

# *Predicting Intracranial Pressure Monitor Placement in Children with Traumatic Brain Injury*

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**useR!**  
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Department of Biomedical Informatics

SCHOOL OF MEDICINE

UNIVERSITY OF COLORADO **ANSCHUTZ MEDICAL CAMPUS**



# Disclosures

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Team of people contributed to this work:

Laura Helmkamp, MS; Kathryn Colborn PhD, MSPH; Charlotte Gray, MPH; Margaret Rebull, MA; Yamila L. Sierra, MPH; Rachel Greer, BA; Lexi Petruccelli, BA; Sara Shankman, CPNP-AC, DNP; Todd C. Hankinson, MD, MBA; Fuyong Xing, PhD; David J. Albers, PhD; and Tellen D. Bennett, MD, MS

# Motivation

Traumatic Brain Injury - A violent blow or jolt to the head or body that can cause temporary or permanent complications up to death. Swelling is a common serious complication.

Annually in the United States, traumatic brain injury causes:

- 2,200 pediatric deaths
- 35,000 pediatric hospitalizations

To monitor and track brain swelling, an invasive procedure is performed to install a device called an Intracranial Pressure Monitor (ICP) into the skull. Clinicians currently make decisions about ICP placement with traumatic brain injury without the benefit of an accurate clinical decision support tool

# Study

**Aim** - Develop and validate model(s) that predict placement of an ICP monitor. Models should update individual predictions as new information becomes available during an Intensive Care Unit (ICU) stay.


## Study

- Prospective observational cohort study: September 2014 - January 2024
- 389 children with acute traumatic brain injury admitted to the ICU
- 138 (35%) of the 389 participants received ICP monitoring.
- Approved and granted a waiver of consent by the Colorado Multiple Institutional Review Board



# Data



 Data Collection Instrument	Enrollment	Pre-hospital	ED	ICU	Acute Care	Rehab	Home
Screening and Enrollment	<input type="radio"/>						
Patient	<input type="radio"/>						
Injury	<input type="radio"/>						
Transitions	<input type="radio"/>						
ED			<input type="radio"/>				
ICU				<input type="radio"/>			
Sedating Medication		<input type="radio"/>	<input type="radio"/>	<input type="radio"/>			
Osmolar therapy		<input type="radio"/>	<input type="radio"/>	<input type="radio"/>			
Procedures		<input type="radio"/>	<input type="radio"/>	<input type="radio"/>			
Labs - sodium		<input type="radio"/>	<input type="radio"/>	<input type="radio"/>			
Labs - arterial CO2		<input type="radio"/>	<input type="radio"/>	<input type="radio"/>			
Labs - venous CO2		<input type="radio"/>	<input type="radio"/>	<input type="radio"/>			
Neurologic exam		<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Initial CT			<input type="radio"/>				
Subsequent CT				<input type="radio"/>			
Functional Status Scale (FSS)	<input type="radio"/>			<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Extended Glasgow Outcome Scale (GOSE Peds)							<input type="radio"/>
Seizures				<input type="radio"/>			
ICP monitor	<input type="radio"/>						

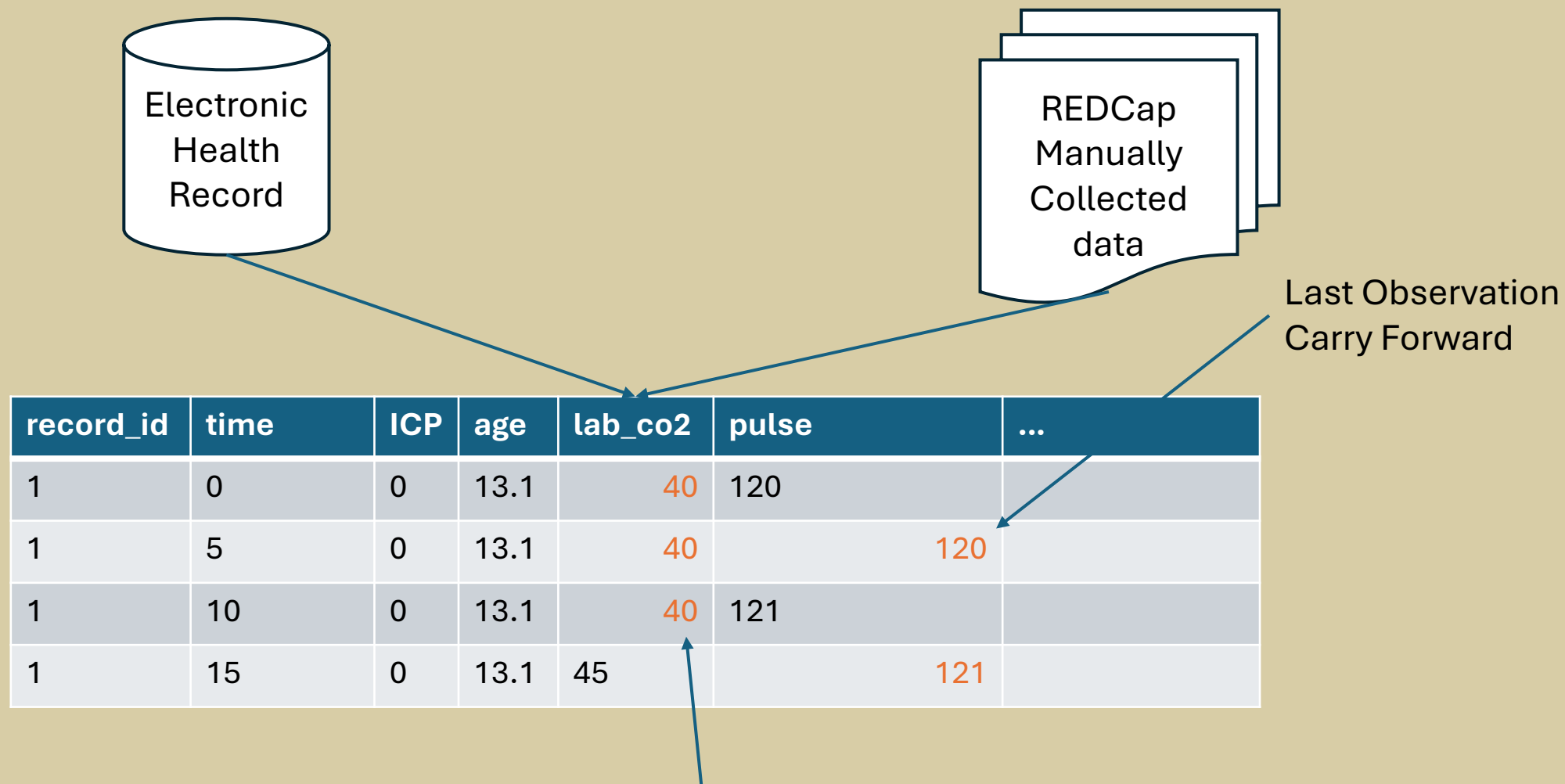
In csv form, REDCap data is **276 columns wide**



