“Bigger Data Beats Better Math, No Question”

“If I invest in more data, then the same model will perform better than switching to a different ML architecture ”

Bigger Data v Better Math

What has more impact in machine learning?

Brent Schneeman
@schnee

The Data


amazon

Fashion MNIST

https://github.com/zalandoresearch/fashion-mnist

70k split 60k training, 10k testing, with these labels

Designed to be a drop in replacement for Digits MNIST

Designed to be more difficult than Digits

Each observation consists of a label and 784 numbers {0,255}, which is a 28x28 grey scale image

Label	Meaning
0	T-shirt/top
1	Trouser
2	Pullover
3	Dress
4	Coat
5	Sandal
6	Shirt
7	Sneaker
8	Bag
9	Ankle Boot

Replacing Digits with Fashion? Easy

Change this line:

```
mnist <- keras::dataset_mnist()
```

Into this one

```
mnist <- keras::dataset_fashion_mnist()
```

Operations on either **`mnist`** object use exact same API

And it looks like

```
> str(mnist)
List of 2
 $ train:List of 2
  ..$ x: int [1:60000, 1:28, 1:28] 0 0 0 0 0 0 0 0 0 0 ...
  ..$ y: int [1:60000(1d)] 9 0 0 3 0 2 7 2 5 5 ...
 $ test :List of 2
  ..$ x: int [1:10000, 1:28, 1:28] 0 0 0 0 0 0 0 0 0 0 ...
  ..$ y: int [1:10000(1d)] 9 2 1 1 6 1 4 6 5 7 ...
```

The Math

(these are not great models, and not greatly tuned)

RandomForest

```
num_trees <- 25
dim(x_train) <- c(nrow(x_train), 784)
dim(x_test) <- c(nrow(x_test), 784)
x_train <- x_train / 255
x_test <- x_test / 255

rf <- randomForest(x_train, as.factor(y_train),
                   ntree=num_trees)
```

xgboost

```
dim(x_train) <- c(nrow(x_train), 784)
dim(x_test) <- c(nrow(x_test), 784)

x_train <- x_train / 255
x_test <- x_test / 255

dtrain <- xgb.DMatrix(x_train, label = y_train)
dtest <- xgb.DMatrix(x_test, label = y_test)
train.gdbt<-xgb.train(params=list(objective="multi:softprob",
                                  num_class=10, eval_metric="mlogloss",
                                  eta=0.2, max_depth=5,
                                  subsample=1, colsample_bytree=0.5),
                      data=dtrain,
                      nrounds=150)
```

“Deep” Neural Net

```
model <- keras_model_sequential()
model %>%
  layer_dense(units = 256, activation = 'relu', input_shape = c(784)) %>%
  layer_dropout(rate = 0.4) %>%
  layer_dense(units = 128, activation = 'relu') %>%
  layer_dropout(rate = 0.3) %>%
  layer_dense(units = 10, activation = 'softmax')
```

Convolutional Neural Net

```
model <- keras_model_sequential() %>%
  layer_conv_2d(filters = 32, kernel_size = c(3,3), activation = 'relu',
                input_shape = c(28, 28, 1)) %>%
  layer_conv_2d(filters = 64,
                kernel_size = c(3,3), activation = 'relu') %>%
  layer_max_pooling_2d(pool_size = c(2, 2)) %>%
  layer_dropout(rate = 0.25) %>%
  layer_flatten() %>%
  layer_dense(units = 128, activation = 'relu') %>%
  layer_dropout(rate = 0.5) %>%
  layer_dense(units = num_classes, activation = 'softmax')
```

So we have
The Data
and we have
The Math


LET THEM FIGHT.

The Test Bench

```
tib <- c(1:9 / 100, 1:9 / 10, 91:100 / 100) %>%
  sort() %>%
  map_dfr(run_size_exp, x_train, y_train, x_test, y_test)
```

Basically, train with 1%, 2%, 3%, ...,10%, 20%, 30%, ..., 98%, 99%, 100% of the training data and infer against the test set and you get

```
frac,exp_name,acc,auc
0.01,rf,0.8291,0.9759206200228384
0.01,xgb,0.8513,0.9859652247914469
0.01,dnn,0.8491,0.9860249426097214
0.01,cnn,0.9018,0.9922435869596523
```

run_size_exp

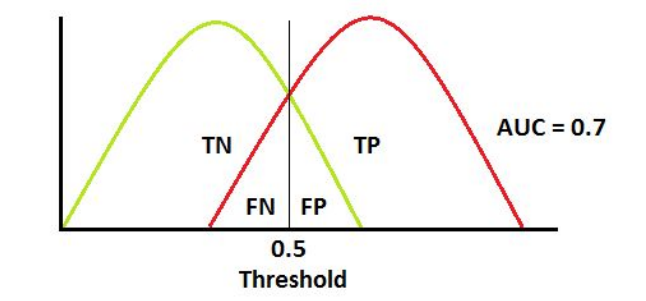
```
samples <- sample(nrow(x_train), floor(nrow(x_train) * frac), replace=FALSE) - 1

x_t <- x_train[samples,,]
y_t <- y_train[samples]

data <- list(x_train = x_t,
             y_train = y_t,
             x_test = x_test,
             y_test = y_test)

math <- c(rf_exp, xgb_exp, dnn_exp, cnn_exp)

preds <- math %>%
  map(exec, !!!data)
```

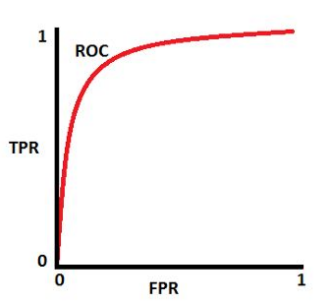
ML Metrics: Accuracy, AUC

Accuracy: how well the model predicted the true class, compared to predictions of all other classes.

