Approximating Solutions to Fluid Dynamics Problems from Constrained Datasets

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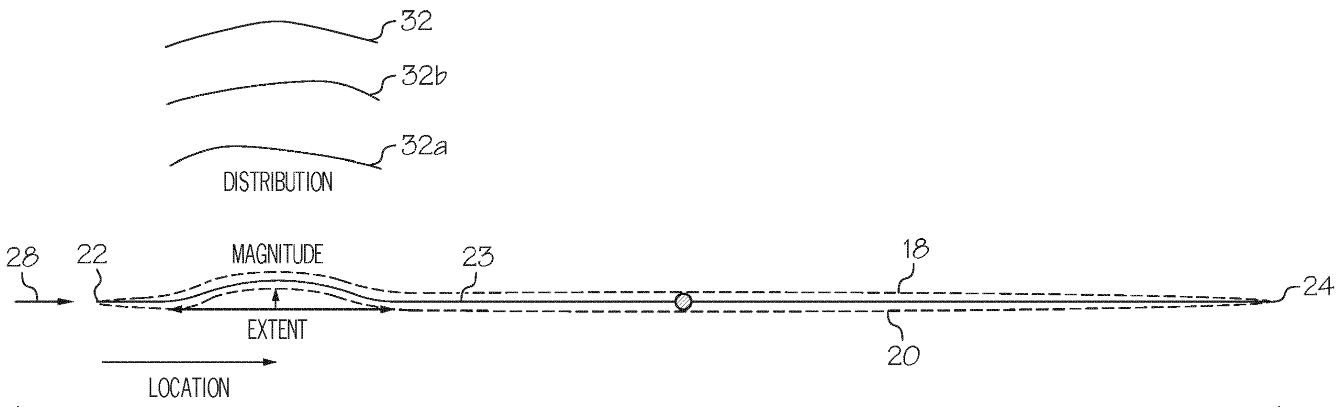
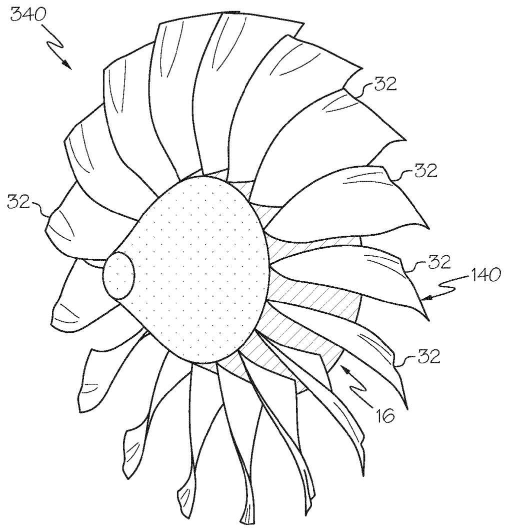
Background

For engineers and scientists running finite element or computational fluid dynamics simulations, one simulation may take hours, days, or weeks.

The goal is to get accurate estimates orders of magnitude faster given the information you already have from the simulations you have already run.





The Baseline – ROMs

Reduced order models (ROMs) address this problem, along with simpler surface / function fitting methods.

But ROMs have issues:

- Hard coded. **Intrusive**.
- You have to know the model, the governing equations.
- For highly nonlinear problems, simulation time may not improve over the full order model.

$$x_1 \begin{bmatrix} a_{11} \\ a_{21} \\ \vdots \\ a_{m1} \end{bmatrix} + x_2 \begin{bmatrix} a_{12} \\ a_{22} \\ \vdots \\ a_{m2} \end{bmatrix} + \cdots + x_n \begin{bmatrix} a_{1n} \\ a_{2n} \\ \vdots \\ a_{mn} \end{bmatrix} = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_m \end{bmatrix}$$

$$\frac{\partial u}{\partial t} + u \frac{\partial u}{\partial x} = \nu \frac{\partial^2 u}{\partial x^2}$$