record_id	vital	Units	Value	Datetime
1	pulse	bpm	90	2027-01-01 13:01
1	pulse oximetry	%	98	2027-01-01 13:01
1	respirations		24	2027-01-01 13:01
1	pulse	bpm	91	2027-01-01 14:01

<https://github.com/magic-lantern/2025-useR>

# Data



Healthy default filled in for NULL

Plus more Data and Feature Engineering ~35 variables, 270k rows

# Data

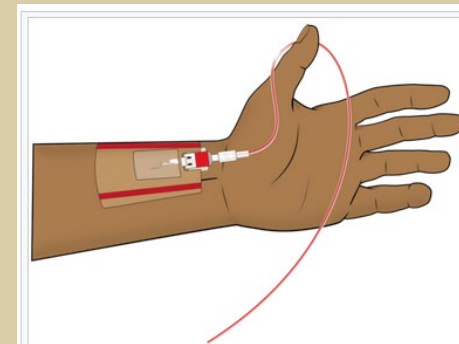
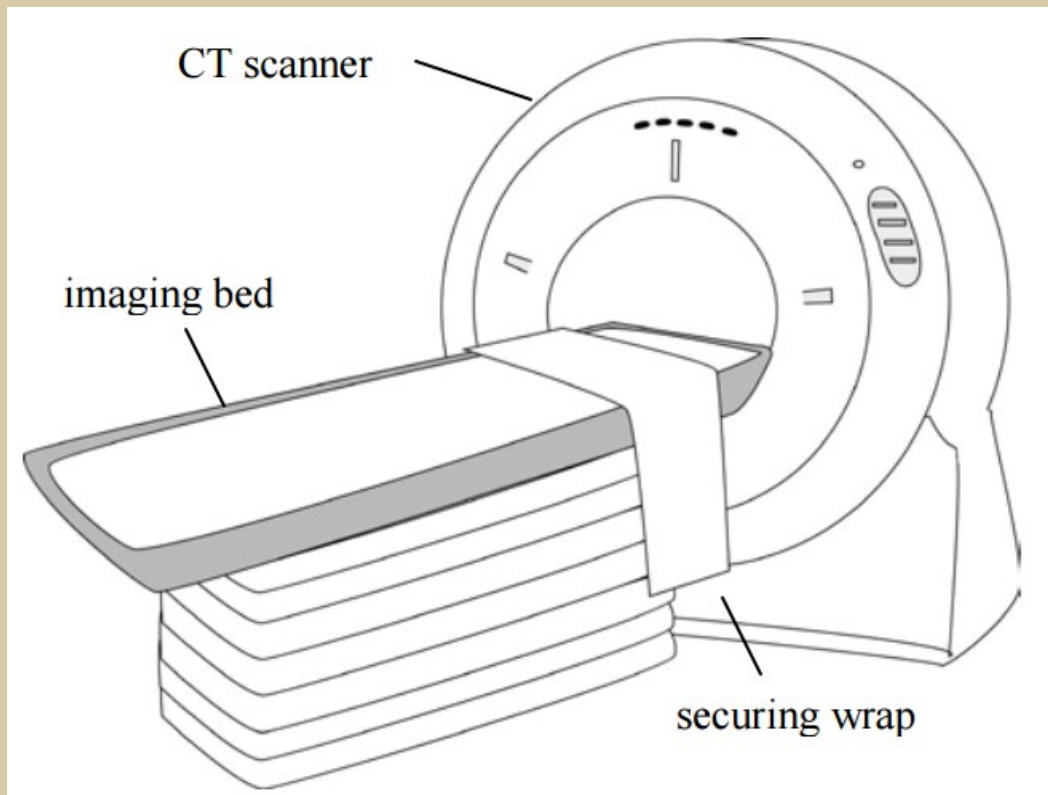
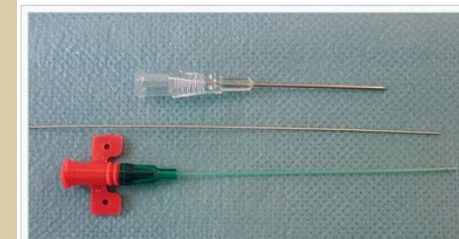