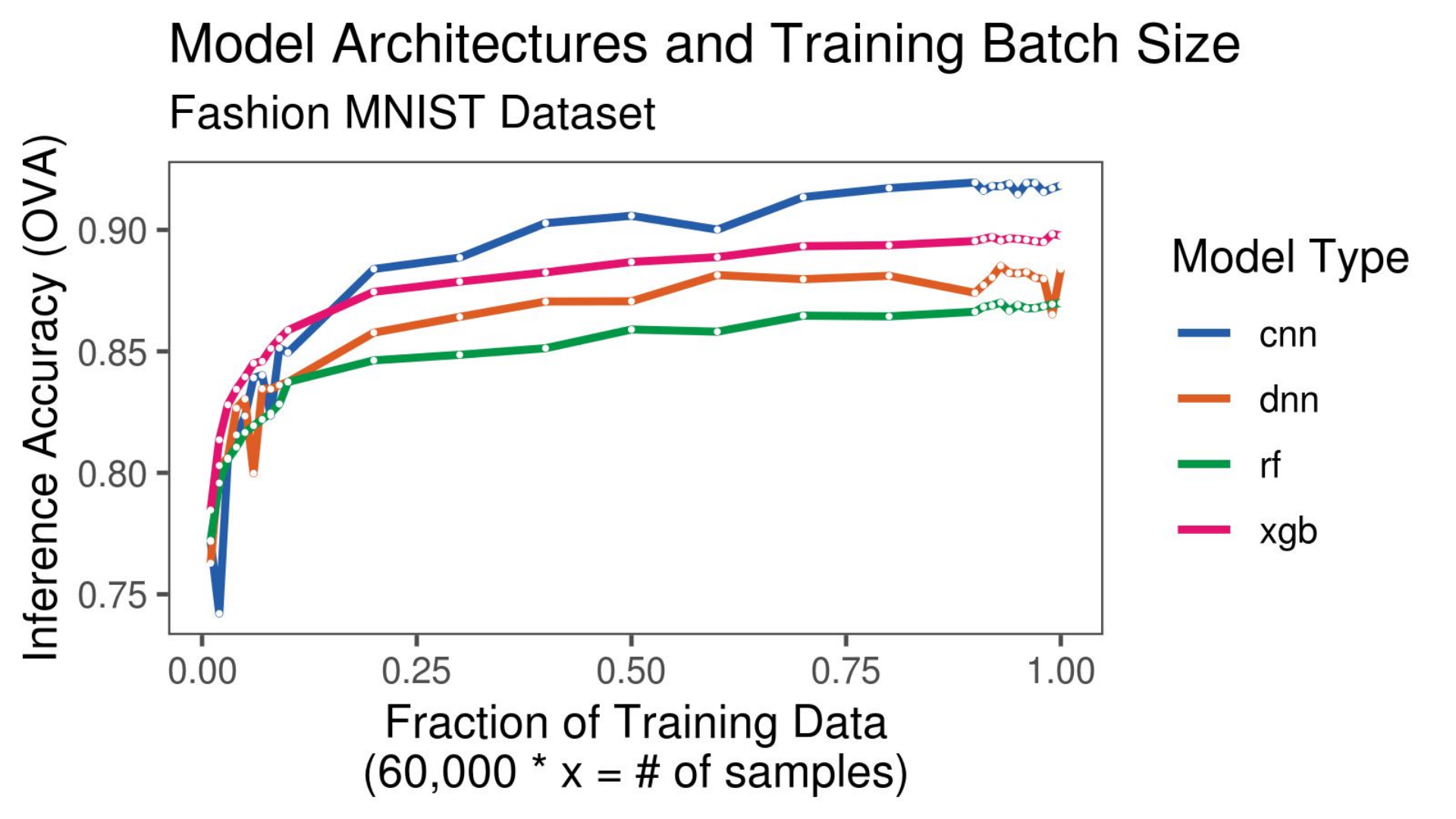
AUC: Area Under the Curve:

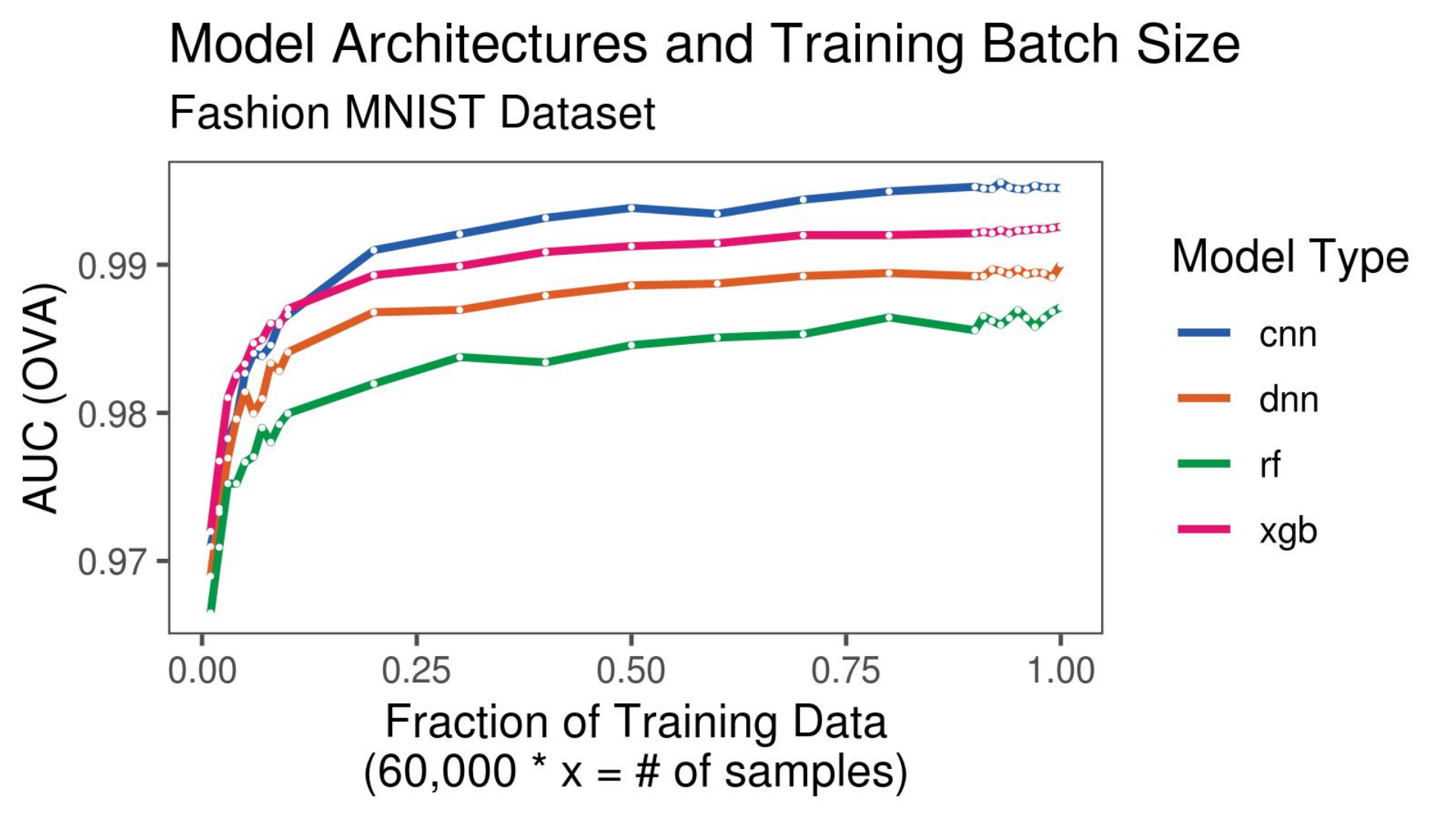
How well the model is able to separate classes





Images: https://towardsdatascience.com/understanding-auc-roc-curve-68b2303cc9c5


Model Architectures and Training Batch Size
Fashion MNIST Dataset
Inference Accuracy (OVA)
0.90
0.85
0.80
0.75
0.00
0.25
0.50
0.75
1.00
Fraction of Training Data
(60,000 * x = # of samples)
Model Type
cnn
dnn
rf
xgb

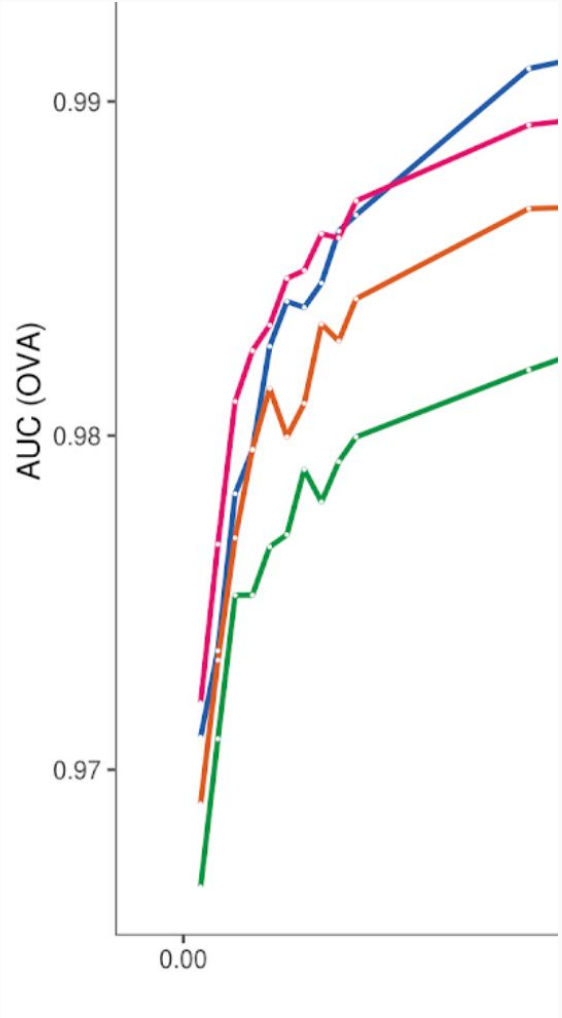

Model Architectures and Training Batch Size
Fashion MNIST Dataset
AUC (OVA)
0.99
0.98
0.97
0.00
0.25
0.50
0.75
1.00
Fraction of Training Data
(60,000 * x = # of samples)
Model Type
cnn
dnn
rf
xgb

