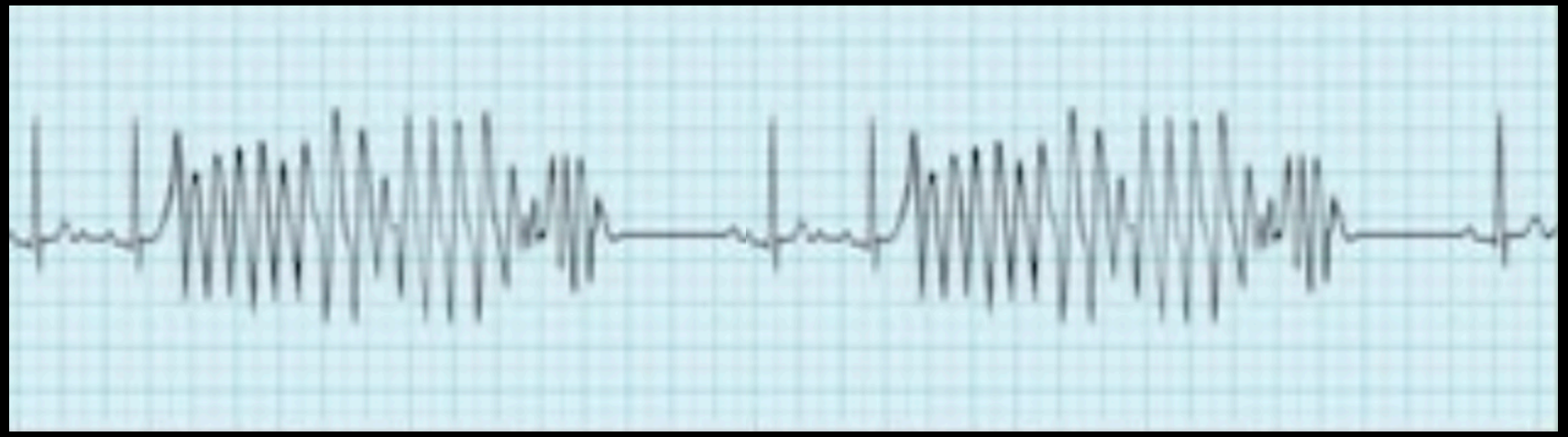


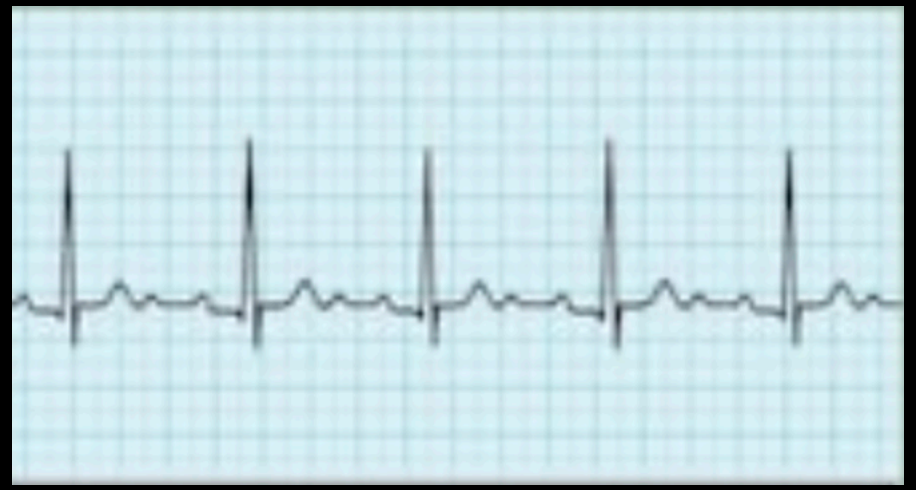
At risk
(ventricular tachycardia)

Variables: Beats per minute, seconds between beats, irregularities per minute

Normal
(ventricular tachycardia)

Federated Averaging

- Variables and weights
  - Beats per minute (w1)
  - Seconds between beats (w2)
  - Irregularities per minute (w3)
- Example model
  - Y = w1 * bpm + w2 * spacing + w3 * irregularities
  - If Y > 1 then “at risk”. Else “healthy”.
- Average weights
  - Device 1: w1 = 0.07, w2 = 0.03, w3 = 0.116
  - Device 2: w1 = 0.09, w2 = 0.01, w3 = 0.122
  - Average: w1 = 0.08, w2 = 0.02, w3 = 0.119



Final Thoughts

- Machine Learning can be incredibly beneficial
- Machine Learning can be incredibly harmful
  - Geo-location tracking

Recap

- Data Science Workflow
- ML Tools and Frameworks
- Example use case
- Federated Learning
- Final thoughts

Questions?