Illustration of an arterial catheter inserted in the left radial artery and covered with a dressing



Arterial catheter (Seldinger technique)

**Exclude/include** CT extracted features and **exclude/include** Invasive BP

# Data

**Exclude** CT extracted features and **exclude** Invasive BP

record_id	time	ICP	age	lab_co2	pulse	...
1	0	0	13.1	40	120	
1	5	0	13.1	40	120	
1	10	0	13.1	40	121	
1	15	0	13.1	45	121	

**Include** CT extracted features and **exclude** Invasive BP

record_id	time	ICP	age	lab_co2	ct_fracture.factor	ct_...	ct_...	...	...
1	0	0	13.1	40	0				
1	5	0	13.1	40	0				
1	10	0	13.1	40	0				
1	15	0	13.1	45	0				

**Exclude** CT extracted features and **include** Invasive BP

record_id	time	ICP	age	lab_co2	inv_bp_available	...
1	0	0	13.1	40	0	
1	5	0	13.1	40	0	
1	10	0	13.1	40	0	
1	15	0	13.1	45	1	

**Include** CT extracted features and **include** Invasive BP

record_id	time	ICP	age	ct_fracture.factor	ct_...	ct_...	inv_bp_available	...
1	0	0	13.1	0			0	
1	5	0	13.1	0			0	
1	10	0	13.1	0			0	
1	15	0	13.1	0			1	

Additionally split data temporally into training and testing datasets

Moons KGM, Altman DG, Reitsma JB, *et al.* Transparent Reporting of a multivariable prediction model for Individual Prognosis or Diagnosis (TRIPOD): explanation and elaboration. *Ann Intern Med.* 2015;162:W1-73. doi: 10.7326/M14-0698

<https://github.com/magic-lantern/2025-useR>



# Modeling

- Standard logistic regression
- Penalized logistic regression (lasso & ridge)
- Support vector machines (SVM)
- Generalized estimating equations
- Generalized additive models
- Neural Network (NN) with Long Short-Term Memory layers (LSTM)



<https://clipground.com/images/food-buffet-clipart-3.jpg>

# Modeling – Regression p1

```
1 #'
2 #' Define several formulae for the glm type models. . . Same baseline inputs with
3 #' inclusion and exclusion of ct and invasive bp.
4 glm_formula <- list()
5
6 glm_formula$noct_noinvbp <-
7   .. icpever ~
8   ..   timeint +
9   ..   age +
10  ..   female +
11  ..   inj_mvc +
12  ..   inj_abuse +
13  ..   # inj_fall + . . # REFERENCE LEVEL for injury mechanism
14  ..   inj_other +
15  ..   ni_sbp +
16  ..   ni_dbp +
17  ..   etco2 +
18  ..   heartrate +
19  ..   spo2 +
20  ..   resprate +
21  ..   temp +
22  ..   total_score +
23  ..   motor_score +
24  ..   # pupils_bothreactive + . . # REFERENCE LEVEL for pupils
25  ..   pupils_onefixed +
26  ..   pupils_bothfixed +
27  ..   pupils_unknown +
28  ..   lab_na +
29  ..   lab_co2 +
30  ..   lab_co2venous
```

# Modeling – Regression p2

```
33 if (n_distinct(icp_data_3$noninv_ncnt_vit) > 1) {
34   glm_formula$noct_noinvbp <- update(glm_formula$noct_noinvbp, . ~ . + noninv_ncnt_vit)
35 }
36
37 glm_formula$noct_invbp <- update(glm_formula$noct_noinvbp, . ~ . + inv_bp_available)
38
39 glm_formula$ct_noinvbp <-
40   update(glm_formula$noct_noinvbp,
41     . ~ . + ct_fracture.factor + ct_edema.factor + ct_shift.factor +
42     ct_compression.factor + ct_intraparhem.factor + ct_subarachem.factor
43     + ct_intravenhem.factor + ct_subduralhem.factor +
44     ct_epiduralhem.factor)
45
46 glm_formula$ct_invbp <- update(glm_formula$ct_noinvbp, . ~ . + inv_bp_available)
47
48
49 #'
50 #' ### Training GLMs
51 #'
52 #' We will fit several models on the training data.
53 #'
54 #' #### Standard logistic regression models.
55 #'
56 #' + label = "standard glm training fit"
57 tic("Fitting GLM Models")
58 icpever_glm <-
59   lapply(glm_formula,
60     function(x) {
61       glm(x,
62         data = icp_data_3,
63         subset = set == "Training",
64         family = binomial())
65     })
66 names(icpever_glm) <- paste0("glm_", names(icpever_glm))
```