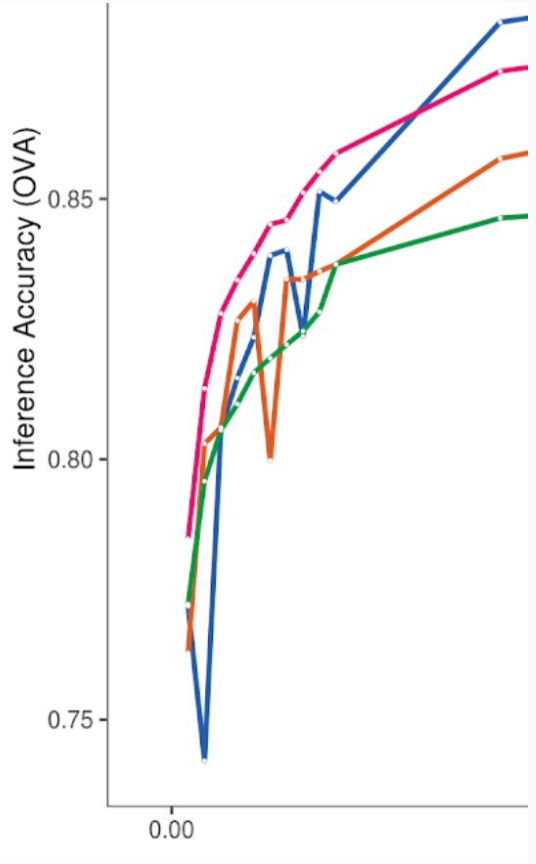
What did we learn?

LHS of the Data

At 1%, we have 60 observations per class. 2% is 120 observations...

- Adding training data leads to steep improvement in response
  - BIGGER DATA!
- Moving to different models leads to steep improvements
  - BETTER MATH!

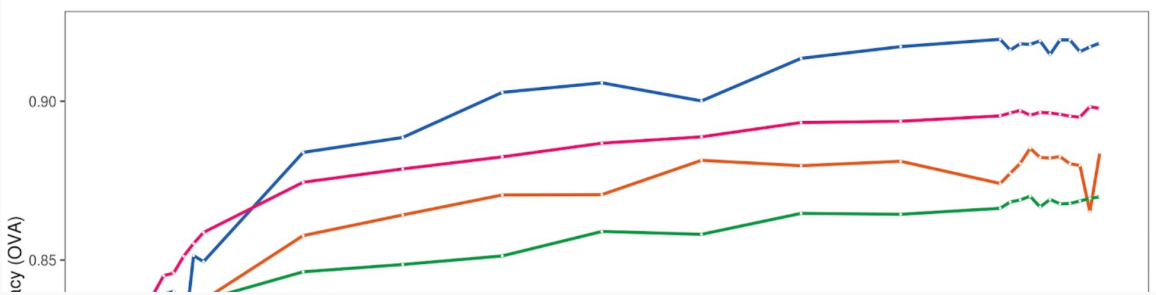


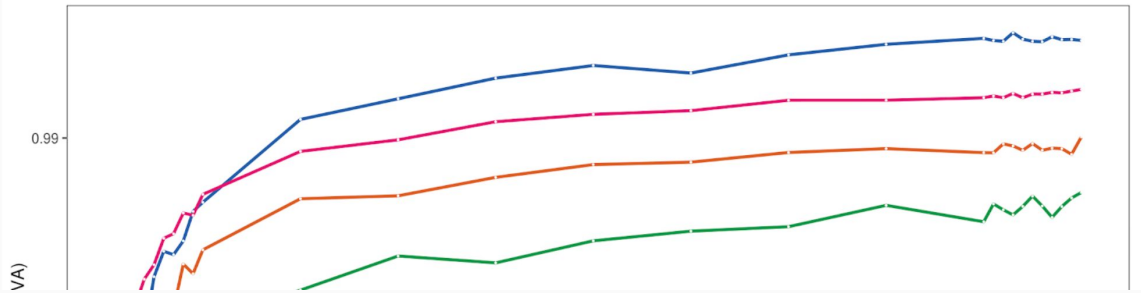


RHS of the Data

At 30%, we have 1800 observations per class. 40% is 2400 observations...

- Adding training data leads to moderate improvement in response
  - BIGGER DATA!
- Moving to different models leads to step improvements
  - BETTER MATH!





“Bigger Data Beats Better Math, No Question”

WHOOPS!

If you are already at the “BEST” MATH, BIGGER DATA is a good strategy

In practice: use whatever works best on ImageNet…

Andrej Karpathy, CS231N

What about Better Data?

What is Better Data?

Training a classifier (“shirt, trouser, handbag, …”) requires training data.

Training a good classifier requires high-confidence in your training data.

Fashion has 60,000 observations for training: 6,000 examples of each class that we assume are correct to learn from

What if that assumption is not correct?

How can we invalidate the assumption of correctness?

That’s right,
expose the data
labels to Pure Evil

Teratogenic Effects of Pure Evil in Ursus Teddius Domesticus, Dr. Allison von Lonsdale, Institute for Dangerous Research, Department of Mad Biology.

