

R + Tensorflow =  
Reproducibility,  
Transparency, &  
Trust

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IBM Center for Open-Source Data & AI Technologies (<http://codait.org>)



# Agenda

- TensorFlow and R
- Tools/Workflows
- Reproducibility
- Visualization

# Speakers



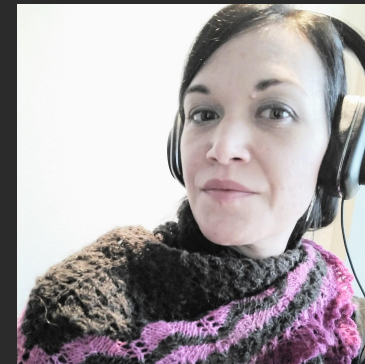
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 mmpork

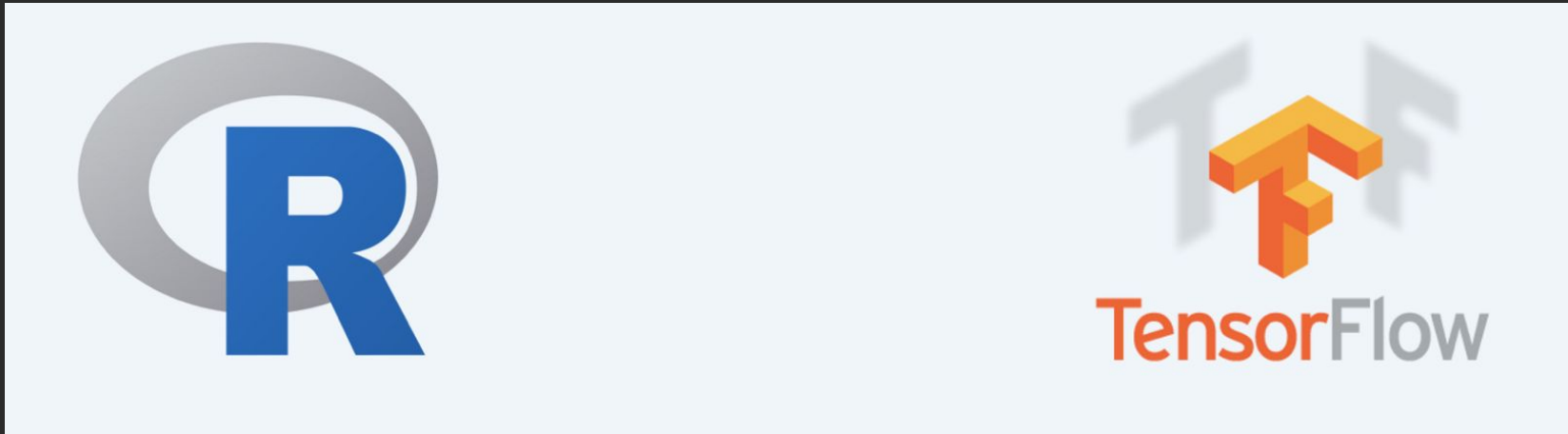
<http://rhappy.fun/>

# What is R?

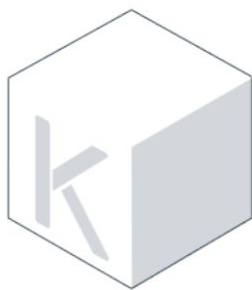


- Free and Open Source Language and Environment
- Popular language for data scientists
- It has more extensions than any other data science software
- Primary tool for statistical research
- RStudio - an IDE with a lot of functionality
- **Awesome Community** (#rstats + R-Ladies + R Forwards)

# Why TensorFlow + R?



# TensorFlow APIs



Keras API

The Keras API for TensorFlow provides a high-level interface for neural networks, with a focus on enabling fast experimentation.



Estimator API

The Estimator API for TensorFlow provides high-level implementations of common model types such as regressors and classifiers.



Core API

The Core TensorFlow API is a lower-level interface that provides full access to the TensorFlow computational graph.

# Main R Packages + Supporting Tools

## TensorFlow API

- **keras**
- **tfestimators** - Implementations of model types such as regressors and classifiers
- **tensorflow** - Low-level interface to the TensorFlow computational graph
- **tfdatasets** - Work with large datasets

## Tools

- **tfruns** - Manage experiments (runs)
- **tfdeploy** - Share models across formats
- **cloudml** - Interface to Google Cloud ML

# Tools/Workflows

# tfruns

Track and Visualizing Training Runs



# tfruns - Track and Visualizing Training Runs



- **Track** the hyperparameters, metrics, output, and source code of every training run.
- **Compare** hyperparameters and metrics across runs to find the best performing model.
- **Generate reports** to visualize individual training runs or comparisons between runs.

# tfruns - Track and Visualizing Training Runs

```
# Define Model -----  
  
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')  
  
model %>% compile(  
  loss = 'categorical_crossentropy',  
  optimizer = optimizer_rmsprop(lr = 0.001),  
  metrics = c('accuracy')  
)  
  
# Training & Evaluation -----  
  
history <- model %>% fit(  
  x_train, y_train,  
  batch_size = batch_size,  
  epochs = 20,  
  verbose = 1,  
  validation_split = 0.2  
)  
  
plot(history)  
  
score <- model %>% evaluate(  
  x_test, y_test,  
  verbose = 0  
)
```

```
source("mnist_mlp.R")
```