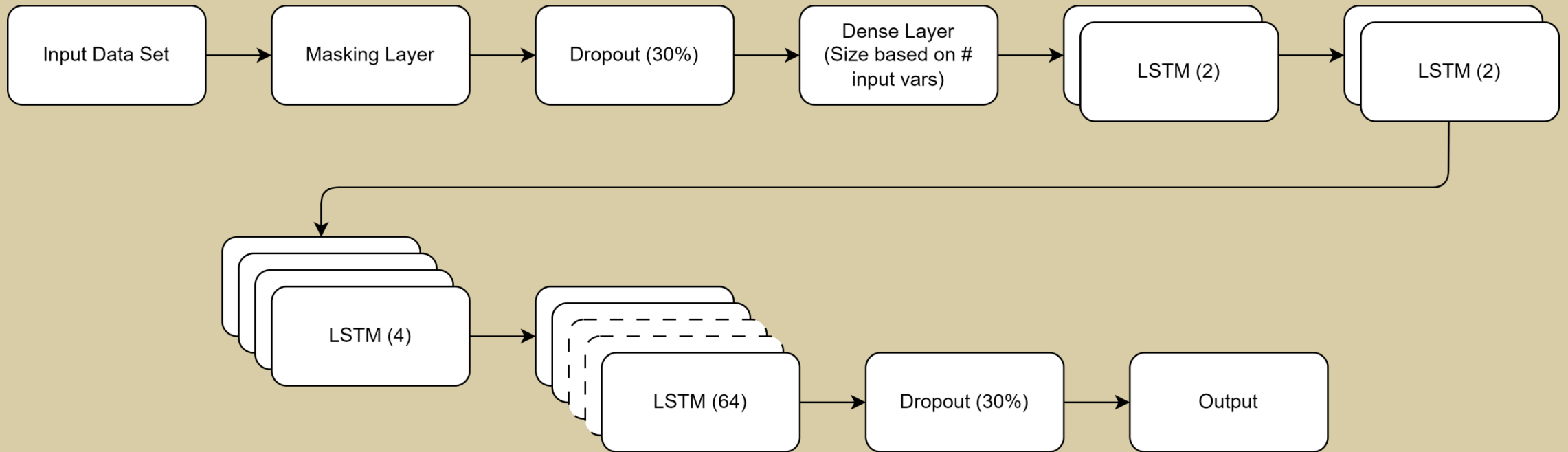
# Modeling – LSTM p1

```
1 function(x_train,
2         x_test,
3         y_train,
4         y_test,
5         num_epochs = 10,
6         batch_size = 10,
7         validation_split = 0.2,
8         dropout = 0.35,
9         random_seed = RANDOM_SEED,
10        tensorboard_label = 'run',
11        opt = NULL,
12        layers = c(128, 32, 16, 0),
13        checkpoint_file = "model_checkpoint.keras") {
14  # reset random seed and keras states so results are reproducible
15  reset_state(random_seed)
16  ..
17  ##### Network architecture definition
18  seqmodel <- keras_model_sequential(input_shape = c(dim(x_train)[2], dim(x_train)[3]))
19  # without input shape
20  # building a model with no input shape results in exact same accuracy as with input shape
21  # however, models without an `input_shape` passed to the first layer cannot reload their
22  # optimizer state (cannot continue training)
23  seqmodel %>%
24  # note -- keras allows specifying of some or none of the input_shape size
25  # have to use list(NULL) as c(NULL) automatically discards the NULL entry
26  # only specify predictors size for input_shape
27  layer_masking(mask_value = 0) %>%
28  layer_dropout(rate = dropout) %>%
29  layer_dense(units = dim(x_train)[3], activation = "relu")
30  # could try bidirectional LSTM with code like
```

# Modeling – LSTM p2

```
32
33 ··# can specify layers as (layer1, layer2, ..., layern)
34 ··# once a layer with 0 is encountered all subsequent values should be 0
35 ··# e.g. (128, 64, 0, 0, 0) is ok
36 ··# ..... (128, 0, 64, 0) ..... is invalid
37 ··for (i in seq_along(layers)) {
38 ··  if (layers[i] > 0) {
39 ··    ··# if there is a next layer that is not empty, need to include return sequences for LSTM to work
40 ··    ··if ((i + 1) <= length(layers) & layers[i + 1] > 0) {
41 ··      ··# print(paste("i:", i, "adding layer (" , layers[i], ") with return_sequences"))
42 ··      ··seqmodel %>%
43 ··      ··layer_lstm(units = layers[i], return_sequences = TRUE)
44 ··      ··# tried `bias_initializer = "ones"` option, but made results worse given other
45 ··      ··# hyperparameters that already worked... Might need to start all over for good
46 ··      ··# results
47 ··    } else {
48 ··      ··# print(paste("i:", i, "adding layer (" , layers[i], ") with NO return_sequences"))
49 ··      ··seqmodel %>%
50 ··      ··layer_lstm(units = layers[i])
51 ··    }
52 ··  }
53 }
54
```

# Modeling – LSTM p4





# Modeling – LSTM p3

```
54
55 seqmodel.%>%
56   layer_dropout(rate = dropout).%>%
57   layer_dense(units = 1, activation = "sigmoid")
58 # with relu and 80 epochs validation accuracy 0.5492
59 # with sigmoid and 80 epochs validation accuracy 0.
60 # 88% end accuracy before adding dropout layer
61
62 if (is.null(opt)) {
63   seqmodel.%>% compile(
64     loss = 'binary_crossentropy',
65     optimizer = 'rmsprop',
66     metrics = c('f1_score', 'binary_accuracy', tf$keras$metrics$Precision(), tf$keras$metrics$Recall()))
67 } else {
68   seqmodel.%>% compile(
69     loss = 'binary_crossentropy',
70     optimizer = opt,
71     metrics = c('f1_score', 'binary_accuracy', tf$keras$metrics$Precision(), tf$keras$metrics$Recall()))
72 }
73
74 print('Model summary:')
75 summary(seqmodel)
76
77 checkpoint_file_path <- paste0(save_dir, "checkpoint/", checkpoint_file)
78 print(paste("Best model checkpoint saved to:", checkpoint_file_path))
79
```