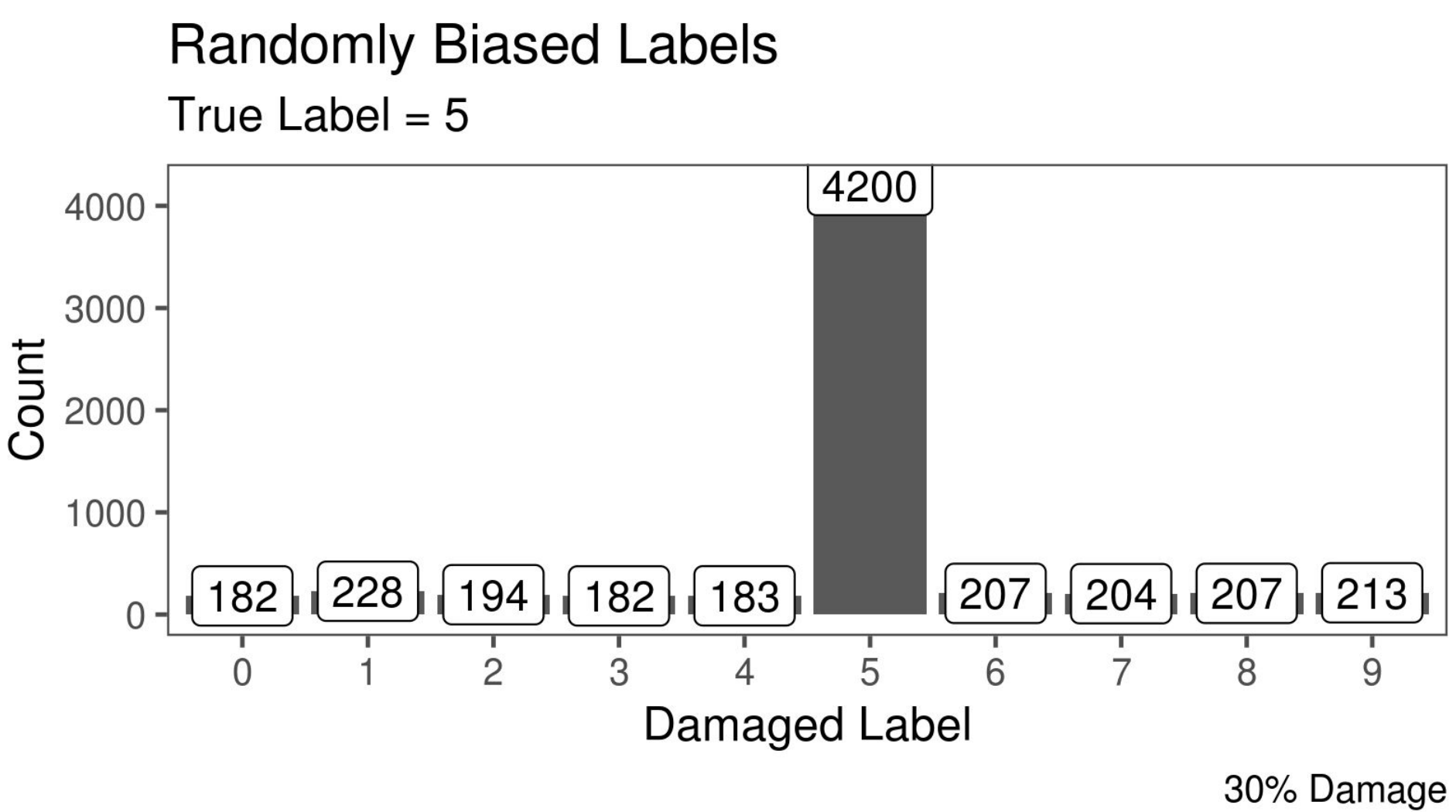
HIM and Mojo Jojo from the Powerpuff Girls