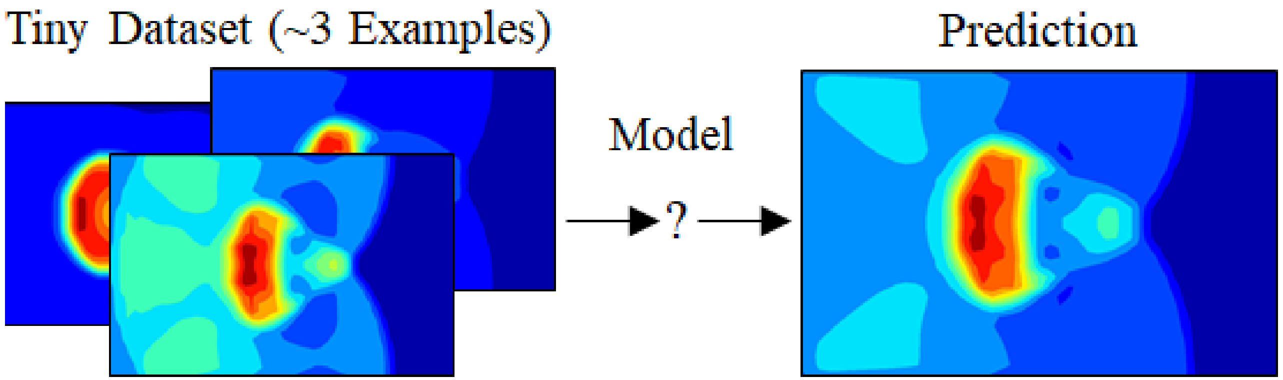
UNSTEADY TERM

CONVECTIVE TERM

VISCOUS TERM

The Problem

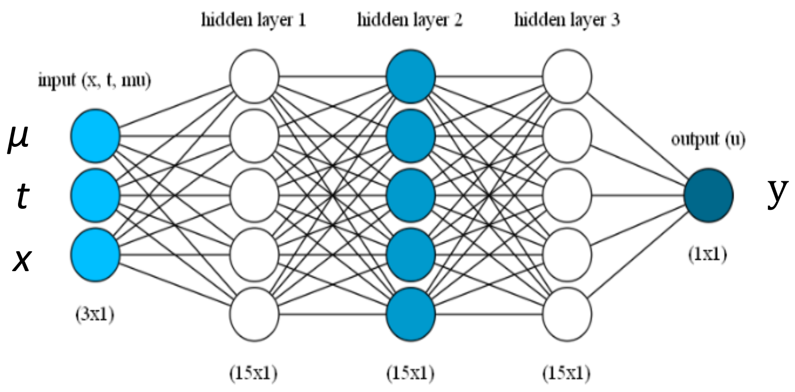
How well can we build models that use limited experience to make good predictions?



Surface Fitting
Basis Functions
ROMs
<u>Neural Networks</u>

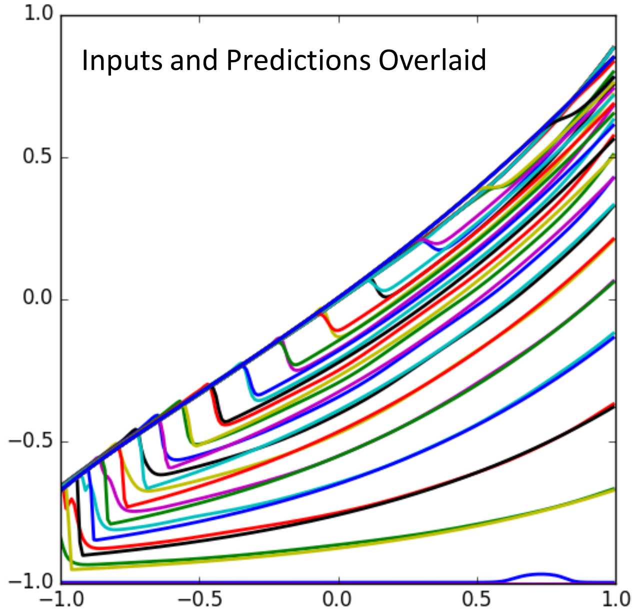
MLP Results

With a lot of hyper-parameter tuning and the implementation of exponential decay on the learning rate, it was also found that a single deeper fully connected network [8 nodes x 5 layers] could learn to fit the data, interpolate, and extrapolate in a way that competes with cluster networks, with some trade-offs.



MLP Architecture

μ = 3 (test, interpolate)

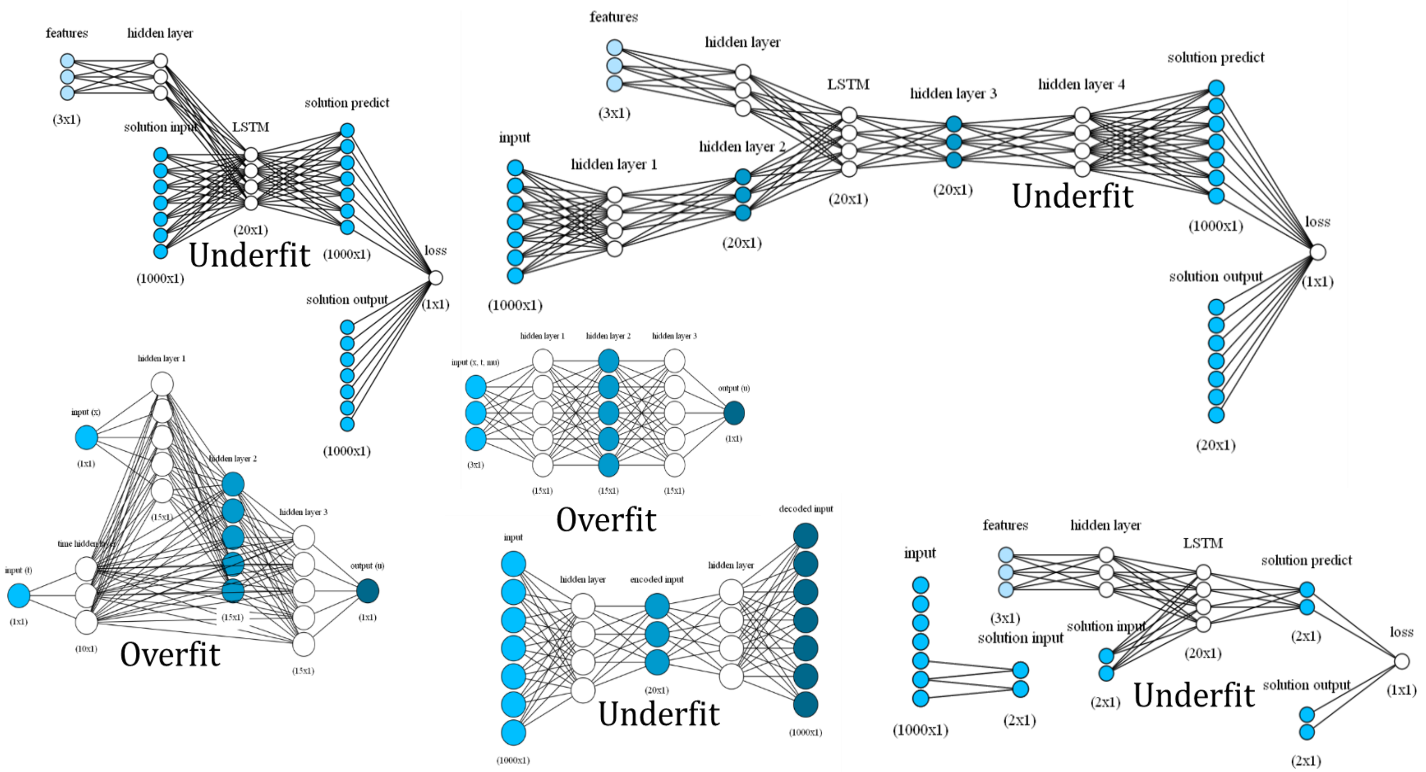


Architecture Search

Different network architectures were tested: LSTMs, variational autoencoders, fully connected, graph, and message passing networks, etc.