# Modeling – LSTM p5

```
80 history <- seqmodel %>% fit(
81   x_train,
82   y_train,
83   epochs = num_epochs,
84   batch_size = batch_size,
85   validation_split = validation_split,
86   callbacks = list(
87     callback_tensorboard(paste0(save_dir, "tensorboard/", tensorboard_label)),
88     callback_reduce_lr_on_plateau(monitor = "val_loss",
89                                   factor = 0.5,
90                                   patience = 20,
91                                   verbose = 1,
92                                   min_lr = 0.0000001),
93     callback_early_stopping(monitor = "val_loss",
94                              min_delta = 0.0001,
95                              patience = 40,
96                              verbose = 1,
97                              mode = c("min")),
98     # since we have early stopping, this shouldn't be necessary
99     # also checkpoint can only be every epoch, so will greatly increase disk usage
100    callback_model_checkpoint(checkpoint_file_path,
101                              monitor = "val_loss",
102                              save_best_only = TRUE,
103                              save_weights_only = FALSE,
104                              mode = "min",
105                              save_freq = "epoch")
106  )
107  # , shuffle = FALSE # this option results in > 2x more epochs to get to same accuracy
108  # include this to adjust model weights based on class
109  # class_weight = list("0" = 1, "1" = length(which(y_train == 0)) / length(which(y_train == 1))),
110 )
111 return(list('model' = seqmodel, 'history' = history))
112 }
```

# Modeling LSTM Hyperparameters

29,568,000 combinations

```
23 num_simultaneous_jobs <- 7
24 EPOCH_RUN_TIME <- 40 # time in seconds based on single simultaneous job
25 job_file <- "jul10best.txt"
26 k_folds <- 5 # normally use 5 when finding best hyperparameters
27 # at least with other chosen hyperparameters, 200 epochs gives the best result
28 # doing early stopping if no improvements, so will just use 500 for everything
29 epochs <- c(500)
30 batch_size <- c(1024) # seems to have little effect on accuracy; big difference
31 learn_rate <- c(0.1, 0.05, 0.01, 0.005)
32 validation_split <- c(0.2, 0.3, 0.4)
33 dropout <- c(0.05, 0.1, 0.2, 0.3, 0.4)
34 run_final <- TRUE
35 # which optimizers to use? see:
36 # http://cs231n.github.io/neural-networks-3/
37 # https://runder.io/optimizing-gradient-descent/index.html
38 optimizer <- c(
39   "rmsprop=optimizer_rmsprop",
40   "adam=optimizer_adam",
41   "sgd=optimizer_sgd",
42   "adadelta=optimizer_adadelta"
43 )
44 predict_advance_times <- c(0)
45 time_block_size <- 5
46 icpever_pred <- TRUE
47
48 # create grid of network architecture options from these variables
49 num_layers <- seq(4)
50 layer_size <- c(2, 4, 8, 16, 32, 48, 64)
51
52 random_seed <- c(42, 634906796, 1977035194, 1699415226, 1673646895, 1393266542,
53   1083032605, 136228259, 1361975978, 1627064900, 43586684)
54
55 # primarily for final run, want to compare model against restricted input model
56 exclude_vars <- c("inv", "ct", "ct", "inv", "")
57
```

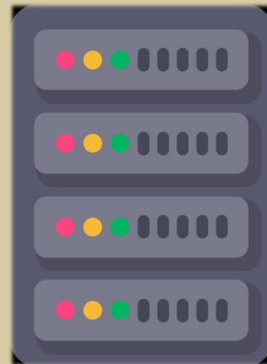
# Modeling - LSTM hyperparm

```
81 base_g <- expand.grid(k_folds = k_folds,
82                       epochs = epochs,
83                       batch_size = batch_size,
84                       learn_rate = learn_rate,
85                       validation_split = validation_split,
86                       dropout = dropout,
87                       random_seed = random_seed,
88                       optimizer = optimizer,
89                       predict_advance_times = predict_advance_times,
90                       run_final = run_final,
91                       time_block_size = time_block_size,
92                       icpever_pred = icpever_pred,
93                       exclude_vars = exclude_vars)
94
95 if (!is.na(layers)) {
96   base_g$layers <- layers
97   g <- as.data.table(base_g)
98 } else {
99   layer_g <- expand.grid(num_layers = num_layers,
100                         layer1_size = layer_size,
101                         layer2_size = layer_size,
102                         layer3_size = layer_size,
103                         layer4_size = layer_size)
104
105   # not sure how to get expand.grid to do what I want, so cleanup and remove extra stuff
106   g <- layer_g %>%
107     dplyr::mutate(layer2_size = ifelse(num_layers <= 1, NA, layer2_size)) %>%
108     dplyr::mutate(layer3_size = ifelse(num_layers <= 2, NA, layer3_size)) %>%
109     dplyr::mutate(layer4_size = ifelse(num_layers <= 3, NA, layer4_size)) %>%
110     tidyr::unite("layers", layer1_size, layer2_size, layer3_size, layer4_size, sep = ", ", na.rm = TRUE) %>%
111     dplyr::select(-num_layers) %>%
112     unique
113
114   gdt <- as.data.table(g)
115   base_gdt <- as.data.table(base_g)
116   g <- unique(CJ.dt_2(gdt, base_gdt))
117 }
118
```