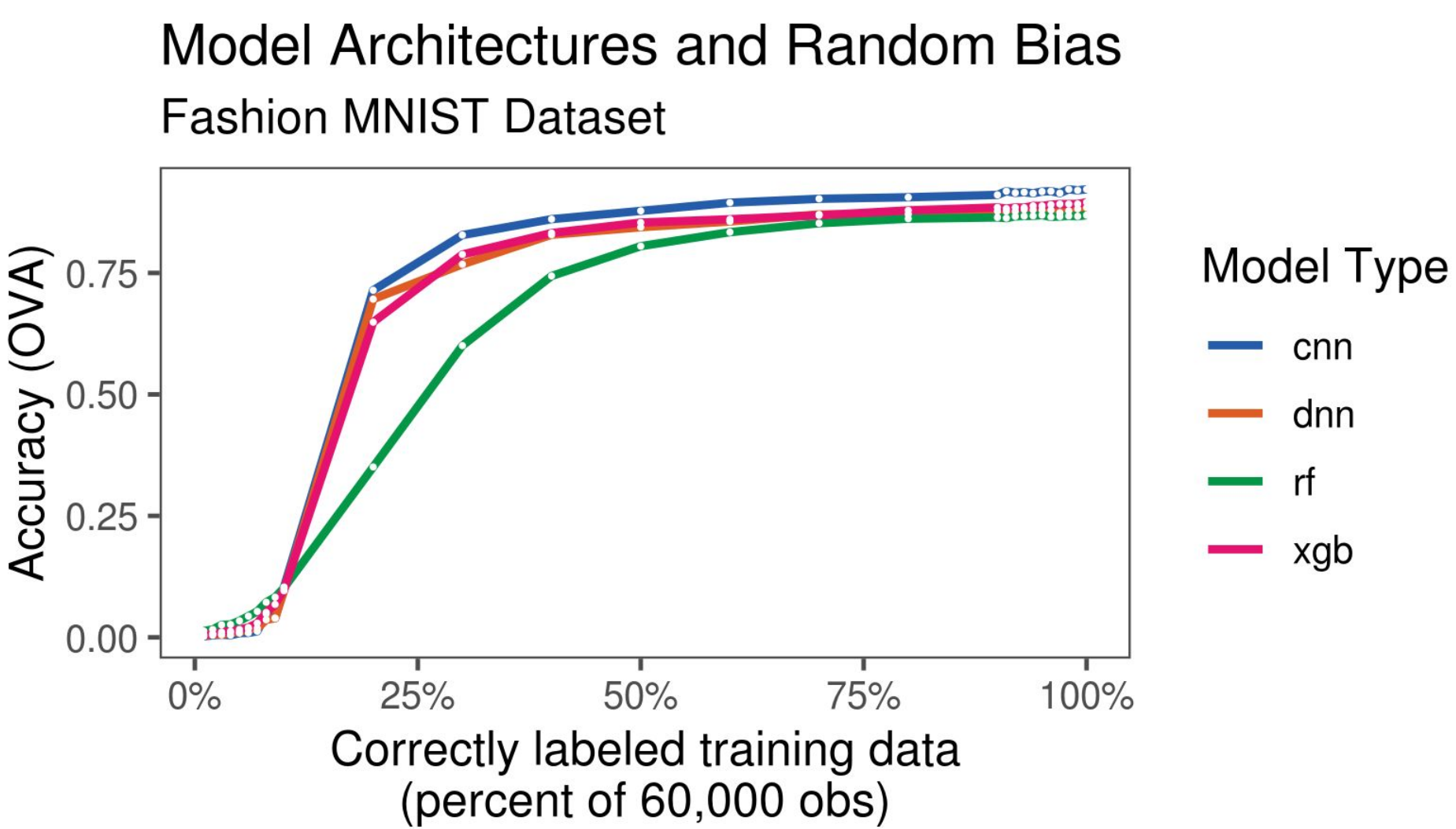
Applying evil to training data

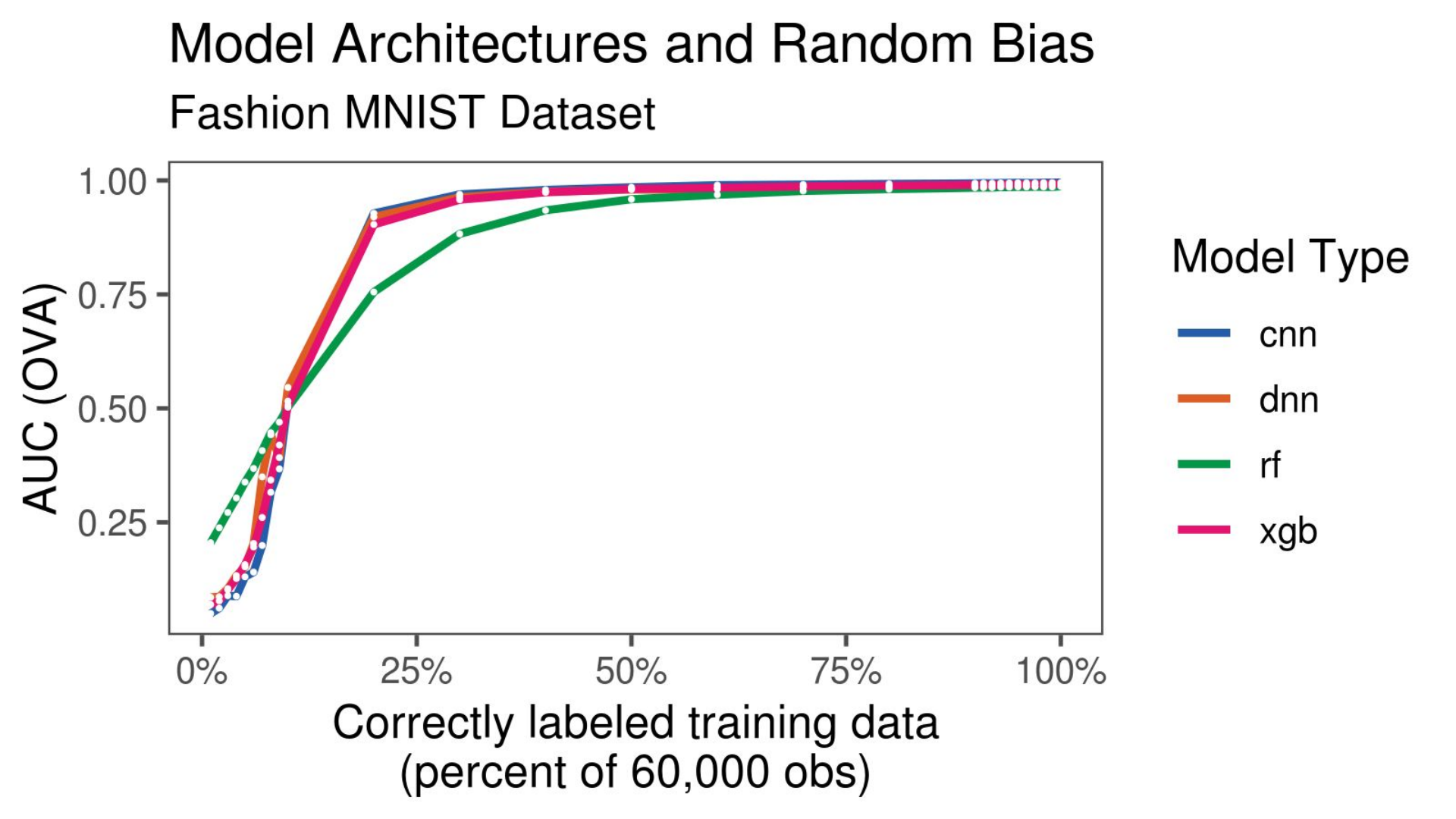
Damage the labels

```
damage_tib <- c(0:9 / 100, 1:9 / 10, 91:99 / 100) %>%
  sort() %>%
  map_dfr(run_random_damage_exp, x_train, y_train, x_test, y_test)
```

Randomly changes a “true” label to one of the other 9, and then train and test


Randomly Biased Labels
True Label = 5
Count
4000
3000
2000
1000
0
182
228
194
182
183
4200
207
204
207
213
0
1
2
3
4
5
6
7
8
9
Damaged Label
30% Damage


Model Architectures and Random Bias
Fashion MNIST Dataset
Accuracy (OVA)
0.00
0.25
0.50
0.75
0%
25%
50%
75%
100%
Correctly labeled training data
(percent of 60,000 obs)
Model Type
cnn
dnn
rf
xgb


Model Architectures and Random Bias
Fashion MNIST Dataset
AUC (OVA)
1.00
0.75
0.50
0.25
0%
25%
50%
75%
100%
Correctly labeled training data
(percent of 60,000 obs)
Model Type
cnn
dnn
rf
xgb

But is that really the most evil we can be to data?

Random Bias -> Constant Bias

With a random bias, every mis-label has a 1-in-9 chance of being some other label - the counter-signal is smeared out

Machine Learning needs strong signals to learn and the information content in the 1-in-9 isn't relatively strong

Will a constant bias be more damaging?