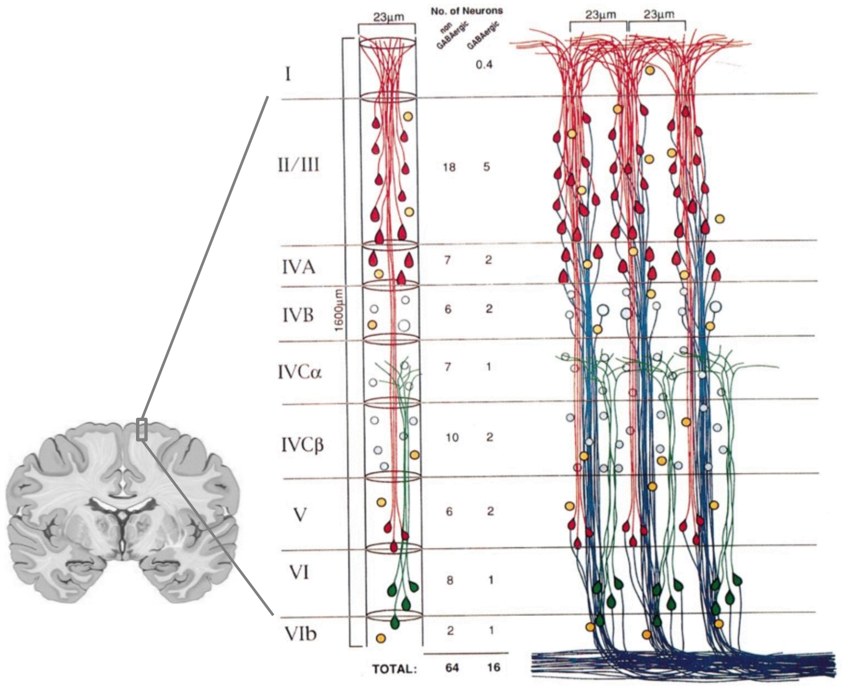
Different training strategies and hyperparameters were explored: learning rate decay, regularization options, dropout, nonlinearity types, loss function norms.

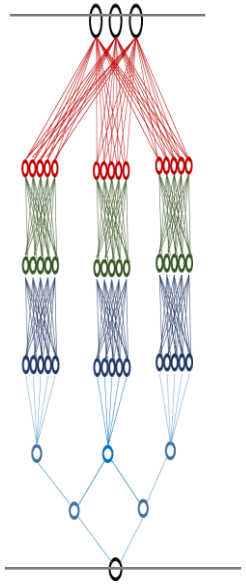
All standard networks struggled to generalize and tended to either <u>overfit</u> or <u>underfit</u>.

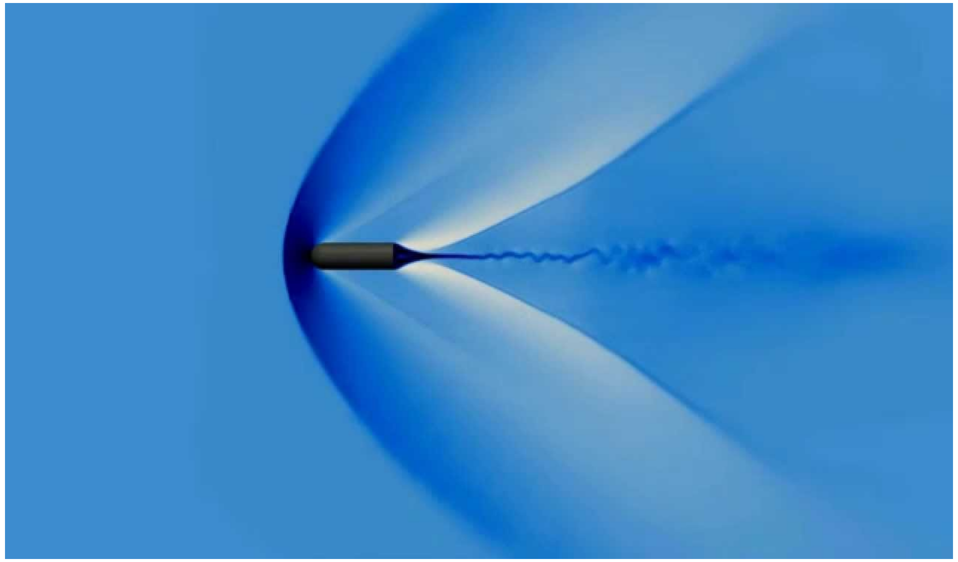


Inspiration from Cortical Columns

The human cortex seems to be segmented into narrow chains of nearly independent networks containing relatively few neurons each (approximately 10,000) described in 1978 by Mountcastle .