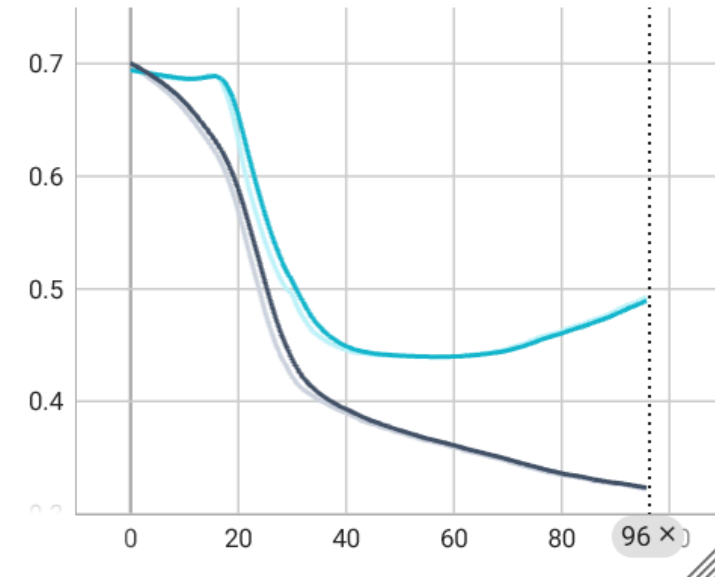
# Modeling – LSTM training

```
cd ~/aim2data_long_job
# run these jobs on GPU0
CUDA_VISIBLE_DEVICES=0 parallel --jobs 4 --delay 120 --timeout=14400 --resume-failed --bar --joblog rnd_gpu0.log < rnd_gpu0_jobs.txt
# Run these jobs on GPU1
CUDA_VISIBLE_DEVICES=1 parallel --jobs 4 --delay 120 --timeout=14400 --resume-failed --bar --joblog rnd_gpu1.log < rnd_gpu1_jobs.txt
# run these jobs on CPU
CUDA_VISIBLE_DEVICES=-1 parallel --jobs 28 --delay 120 --timeout=86400 --memfree 150G --resume-failed --bar --joblog rnd_cpu.log < rnd_cpu_jobs.txt
```

- (4) Intel Xeon Gold 6416H 'Sapphire Rapids-SP' 2.2 GHz 18-core CPU
- (32) 64GB (~2TB) DDR5 4800 MHz ECC/Registered Memory
- (2) NVIDIA "Ampere" A100 PCI-E+NVLink 80GB
- (4) 7.68TB Intel SSD D3-S4520 2.5" SATA 6Gbps
- (1) 15.36TB Micron 9400 PRO 2.5" U.3 NVMe SSD