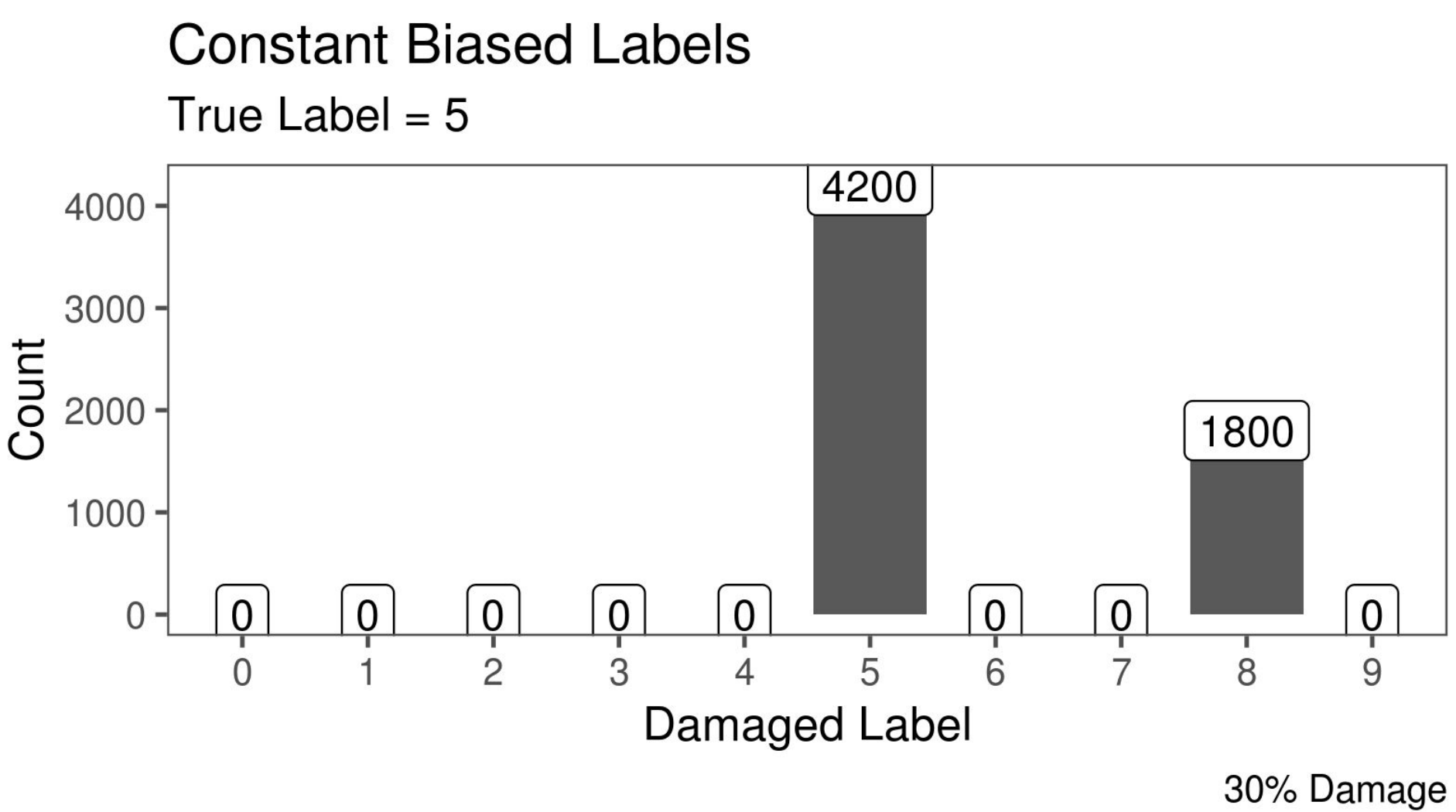

I APPROVE OF THIS APPROACH

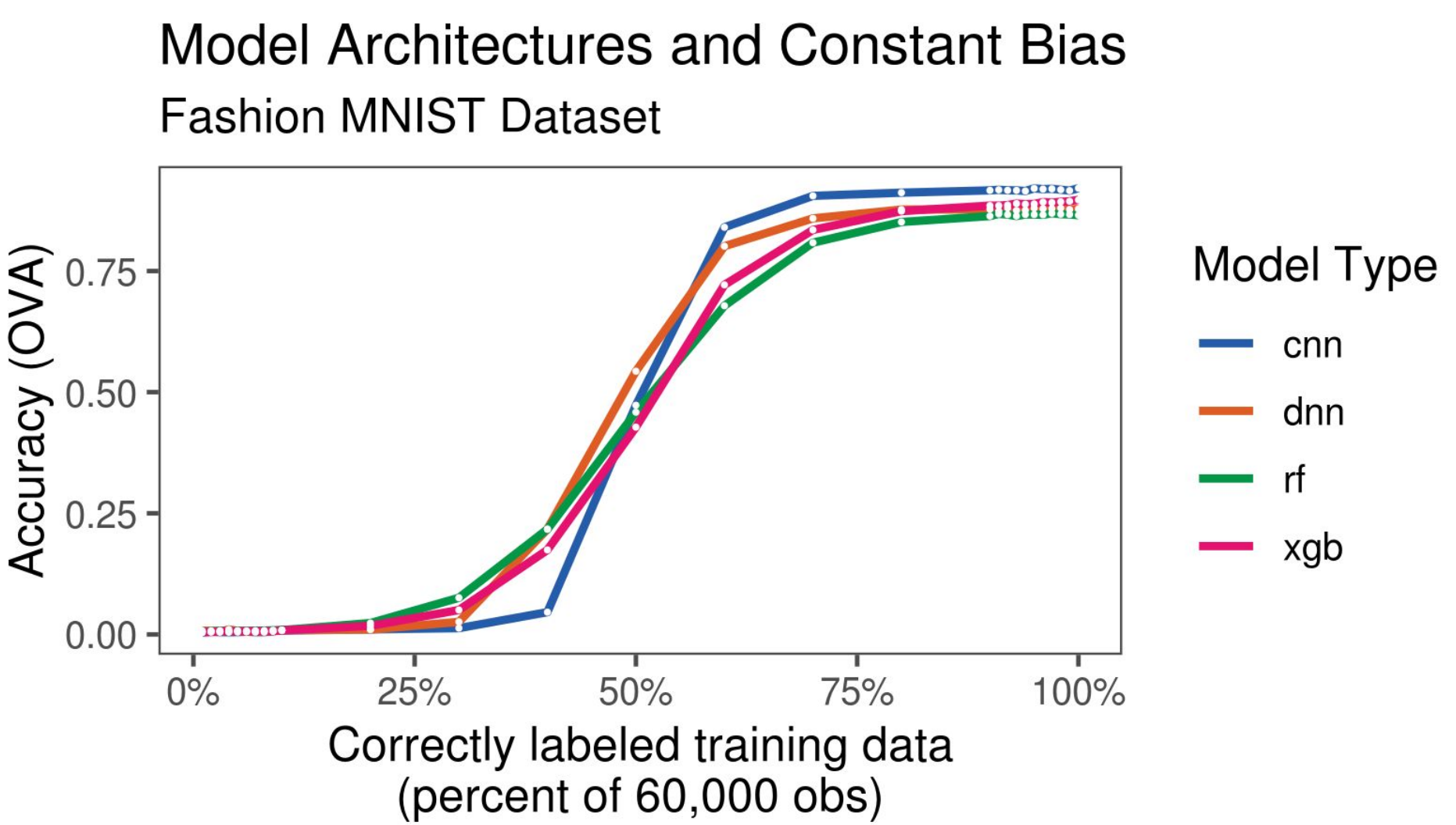
Applying evil to training data, take 2

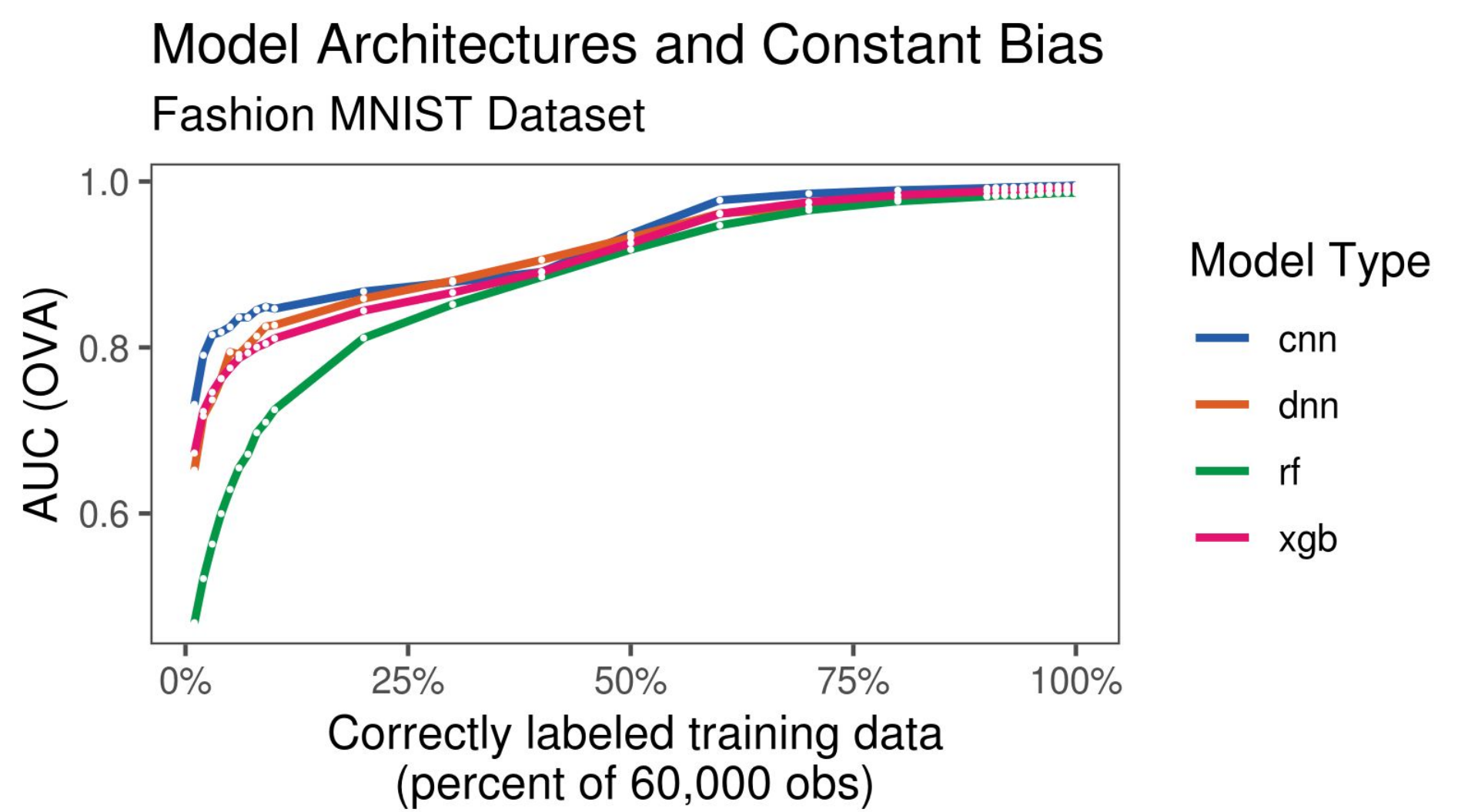
Damage the labels

```
damage_tib <- c(0:9 / 100, 1:9 / 10, 91:99 / 100) %>%
  sort() %>%
  map_dfr(run_constant_damage_exp, x_train, y_train, x_test, y_test)
```