OR

```
library(tfruns)  
tfruns::training_run("mnist_mlp.R")
```

# tfruns

Training Run

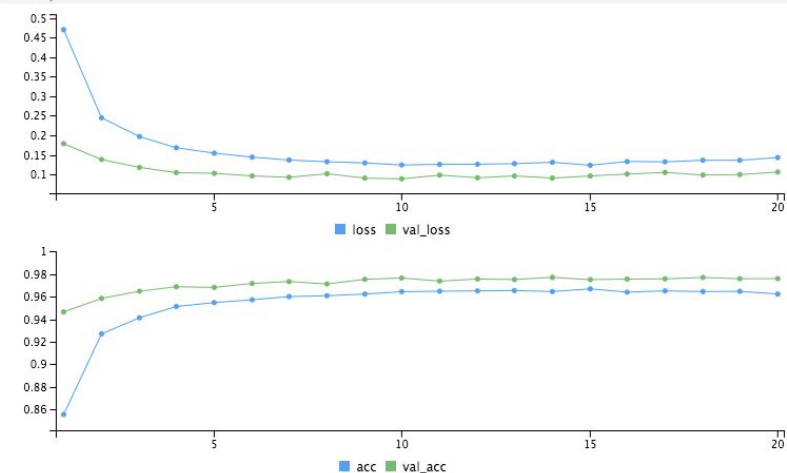
SUMMARY

OUTPUT

CODE

2018-07-09T20-55-44Z

History



Model

Layer (type)	Output Shape	Param #
dense_1 (Dense)	(None, 256)	200960
dropout_1 (Dropout)	(None, 256)	0
dense_2 (Dense)	(None, 128)	32896
dropout_2 (Dropout)	(None, 128)	0
dense_3 (Dense)	(None, 10)	1290
Total params: 235,146		
Trainable params: 235,146		
Non-trainable params: 0		

Run

context	local
script	mnist_mlp.R
started	2018-07-09 20:55:44 GMT
time	00:01:02

Metrics

loss	0.1433
acc	0.9624
val_loss	0.1063
val_acc	0.9761

Evaluation

eval_loss	0.1082
eval_acc	0.9753

Optimization

loss	categorical_crossentropy
optimizer	<keras.optimizers.RMSprop>
lr	0.001

Training

samples	48,000
validation_samples	12,000
epochs	20
batch_size	128

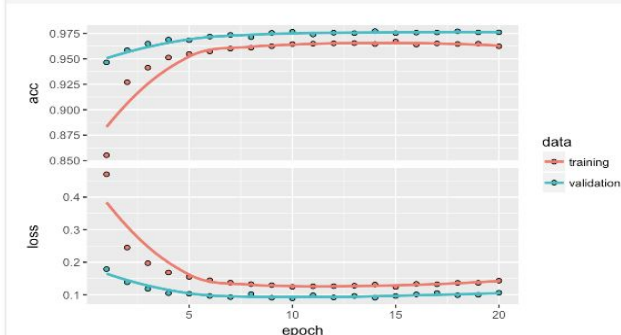
Training Run

SUMMARY

OUTPUT

CODE

Plots



Console

```
1  
2 > library(keras)  
3  
4 > # Data Preparation -----  
5  
6 > use_session_with_seed(2)  
7  
8 > batch_size <- 128
```

Training Run

SUMMARY

OUTPUT

CODE

2018-07-09T20-55-44Z

mnist\_mlp.R

```
1 library(keras)  
2  
3 # Data Preparation -----  
4  
5 use_session_with_seed(2)  
6  
7 batch_size <- 128  
8 num_classes <- 10  
9  
10  
11 # The data, shuffled and split between train and test sets  
12 c((x_train, y_train), c(x_test, y_test)) %<-% dataset_mnist()  
13  
14 x_train <- array_reshape(x_train, c(nrow(x_train), 784))  
15 x_test <- array_reshape(x_test, c(nrow(x_test), 784))  
16  
17 # Transform RGB values into [0,1] range  
18 x_train <- x_train / 255  
19 x_test <- x_test / 255  
20  
21 cat(nrow(x_train), 'train samples\n')  
22 cat(nrow(x_test), 'test samples\n')  
23  
24 # Convert class vectors to binary class matrices  
25 y_train <- to_categorical(y_train, num_classes)  
26 y_test <- to_categorical(y_test, num_classes)  
27  
28 # Define Model -----  
29  
30 model <- keras_model_sequential()  
31 model %>%  
32 layer_dense(units = 256, activation = 'relu', input_shape = c(784)) %>%  
33 layer_dropout(rate = 0.4) %>%  
34 layer_dense(units = 128, activation = 'relu') %>%  
35 layer_dropout(rate = 0.3) %>%  
36 layer_dense(units = 10, activation = 'softmax')  
37
```

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Slides available at: <http://bit.ly/rtensoflow>