epoch\_loss

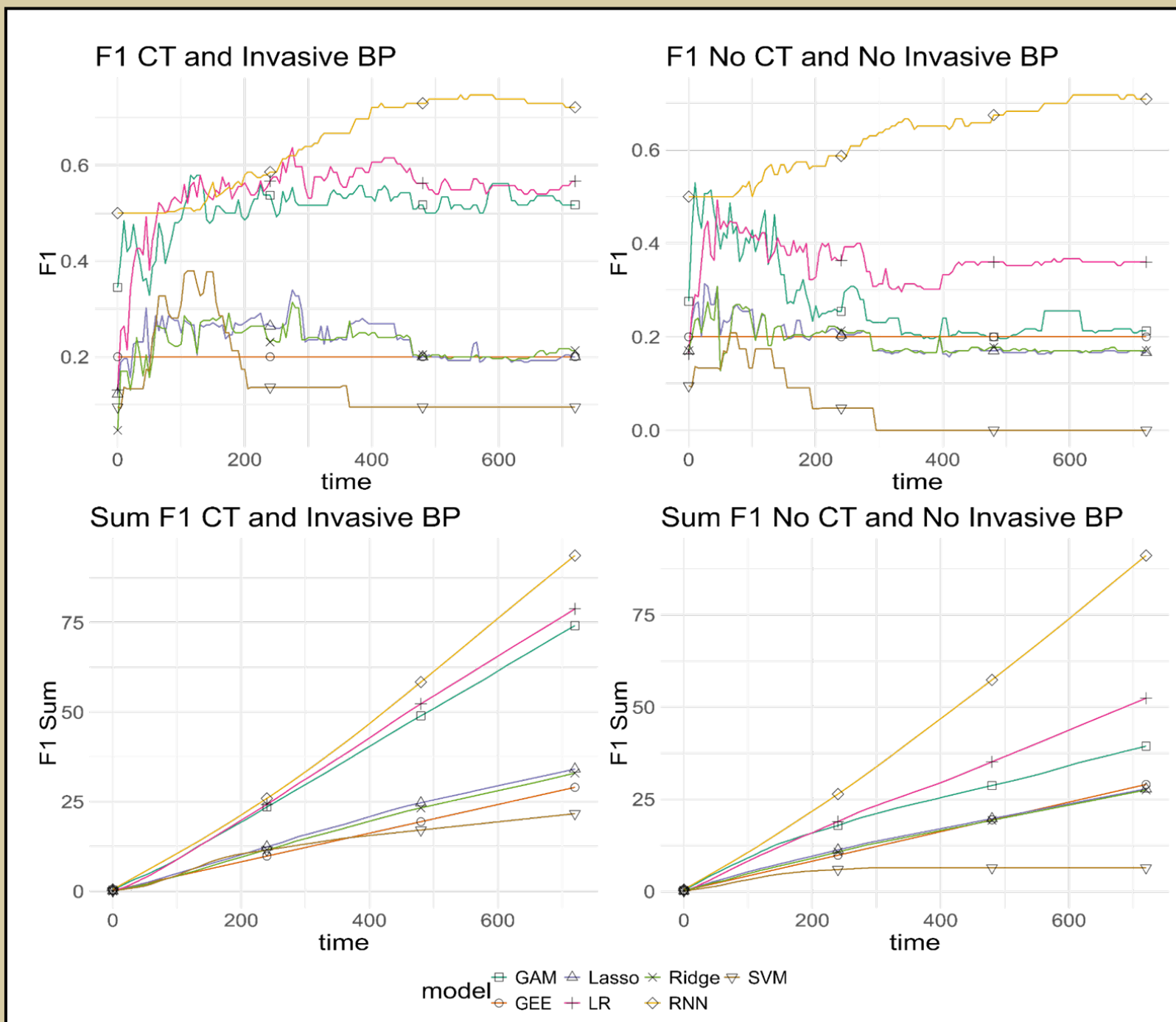


Run ↑

- all\_data\_fold\_1\_epochs\_500\_bs\_1024\_split\_0.2\_drop\_1  
train
- all\_data\_fold\_1\_epochs\_500\_bs\_1024\_split\_0.2\_drop\_1  
validation



# Results



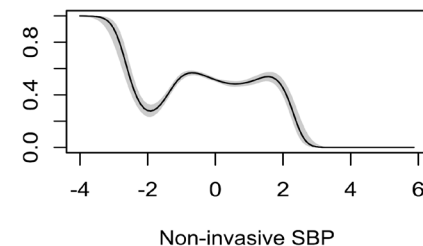


# Interpretability - Linear

Variable	LR	Lasso	Ridge	Absolute Rank
CT - Intraparenchymal Hemorrhage	0.88	0.864	0.676	2
Injury Mechanism - Known or Suspected Abuse	0.903	0.877	0.559	2
CT - Cerebral edema	0.742	0.734	0.604	4
CT - Midline shift	0.335	0.327	0.288	10
Pupils - Both Fixed	0.295	0.292	0.266	11
Age	0.29	0.284	0.191	13
Non-invasive DBP	0.279	0.277	0.238	13
CT - Skull fracture	0.287	0.273	0.174	16
Pupils - Unknown	0.249	0.243	0.201	17
Injury Mechanism - Motor Vehicle Crash	0.274	0.255	0.104	19
Arterial pCO2	0.193	0.187	0.195	19
Injury Mechanism - Other	0.258	0.241	0.111	21
Invasive BP available	0.108	0.105	0.095	24
Female	0.105	0.098	0.072	26
Oxygen Saturation (SpO2)	0.097	0.093	0.084	26
Non-invasive SBP	0.075	0.071	0.079	28
CT - Basilar cistern compression	0.082	0.075	0.052	29
Venous pCO2	0.051	0.049	0.061	31
Number of Vitals Updated	0.028	0.026	0.038	32
Pupils - One Fixed	0.029	0.026	0.007	33
Intercept	-0.938	-2.448	-2.251	1
CT - Intraventricular Hemorrhage	-0.62	-0.614	-0.528	5
CT - Subdural Hematoma	-0.478	-0.467	-0.336	6
CT - Epidural Hematoma	-0.432	-0.419	-0.337	7
GCS-Motor	-0.378	-0.382	-0.346	8
Heart Rate	-0.358	-0.355	-0.295	9
Time Interval	-0.002	-0.879	-0.717	12
CT - Subarachnoid Hemorrhage	-0.292	-0.274	-0.154	15
Respiratory Rate	-0.25	-0.245	-0.177	18
End-tidal CO2	-0.147	-0.145	-0.144	22
Temperature	-0.128	-0.123	-0.107	23
Sodium Level	-0.114	-0.106	-0.067	25
GCS-Total	-0.033	-0.031	-0.092	29

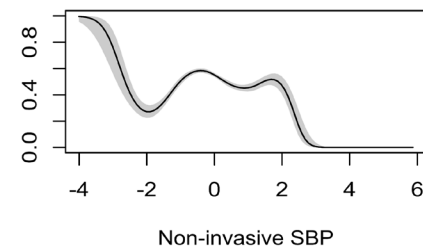
ti(ni\_sbp,6.84)

No CT and No Invasive BP



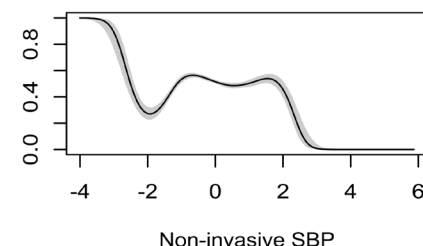
ti(ni\_sbp,6.83)

CT and No Invasive BP



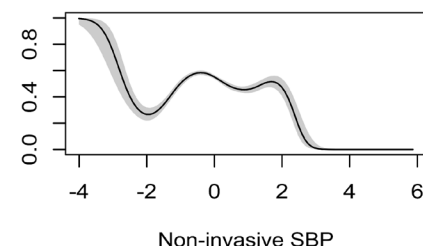
ti(ni\_sbp,6.82)