Changes a label consistently to another label (“0 becomes 1, always”), and then train and test


Constant Biased Labels
True Label = 5
Count
4000
3000
2000
1000
0
4200
1800
0
0
0
0
0
0
0
0
0
0
0
1
2
3
4
5
6
7
8
9
Damaged Label
30% Damage


Model Architectures and Constant Bias
Fashion MNIST Dataset
Accuracy (OVA)
0.00
0.25
0.50
0.75
0%
25%
50%
75%
100%
Correctly labeled training data
(percent of 60,000 obs)
Model Type
cnn
dnn
rf
xgb


Model Architectures and Constant Bias
Fashion MNIST Dataset
AUC (OVA)
1.0
0.8
0.6
0%
25%
50%
75%
100%
Correctly labeled training data
(percent of 60,000 obs)
Model Type
cnn
dnn
rf
xgb

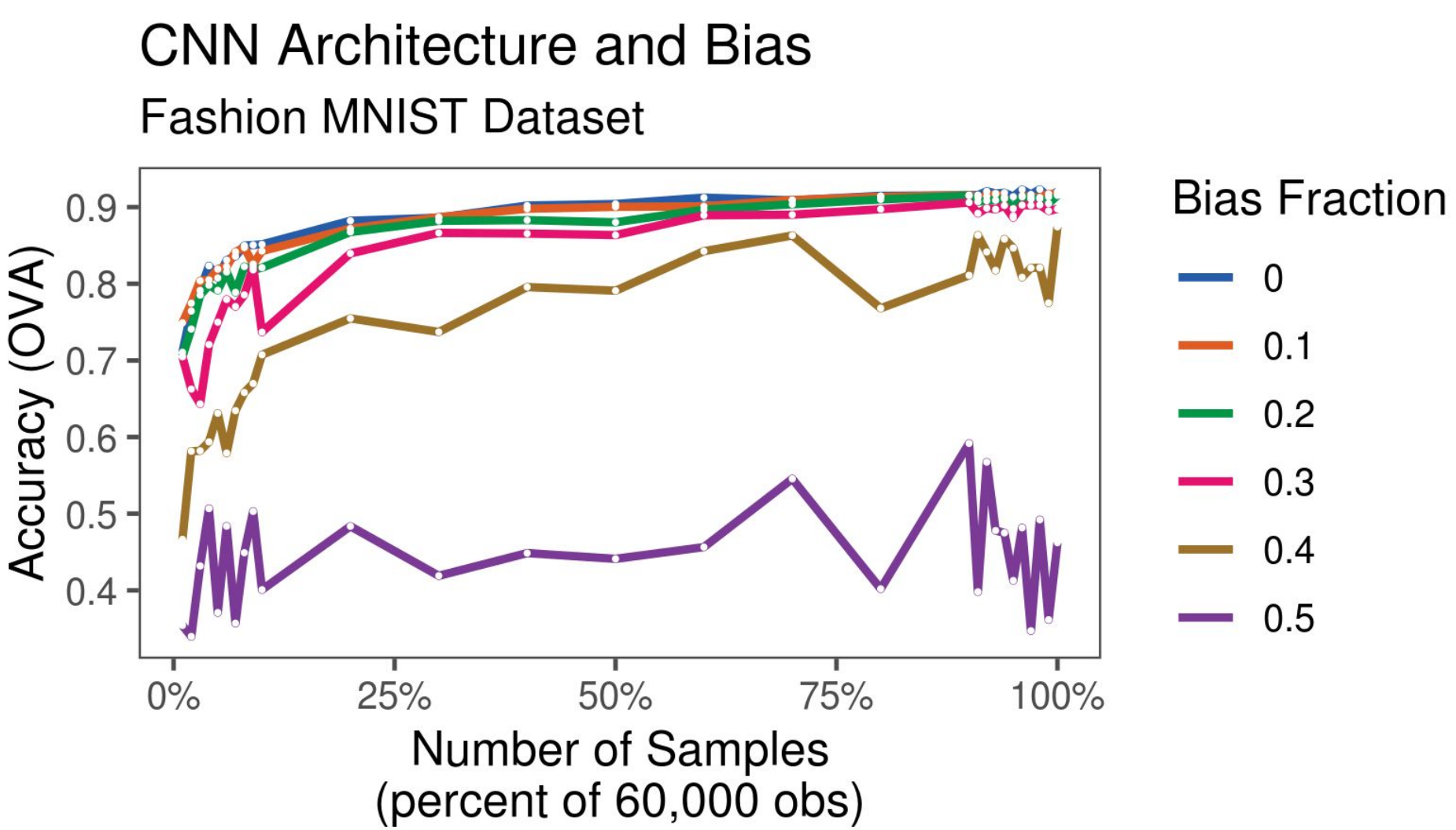
But is that *really* the most evil we can be to data?

Expose the data to a pack of middle school girls - there are some things I will not do to data

What if we ‘fix’ the architecture and vary samples and bias?

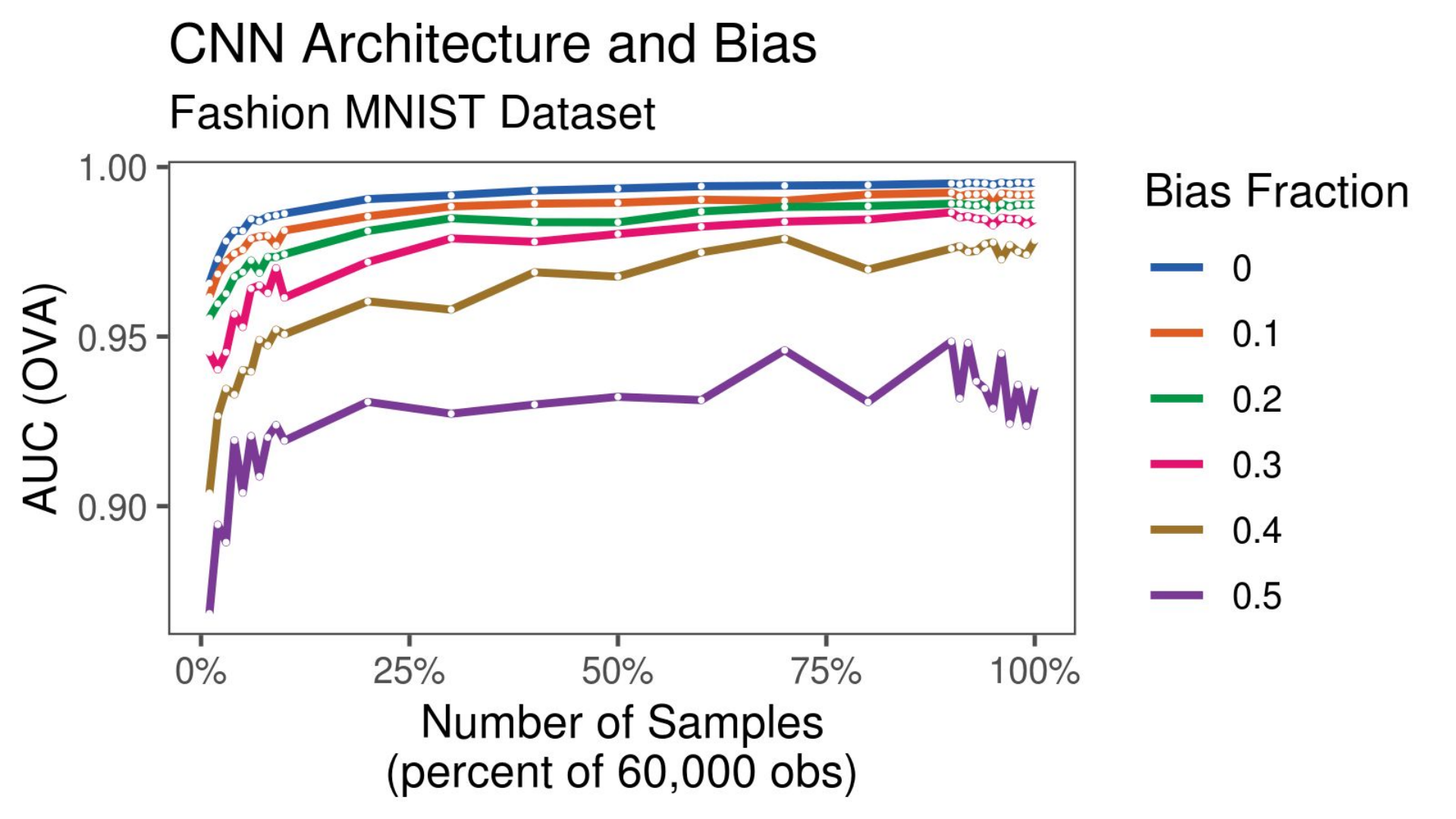
Some test bench code

```
damage_frac <- c(0:5 / 10) %>%
  sort()

sample_frac <- c(1:9/100, 1:9 / 10, 91:100 / 100) %>%
  sort()

cross_prod <- cross_df(list(d=damage_frac, s=sample_frac))

results_tib <-
  map2_dfr(cross_prod$d, cross_prod$s, run_cnn_damage_exp,
  x_train, y_train, x_test, y_test)
```