gdequeiroz /

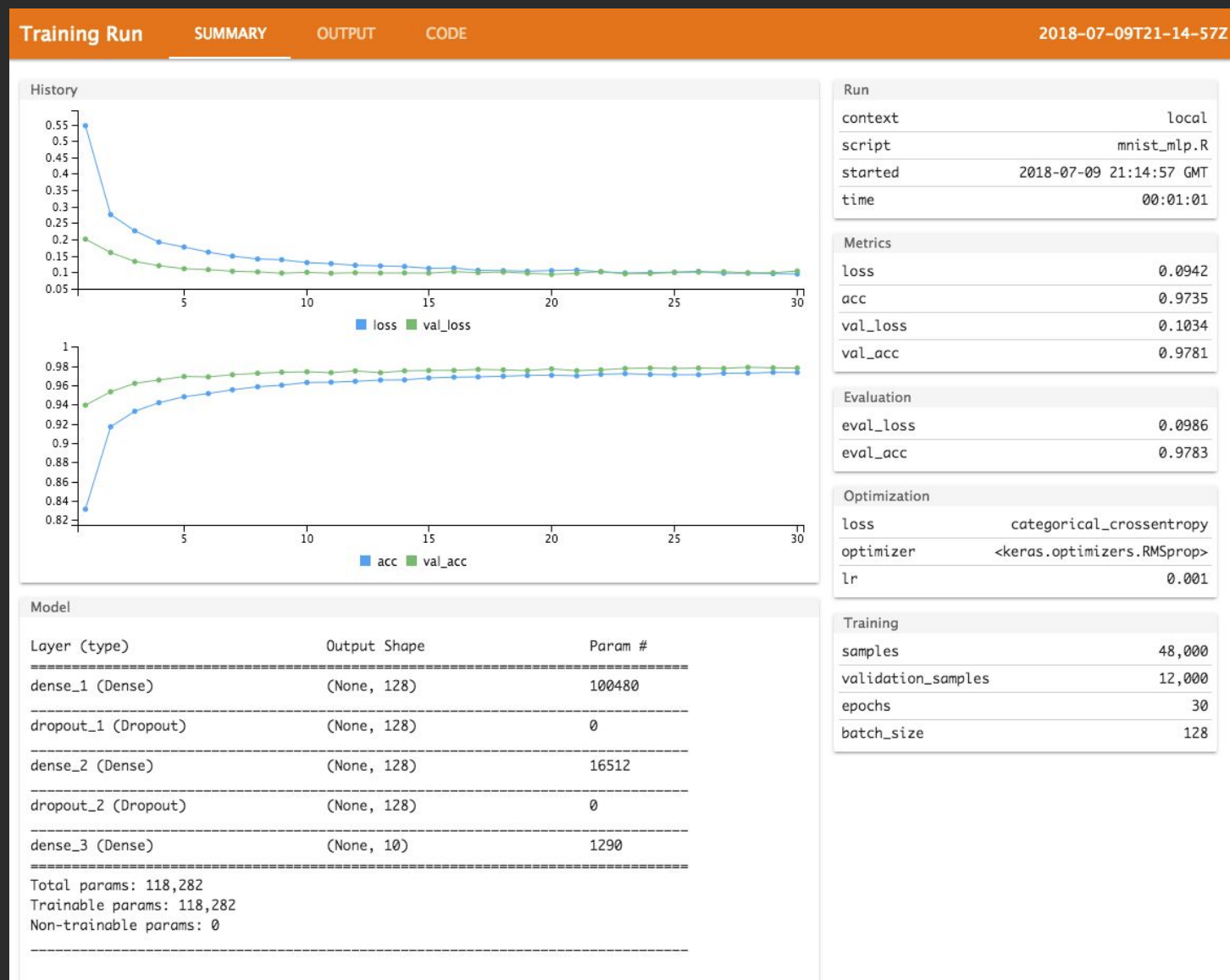


mmmpork

# When running another model

```
# Define Model -----  
model <- keras_model_sequential()  
model %>%  
  layer_dense(units = 128, 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')  
  
model %>% compile(  
  loss = 'categorical_crossentropy',  
  optimizer = optimizer_rmsprop(lr = 0.001),  
  metrics = c('accuracy')  
)  
  
# Training & Evaluation -----  
  
history <- model %>% fit(  
  x_train, y_train,  
  batch_size = batch_size,  
  epochs = 20, 30  
  verbose = 1,  
  validation_split = 0.2  
)
```

```
library(tfruns)  
tfruns::training_run("mnist_mlp.R")
```