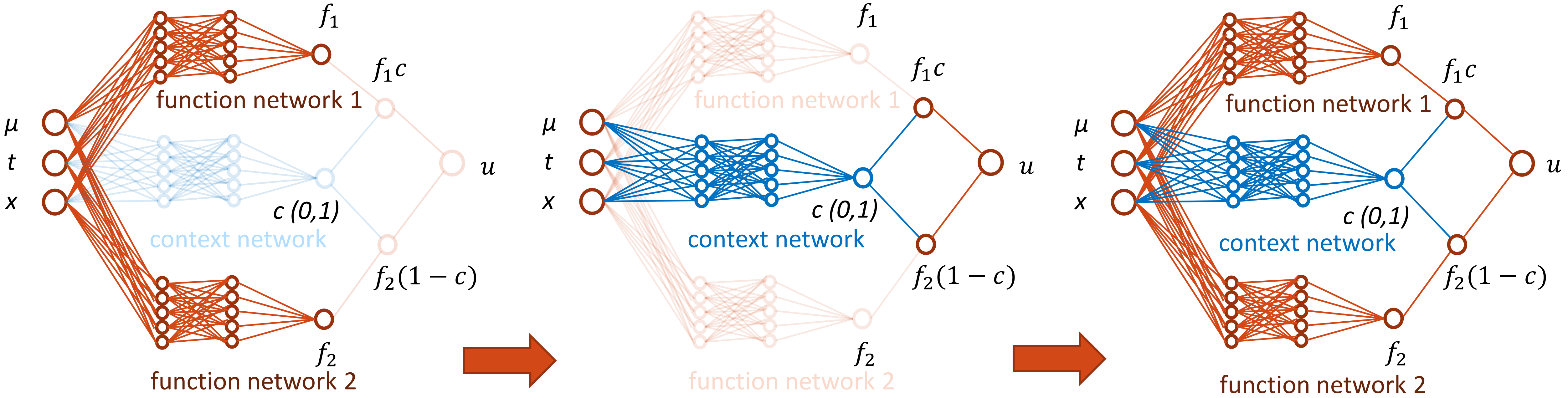






Cluster Network

This architecture is a feed-forward network, except with distinct connected clusters, with paired function and context networks. The context networks determine where to apply the function networks.



Step 1: Train function networks using loss function for classification problems.

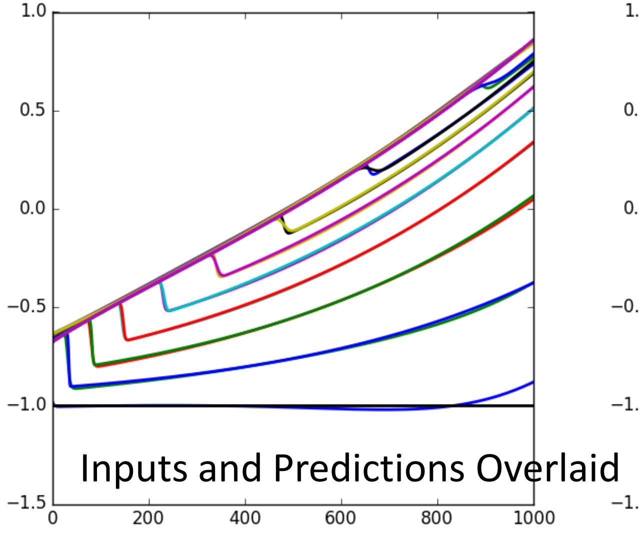
Step 2: Train context networks on regression loss.

Step 3: (Optional) Train both networks on regression loss until converged.

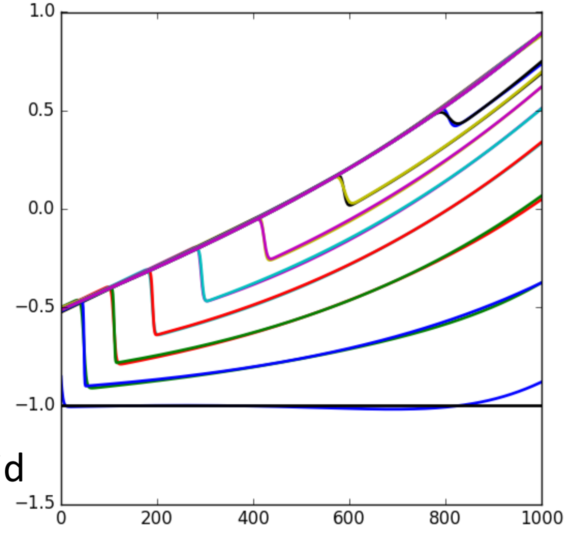
Cluster Network Results

The cluster network model was trained on μ = 1,2,4 and tested on μ = 3,5. It interpolates and extrapolates well, while running faster than state-of-the-art ROMs. The network reconstructs 750,000 inputs (3x250x1000) from 125 saved weights.

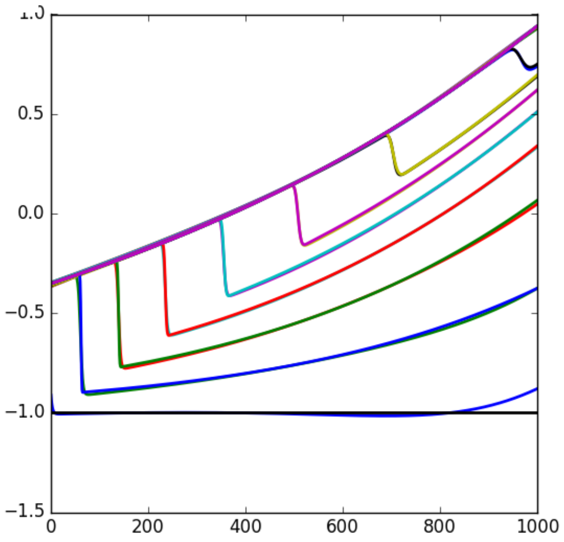
μ = 2 (training)