No CT and Invasive BP



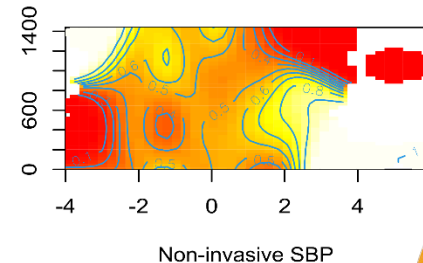
ti(ni\_sbp,6.82)

CT and Invasive BP



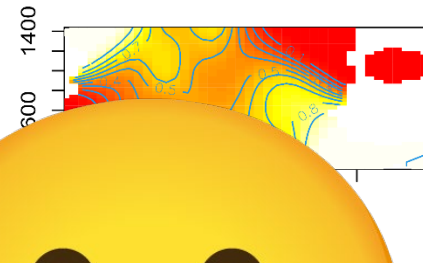
time

No CT and No Invasive BP



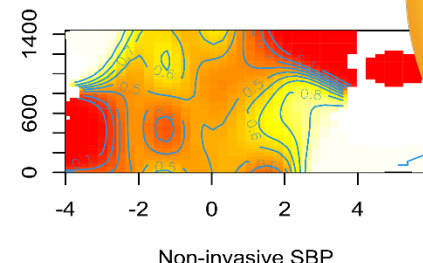
time

CT and No Invasive BP



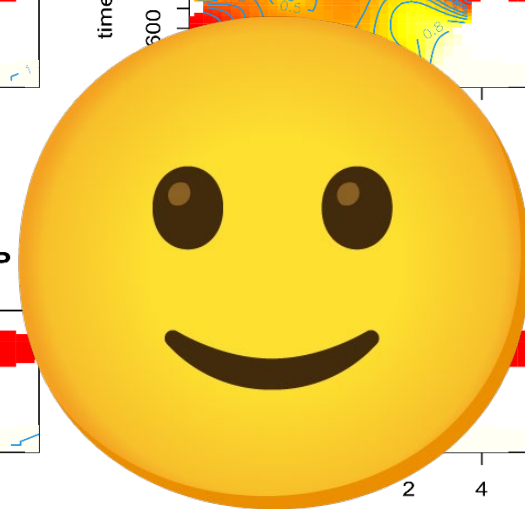
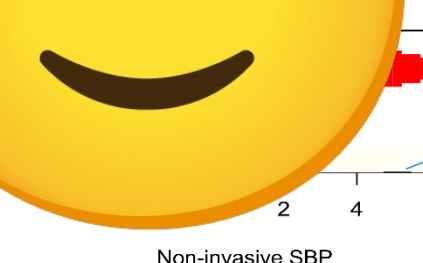
time

No CT and Invasive BP

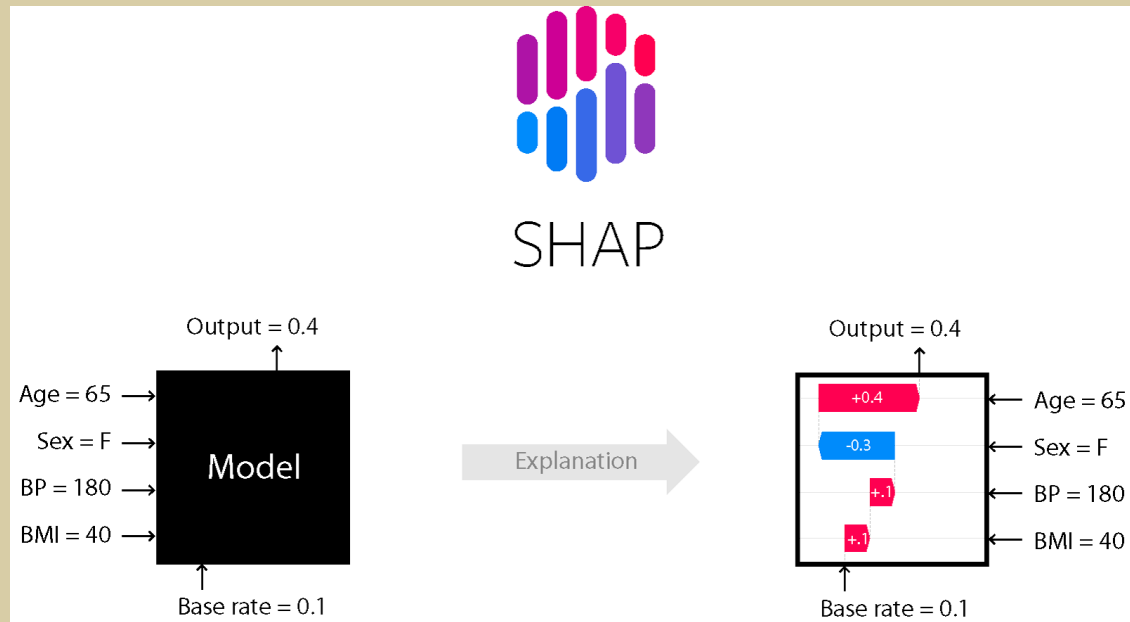


time

No CT and Invasive BP



# Interpretability - LSTM



# Questions?

Slides available at:

<https://github.com/magic-lantern/2025-useR>