CNN Architecture and Bias
Fashion MNIST Dataset
Accuracy (OVA)
0.9
0.8
0.7
0.6
0.5
0.4
0%
25%
50%
75%
100%
Number of Samples
(percent of 60,000 obs)
Bias Fraction
0
0.1
0.2
0.3
0.4
0.5

Observations needed for > 90% accuracy

quality	acc	frac_sample	num_obs	d_obs
1.0	0.902	0.40	24000	NA
0.9	0.900	0.50	30000	0.25
0.8	0.904	0.70	42000	0.40
0.7	0.902	0.94	56400	0.34


CNN Architecture and Bias
Fashion MNIST Dataset
1.00
0.95
0.90
AUC (OVA)
0%
25%
50%
75%
100%
Number of Samples
(percent of 60,000 obs)
Bias Fraction
0
0.1
0.2
0.3
0.4
0.5

Observations needed for > 98% AUC

quality	auc	frac_sample	num_obs	d_obs
1.0	0.981	0.05	3000	NA
0.9	0.981	0.10	6000	1.0
0.8	0.981	0.20	12000	1.0
0.7	0.980	0.50	30000	1.5

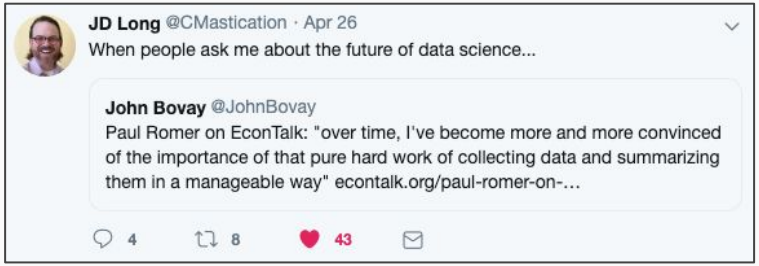
An economic argument for quality

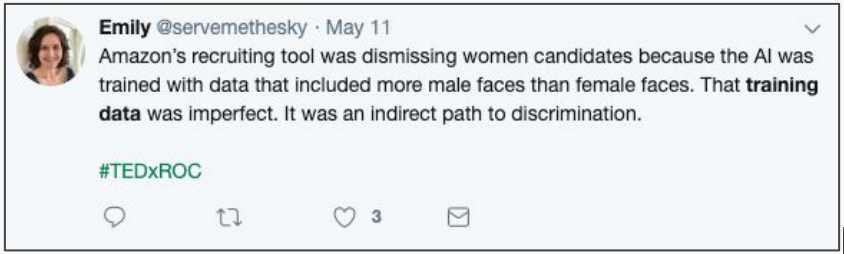
$$\frac{\partial \text{data size}}{\partial \text{quality}} << -1$$

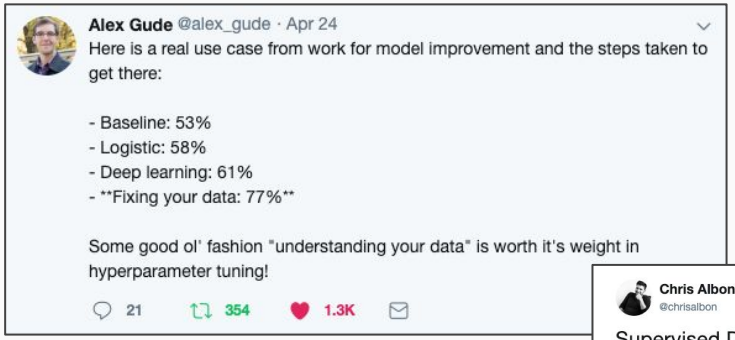
One step in quality does not equal a similarly sized step in the number of observations

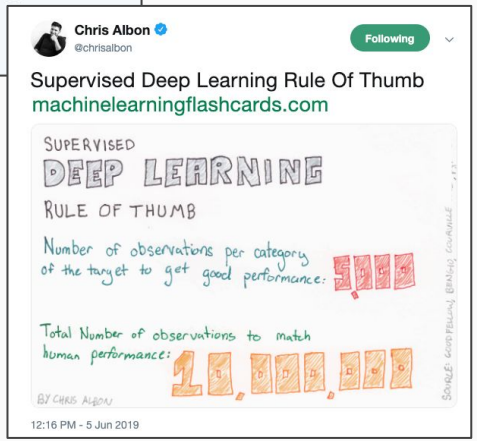
If data is hard to acquire, a little effort on quality goes a long way

Some thoughts from the Internet









In practice: use whatever works best on ImageNet. If you're feeling a bit of a fatigue in thinking about the architectural decisions, you'll be pleased to know that in 90% or more of applications you should not have to worry about these. I like to summarize this point as "*don't be a hero*": Instead of rolling your own architecture for a problem, you should look at whatever architecture currently works best on ImageNet, download a pretrained model and finetune it on your data. You should rarely ever have to train a ConvNet from scratch or design one from scratch.

Andrej Karpathy, CS231N

1. Become one with the data

The first step to training a neural net is to not touch any neural net code at all and instead begin by thoroughly inspecting your data. This step is critical. I like to spend copious amount of time (measured in units of hours) scanning through thousands of examples, understanding their distribution and looking for patterns. Luckily, your brain is pretty good at this.

Andrej Karpathy's ML Rubric

Closing Thoughts

Better Math

- Always worthwhile; research effort, unplannable at the limit

Bigger Data

- Always worthwhile, engineering effort usually

Better Data

- For a given ML metric, ∂data / ∂quality << -1. This implies that overcoming bias is costly

Thanks!

Brent Schneeman

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@schnee

https://github.com/schnee/big-data-big-math

(btw - I'm #OpenToWork)