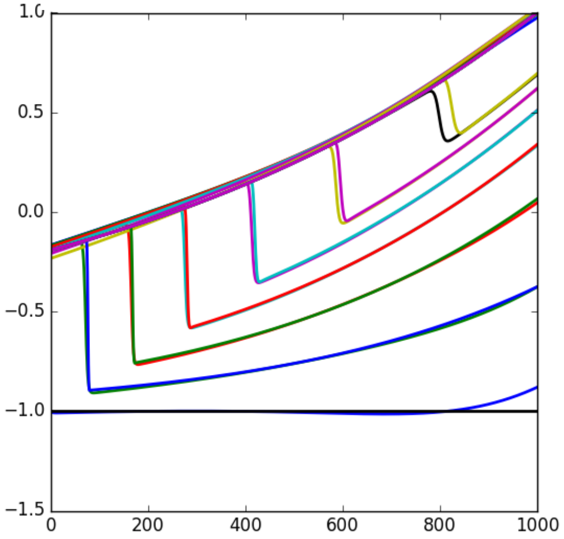
μ = 3 (test, interpolate)



μ = 4 (training)



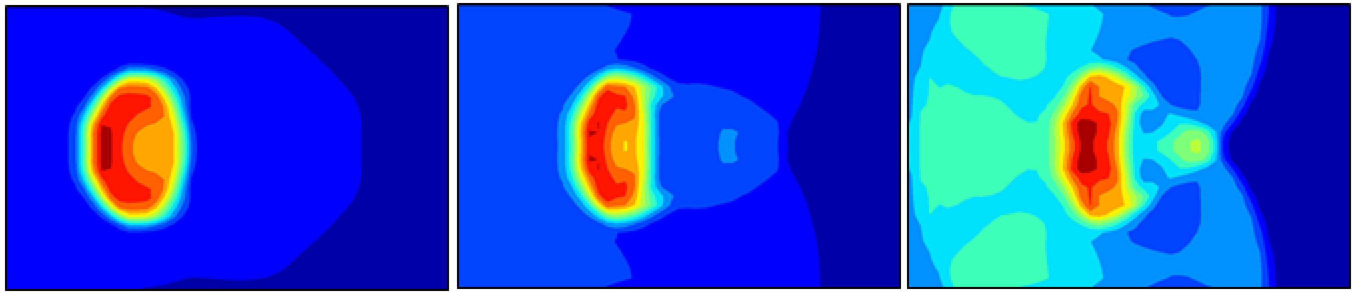
μ = 5 (test, extrapolate)



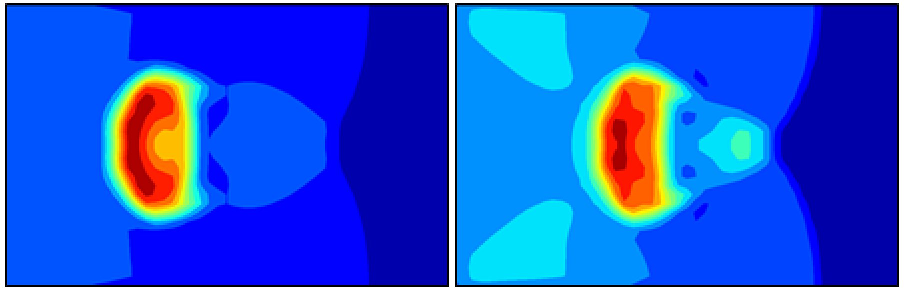
Visualizing the data

In order to visualize the range of solutions in the dataset, a solution at a time point near the end of each simulation is shown here in a density contour plot

Training set: M = (1.4, 2.0, 5.0)

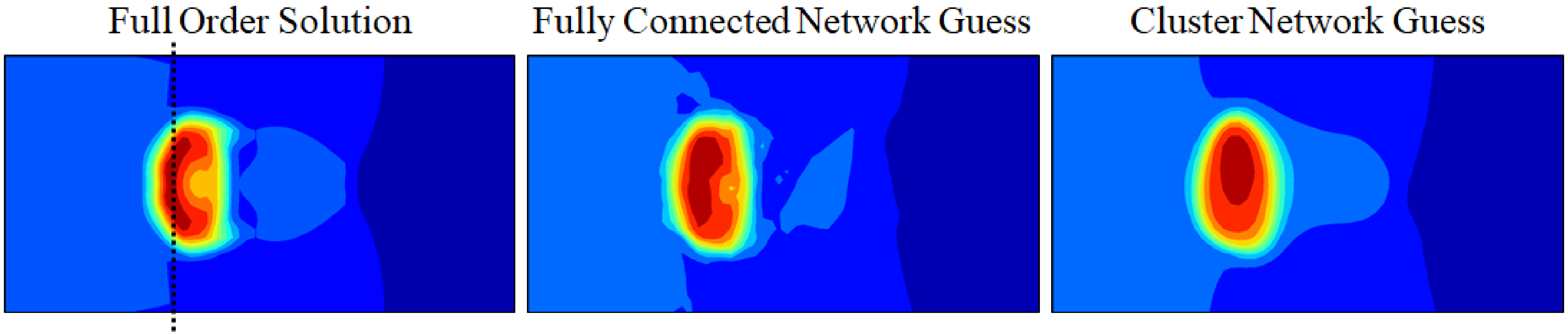


Test set: M = (1.8, 3.0)



Results – Predictions

These contour plots show how well these relatively small networks were able to approximate the solutions at a Mach numbers not in the training set, at M = 1.8.