# When comparing runs (models)

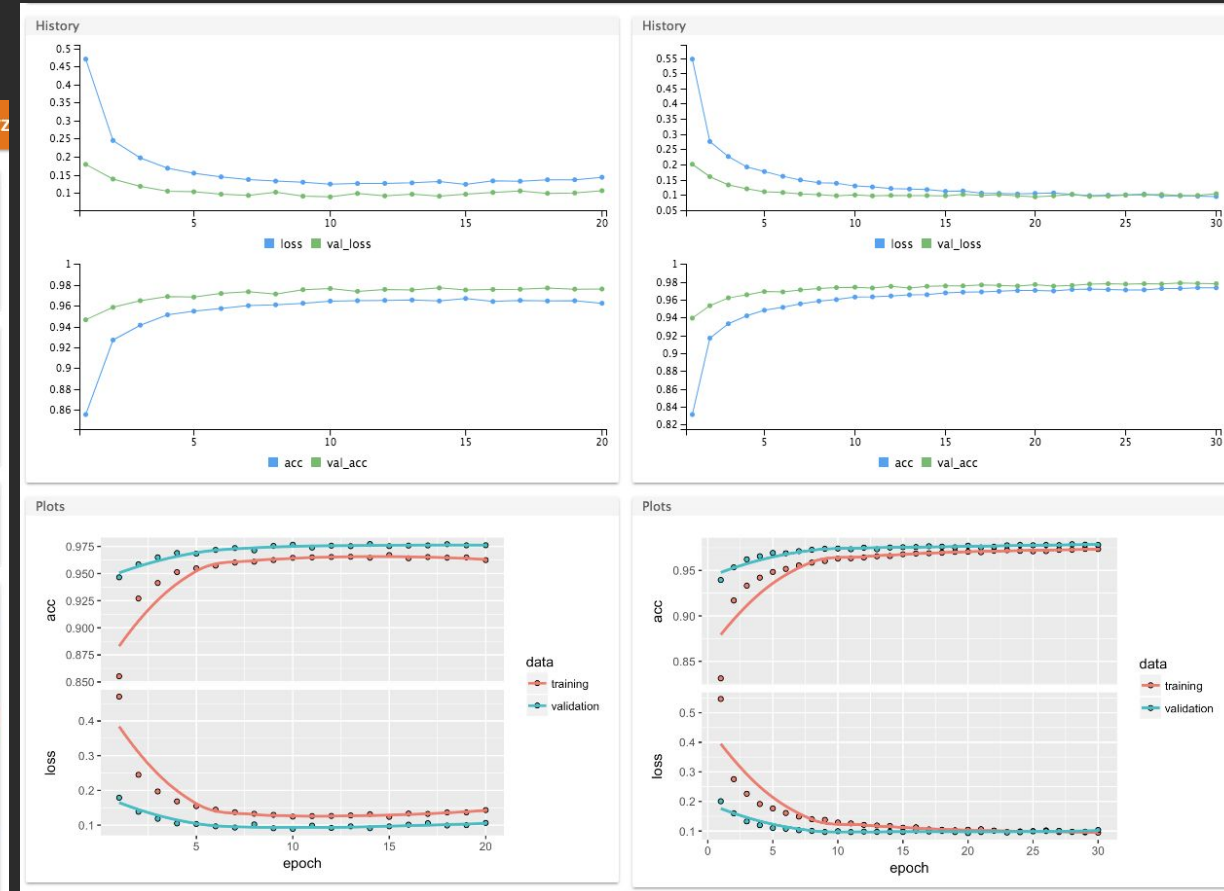
```
tfruns::compare_runs()
```

## Compare Runs

2018-07-09T20-55-44Z 2018-07-09T21-14-57Z

Run		Run	
context	local	context	local
script	mnist_mlp.R	script	mnist_mlp.R
started	2018-07-09 20:55:44 GMT	started	2018-07-09 21:14:57 GMT
time	00:01:02	time	00:01:01
Metrics			
loss	0.1433	loss	0.0942
acc	0.9624	acc	0.9735
val_loss	0.1063	val_loss	0.1034
val_acc	0.9761	val_acc	0.9781
Evaluation			
eval_loss	0.1082	eval_loss	0.0986
eval_acc	0.9753	eval_acc	0.9783

```
mnist_mlp.R
@@ -28,9 +28,9 @@
28 28 # Define Model -----
29 29
30 30 model <- keras_model_sequential()
31 31 model %>%
32 32 - layer_dense(units = 256, activation = 'relu', input_shape = c(784)) %>%
33 32 + layer_dense(units = 128, activation = 'relu', input_shape = c(784)) %>%
34 33 layer_dropout(rate = 0.4) %>%
35 34 layer_dense(units = 128, activation = 'relu') %>%
36 35 layer_dropout(rate = 0.3) %>%
37 36 layer_dense(units = 10, activation = 'softmax')
@@ -46,9 +46,9 @@
46 46
47 47 history <- model %>% fit(
48 48 x_train, y_train,
49 49 batch_size = batch_size,
50 50 - epochs = 20,
51 50 + epochs = 30,
52 51 verbose = 1,
53 52 validation_split = 0.2
54 53 )
55 54
```





# Training Flags - `tfruns::flags()`

```
# Define Model -----
model <- keras_model_sequential()
model %>%
  layer_dense(units = FLAGS$dense_units1, 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')


model %>% compile(
  loss = 'categorical_crossentropy',
  optimizer = optimizer_rmsprop(lr = 0.001),
  metrics = c('accuracy')
)

# Training & Evaluation -----

history <- model %>% fit(
  x_train, y_train,
  batch_size = 128,
  epochs = FLAGS$epochs
  verbose = 1,
  validation_split = 0.2
)
```

# Tuning hyperparameters - `tfruns::tuning_run()`

```
runs <- tfruns::tuning_run("mnist_mlp_FLAGS_TUNING.R", flags = list(  
  dense_units1 = c(256, 128),  
  epochs = c(20, 30)  
))
```



flags = list(256, 20);  
flags = list(128, 20);  
flags = list(256, 30);  
flags = list(128, 30)

4 total combinations of flags (use sample parameter to run a random subset)

Proceed with tuning run? [Y/n]: Y

Training run 1/4 (flags = list(256, 20))

Using run directory runs/2018-07-16T22-09-32Z

```
> library(keras)
```

```
> # Data Preparation -----
```

```
>
```

# Tuning hyperparameters - `tfruns::tuning_run()`

```
> runs[order(runs$eval_acc, decreasing = TRUE), 1:10]
```

Data frame: 4 x 10

	run_dir	eval_loss	eval_acc	metric_loss	metric_acc	metric_val_loss	metric_val_acc	flag_dense_units1	flag_epochs	samples
2	runs/2018-07-16T22-10-54Z	0.0964	0.9821	0.0526	0.9861	0.1107	0.9803	256	30	48000
4	runs/2018-07-16T22-09-32Z	0.0965	0.9798	0.0583	0.9843	0.1008	0.9791	256	20	48000
3	runs/2018-07-16T22-10-21Z	0.0998	0.9769	0.0974	0.9721	0.1066	0.9772	128	20	48000
1	runs/2018-07-16T22-11-53Z	0.1131	0.9766	0.0861	0.9763	0.1065	0.9785	128	30	48000

The best model is the model #2 with 256 dense units and 30 epochs



# Reproducibility

# tfdeploy

## Sharing Models for Convenient Collaboration

- **Archive** Models for reproducible research
- **Export and Import** Models for later reuse
- **Deploy** Models as a Service

# Archive Models for Reproducible Research

Save in HDF5 or human-readable formats YAML + JSON to use it in R

```
```{r}
write(model_to_yaml(model), "models/mnist.yaml")
```