COVID WATCH

Anonymous exposure notification: a mobile app intervention for COVID-19

Presented by Tina White, Founder and Executive Director

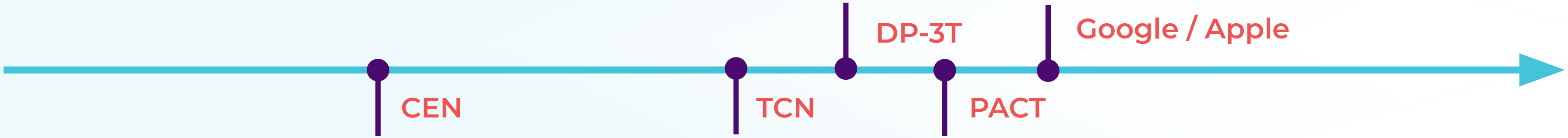
www.covidwatch.org

Our History

Feb 19
Covid Watch started, Stanford / Waterloo research team

March 20
First team to invent and publish the anonymous, decentralized CEN protocol in our white paper

April 6th
Renamed CEN and founded the international TCN coalition of apps, public attention



March 17
First team to open source a Bluetooth exposure alert protocol for Apple and Android

March 24
Proof of concept for anonymous Bluetooth exposure alerts

May 28th
Announced first pilot of Google/Apple EN app in the US

Our Organization

200+

Active security, policy, and public health experts, software engineers and **international** volunteers, 600+ volunteers and collaborators total in workspace

15 Advisers from **Stanford**, University of Waterloo, U Washington, UCSF, UC Berkeley, and more

50 Core Contributors




Privacy Model Comparisons

← Personally Identifying Data Collected →

Anonymous

Bluetooth-only

- The **ACLU** and **EFF** support only these
- **TCN**, **DP^3T**, **PACT**, **Google/Apple APIs**
- Announced: **Canada**
- Released: **Germany**, **Italy, Ireland, Denmark, Japan**

Semi-Private

GPS Trajectories

- **MIT PathCheck**, UW PACT
- Collects GPS data, anonymized by contact tracers
- Current standard in the US
- Utah, North Dakota, South Dakota

Not Private

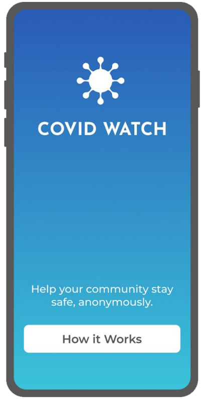
Bluetooth + IDs

- **Singapore**, **Australia**, **France**, **Utah**
- Central ID database, new form of surveillance
- Announced: **UK**

Involuntary

Authoritarian

- **China**
- Full use of all state surveillance technology
- Symptom reporting legally required



1pm

Potato...Potato...Potato

3pm

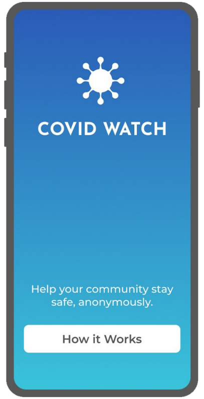
Blueberry... Blueberry... Blueberry

3pm

Banana... Banana... Banana

5pm

Peanut... Peanut... Peanut



WHAT I SAID	WHAT I HEARD	WHAT I HEARD	WHAT I SAID
1pm: Potato 3pm: Blueberry	3pm: Banana	3pm: Blueberry	3pm: Banana 5pm: Peanut

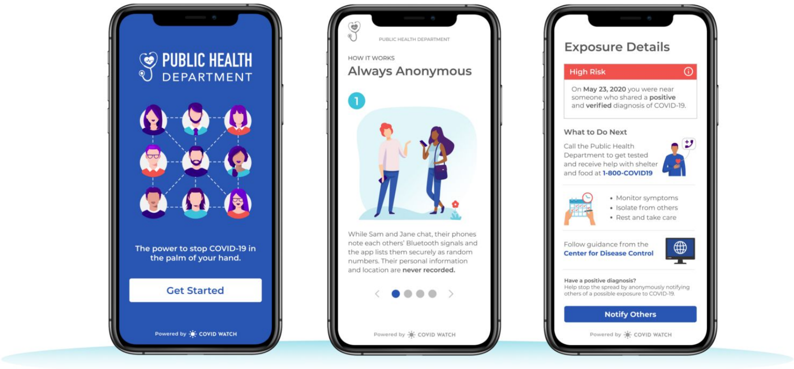
PUSH
+ve diagnosis
(Potato, Blueberry)

Potato
Blueberry

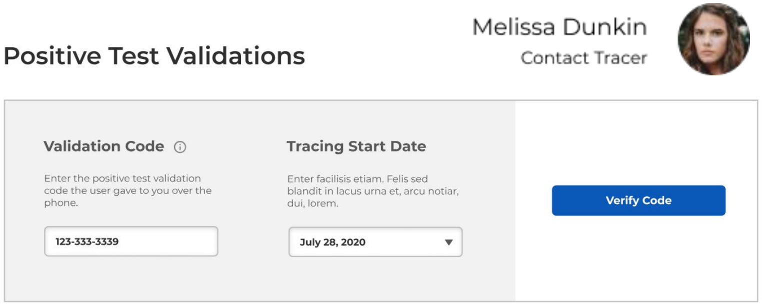
PULL
Potential exposures
(Potato, Blueberry)