```{r}
raw_model <- serialize_model(model)
write(raw_model, "models/mnist_raw.txt")
```

|

```{r, eval=FALSE}
save_model_hdf5(model, filepath = "models/mnist_hdf5.h5")
save_model_weights_hdf5(model, filepath="models/mnist_weights_hdf5.h5")
```
```

Load saved models for instant reuse

```
```{r}
model_dense <- load_model_hdf5("models/mnist_dense_hdf5.h5")
```
```

# Export Models

Use `export_savedmodel()` when you want to use it outside of R

```
```{r, eval=FALSE}
model %>%
  layer_dense(units = 256, activation = 'relu', input_shape = c(784),
              name = "image") %>%
  layer_dense(units = 128, activation = 'relu') %>%
  layer_dense(units = 10, activation = 'softmax',
              name = "prediction")
```
```

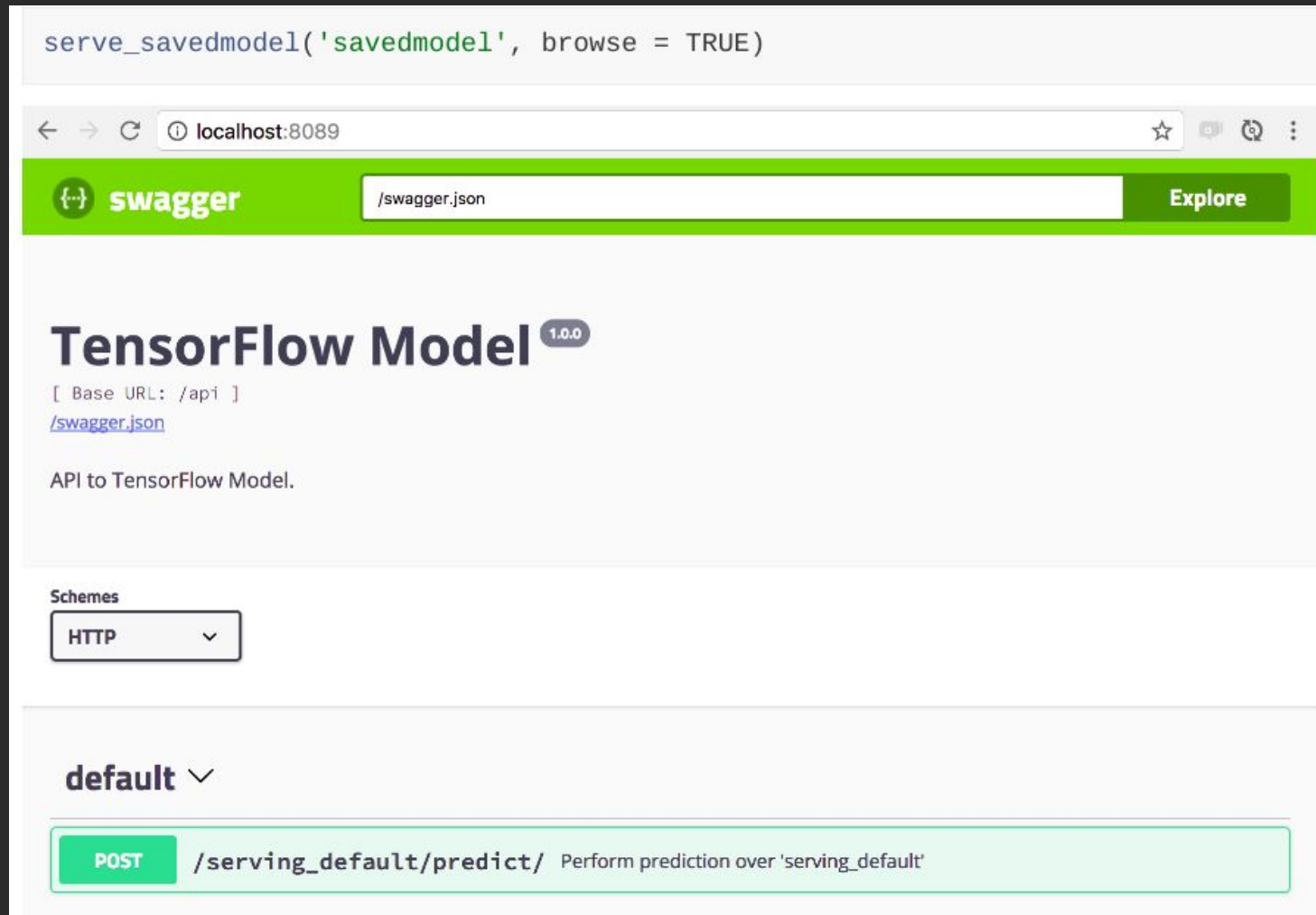
```
```{r}
export_savedmodel(model_dense, "models/savedmodel")
```
```

Keras learning phase set to 0 for export (restart R session before doing additional training)

```
```{r}
view_savedmodel("models/savedmodel")
```
```

# Deploy Models

```
serve_savedmodel('savedmodel', browse = TRUE)
```



The screenshot shows a web browser at localhost:8089 displaying the Swagger UI. The top bar is green with the Swagger logo and a search box containing '/swagger.json'. Below this, the title 'TensorFlow Model' is shown with a version badge '1.0.0'. The base URL is '/api' and the Swagger file is '/swagger.json'. The description is 'API to TensorFlow Model.' Under the 'Schemes' section, 'HTTP' is selected. The 'default' API group is expanded, showing a 'POST' endpoint at '/serving\_default/predict/' with the description 'Perform prediction over 'serving\_default''.

# Transparency

# Explainable AI

## Show Your Work for Transparency + Trust

- **Visualize** model layers in Rmarkdown
- **Regression Analysis** with `kerasformula::kms()`
- **Introspect** blackbox models with LIME

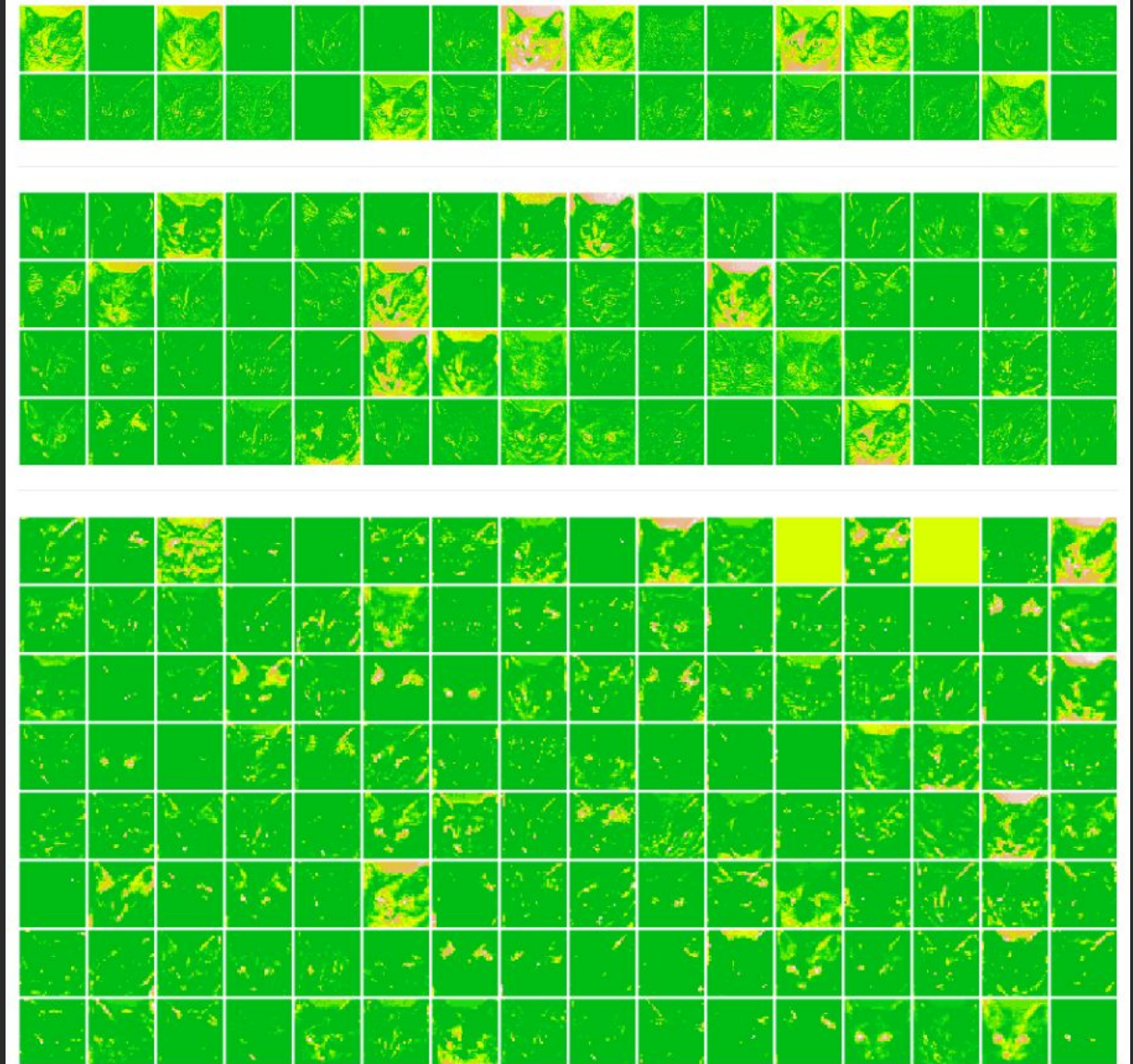


# Visualize Model Layers in Rmarkdown

```
plot(as.raster(img_tensor[1,,]))
```



```
plot_channel(first_layer_activation[1,,5])
```





# Instant Regression with kerasformula::kms()

```
popularity <- kms(pop_input, rstats[1:1000,])  
predictions <- predict(popularity, rstats[1001:2000,])  
predictions$accuracy
```

```
[1] 0.579
```

popularity\$confusion

|               | (-1,0] | (0,1] | (1,10] | (10,100] | (100, 1000] | (1000, 10000] |
|---------------|--------|-------|--------|----------|-------------|---------------|
| (-1,0]        | 37     | 12    | 28     | 2        | 0           | 0             |
| (0,1]         | 14     | 19    | 72     | 1        | 0           | 0             |
| (1,10]        | 6      | 11    | 187    | 30       | 0           | 0             |
| (10,100]      | 1      | 3     | 54     | 68       | 0           | 0             |
| (100, 1000]   | 0      | 0     | 4      | 10       | 0           | 0             |
| (1000, 10000] | 0      | 0     | 0      | 1        | 0           | 0             |