Solution Overview

APP



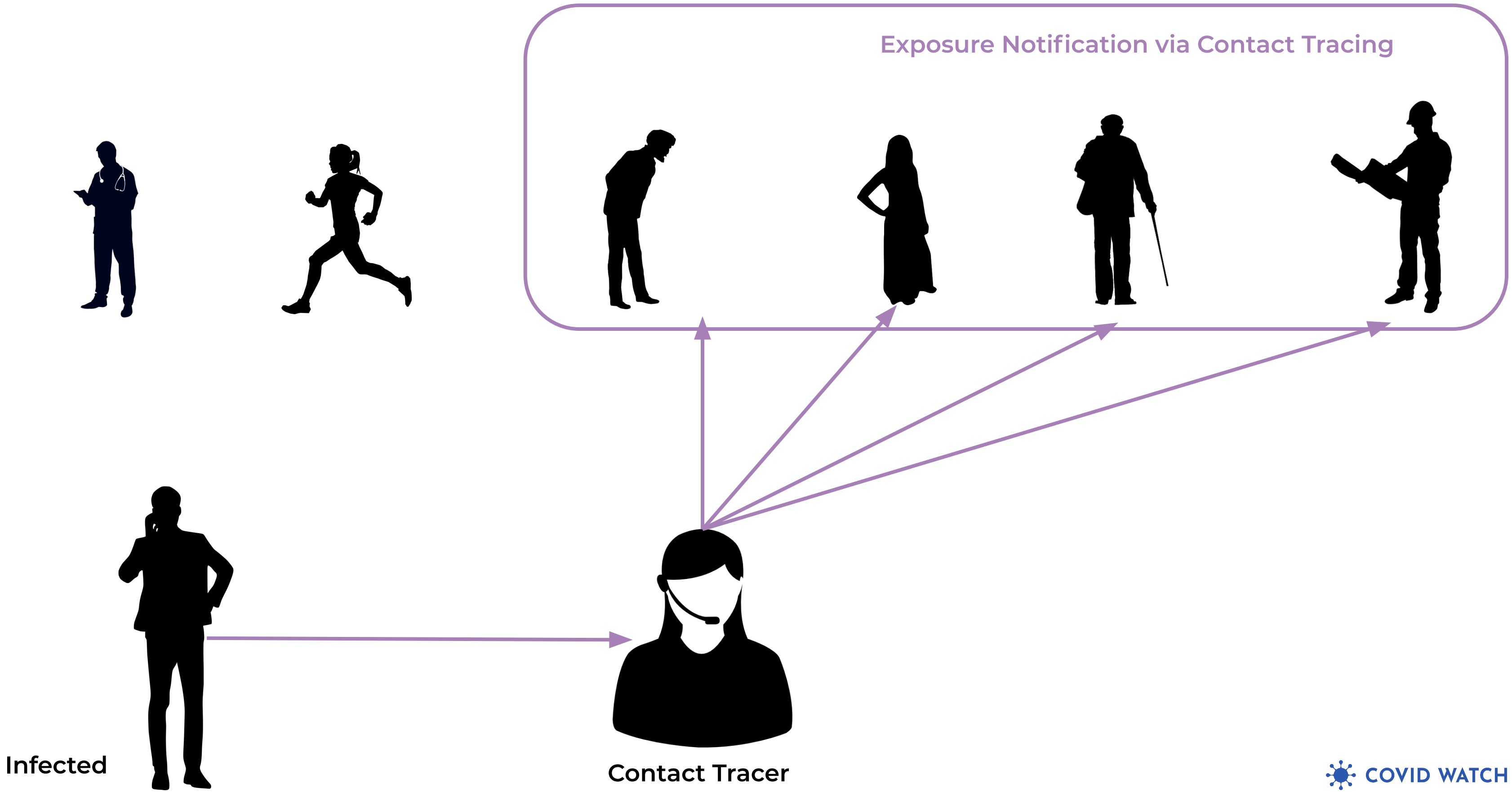
VERIFICATION



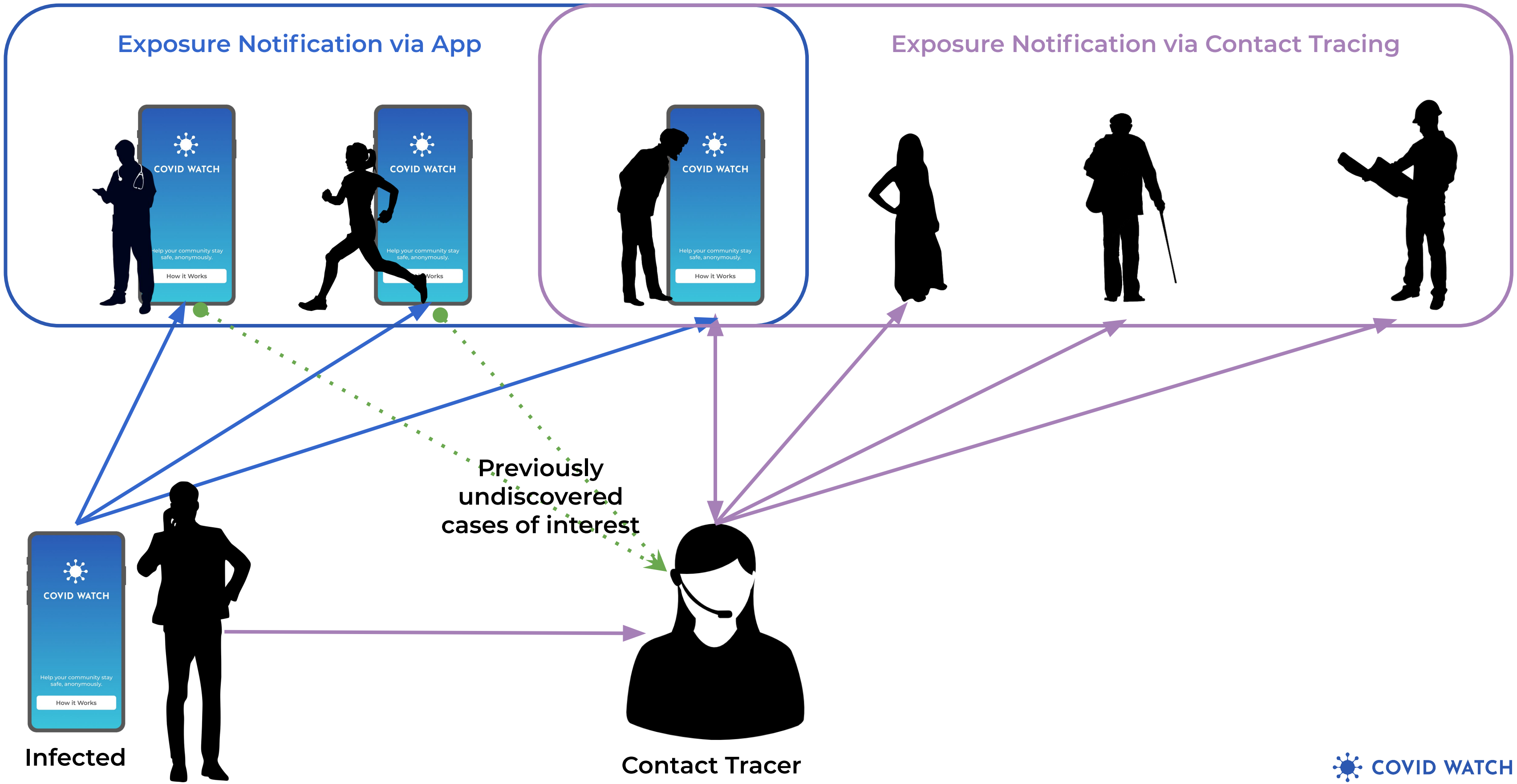
KEY SERVER

Mobile **App** fully compliant with Google/Apple requirements paired with a **Notification Server** and a **Portal** for verification of diagnoses.

Scale Manual Contact Tracing



Scale Manual Contact Tracing

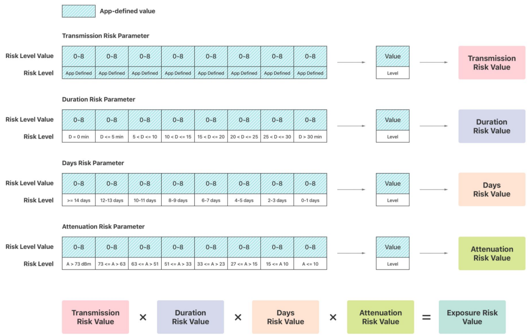


COVID WATCH

Harm Reduction vs Containment