# Introspect blackbox models with LIME

```
# Create Random Forest model on iris data
model <- train(iris_train, iris_lab, method = 'rf')

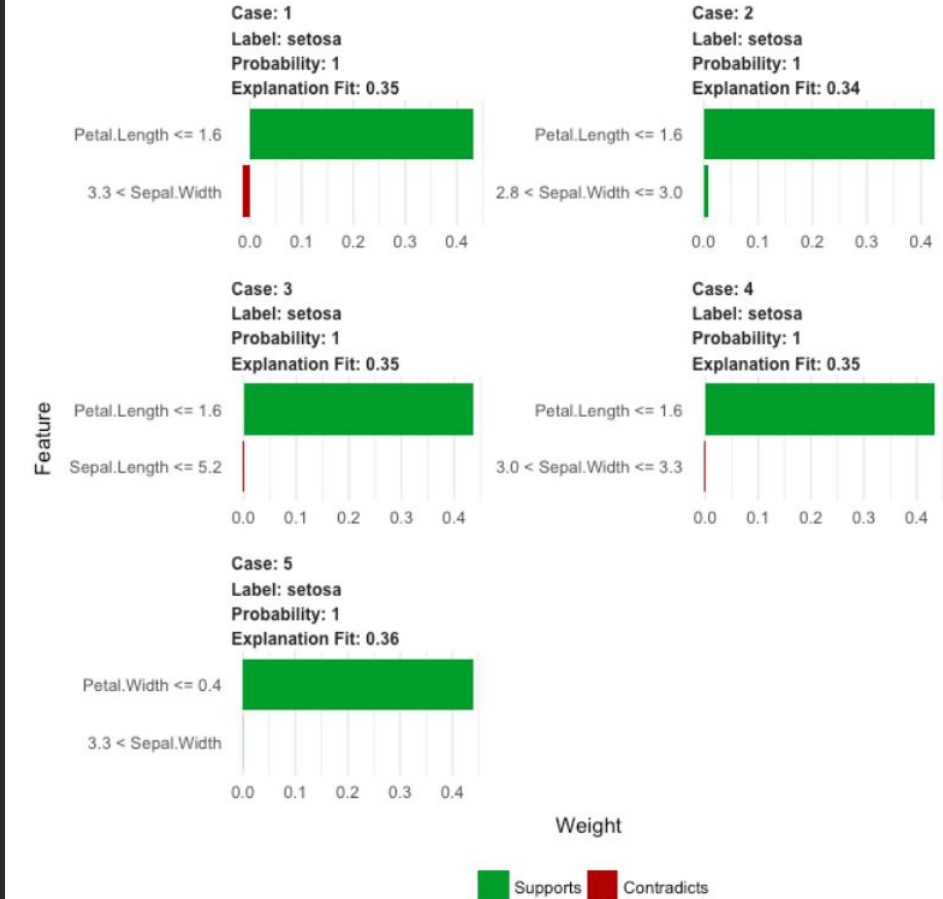
# Create an explainer object
explainer <- lime(iris_train, model)

# Explain new observation
explanation <- explain(iris_test, explainer, n_labels = 1, n_features = 2)
```

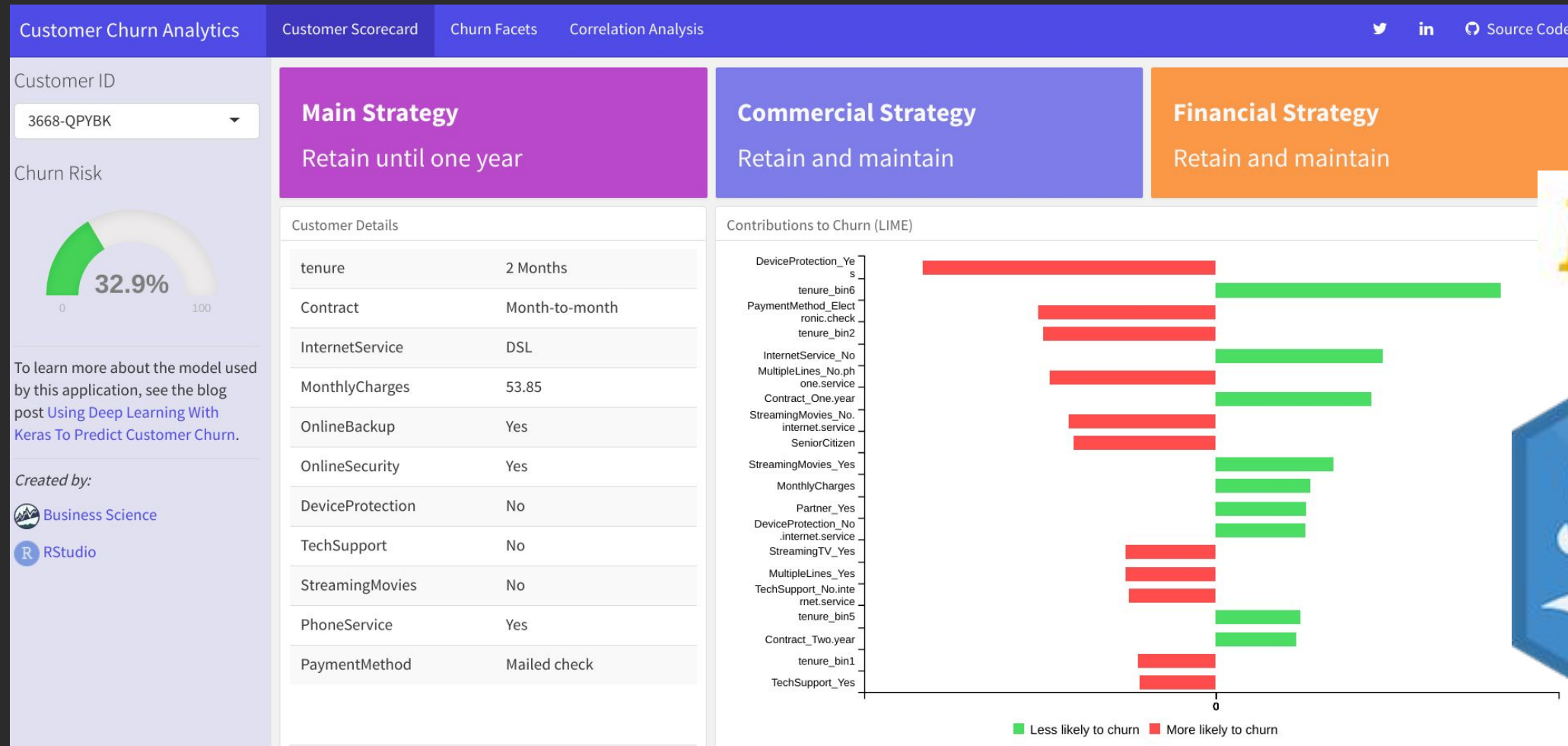
```
explanation <- .load_image_example()
plot_image_explanation(explanation)
```



```
plot_features(explanation)
```



# Put it in Action!



RPubs



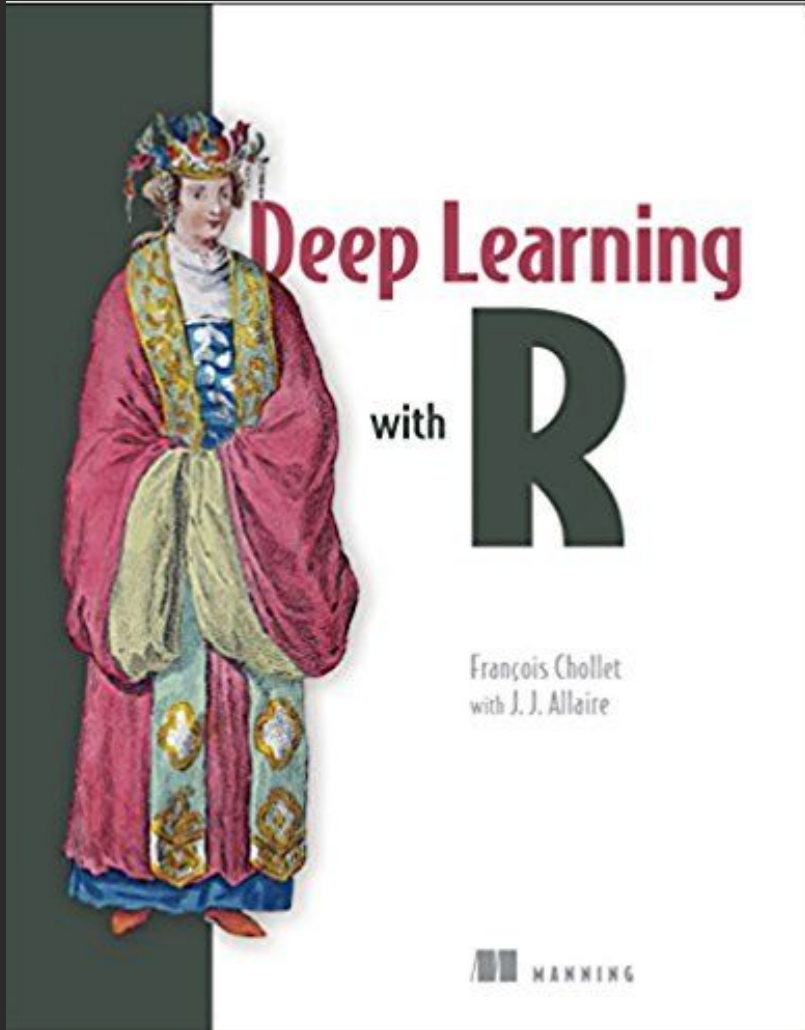
<https://blogs.rstudio.com/tensorflow/posts/2018-01-11-keras-customer-churn/>

See it live! <https://jjallaire.shinyapps.io/keras-customer-churn/>

Slides available at: <http://bit.ly/rtensorflow-oscon18>



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# Resources



- <https://tensorflow.rstudio.com/>
- <https://keras.rstudio.com/>

Slides available at: <http://bit.ly/rtensorflow-oscon18>

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VISIT IBM BOOTH #401 AT  
12:45-1:30 PM ON JULY 18 TO  
JOIN A WORKSHOP ABOUT THE  
CALL FOR CODE CHALLENGE.  
LEARN HOW YOU CAN USE IBM  
WATSON TO ANSWER THE CALL.

FIND OUT HOW AT

[developer.ibm.com/callforcode](https://developer.ibm.com/callforcode)



Call for Code Founding Partner

# Thank you!



[codait.org](https://codait.org)



[developer.ibm.com/code](https://developer.ibm.com/code)



[http://github.com/codait](https://github.com/codait)

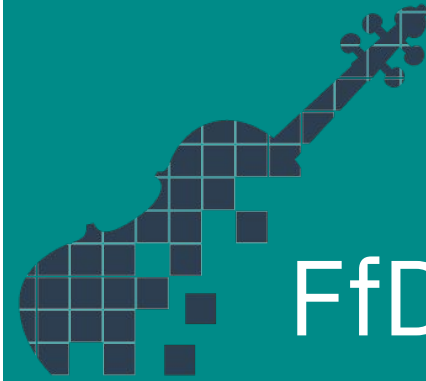


<https://rladies.org/>

[@RLadiesGlobal](https://twitter.com/RLadiesGlobal)



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FfDL

MAX



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