Quarantine for 3 more days
Wear a surgical mask
Get Tested tomorrow
Community Risk Threshold: Low

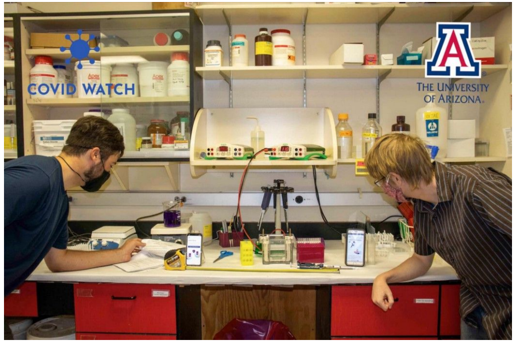
Quarantine for 7 more days
Community Risk Threshold: High

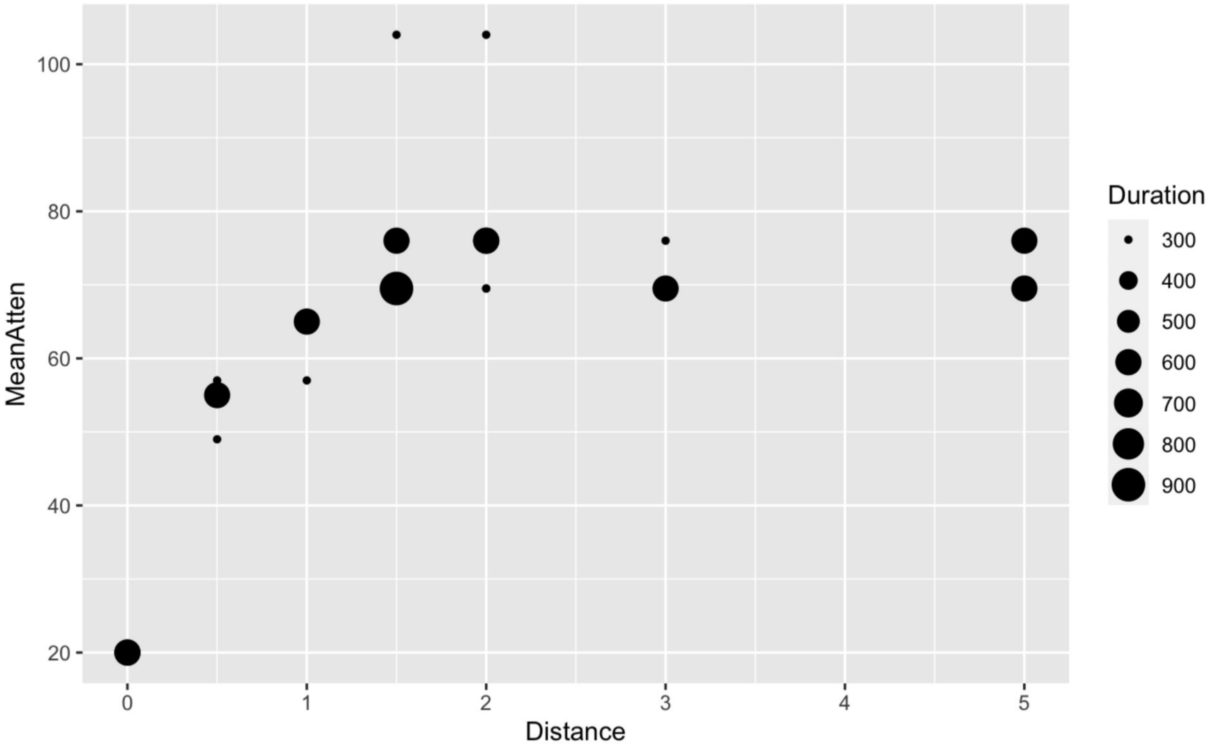


COVID WATCH

Calibration and Beta

Bluetooth Attenuation, Validation of app and portal





COVID WATCH

www.covidwatch.org

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