Part 2: iOS Deploy

Vision

Dashboard

Datasets

Models

← **Flowers**   📊 LABEL STATS   ⬆ EXPORT DATA

IMPORT   **IMAGES**   **TRAIN**   EVALUATE   TEST & USE

Select files to import

To build a custom model, you first need to import a set of images to train it. Each image should be categorized with a label. (Labels are essential for telling the model how to identify an image.)

- Each label should have at least 100 images for best results.

◉ Upload images from your computer
◯ Select a CSV file on Cloud Storage

Upload images from your computer

Supports JPG, PNG, GIF, BMP, ICO, ZIP. Maximum 500 files per upload. Uploaded files will be stored on Cloud Storage.

| flower_photos.zip | 1 file | ✕ |

SELECT FILES

Destination on Cloud Storage
☑ gs:// cloud-ai-platform-91507f72-3075-45fc-8750-ff5c73f5aa44/flow   **BROWSE**

CONTINUE

AI Platform (Unified)

← **test-dataset_20212160186**   ⊞ VIEW DATASET

EVALUATE   DEPLOY & TEST   BATCH PREDICTIONS   MODEL PROPERTIES

- ⊞⁞ Dashboard
- ⊡ Datasets
- 🏷 Labeling tasks
- 📄 Notebooks
- ☰ Training
- 💡 Models
- ◎ Endpoints
- 🔔 Batch predictions

☰ Filter labels

Confidence threshold ❓ ——●—— 0.5

All labels	0
dandelion	0.99975
sunflowers	0.99901
daisy	0.99721
tulips	0.99520
roses	0.99126

All labels

Average precision	0.996
Precision	97.3%
Recall	97%
Created	Feb 15, 2021, 4:44:52 PM
Total images	3,667
Training images	2,933
Validation images	367
Test images	367

Use the slider to see which score threshold works best for your model on the precision-recall tradeoff curve. Learn more about these metrics and graphs
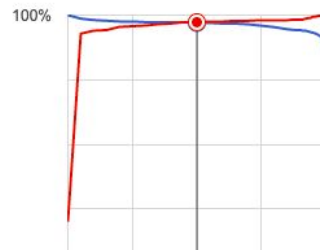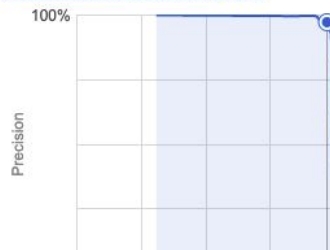
../mlkit-automl   ../mlkit-automl   +

```
mlkit-automl % pod install --verbose --no-repo-update
  Preparing

Analyzing dependencies

Inspecting targets to integrate
  Using `ARCHS` setting to build architectures of target `Pods-MLVisionExample`:
  (``)

Finding Podfile changes
  - FirebaseMLCommon
  - FirebaseMLVision
  - FirebaseMLVisionAutoML

Resolving dependencies of `Podfile`

Comparing resolved specification to the sandbox manifest
  A FirebaseCore
  A FirebaseInstanceID
  A FirebaseMLCommon
  A FirebaseMLVision
  A FirebaseMLVisionAutoML
  A GTMSessionFetcher
  A GoogleAPIClientForREST
  A GoogleMobileVision
  A GoogleToolboxForMac
  A GoogleUtilities
  A Protobuf
  A TensorFlowLite

Downloading dependencies

-> Installing FirebaseCore (6.0.0)
 > Git download
 > Git download
    $ /usr/local/bin/git clone https://github.com/firebase/firebase-ios-sdk.git
```

MLVisionExample › iPhone SE (2nd generation)

MLVisionExample › MLVisionExample › ViewController.swift › No Selection

MLVisionExample
  MLVisionExample
    AppDelegate.swift
    ViewController.swift
    MLKitExtensions.swift
    UIUtilities.swift
    CameraViewController.swift
    ImageClassifier.swift
    Supporting Files
    Info.plist
  Resources
  Products
  Pods
  Frameworks
Pods

```
1  //
2  // Copyright 2019 Google
3  //
4  // Licensed under the Apa
5  // you may not use this f
6  // You may obtain a copy
7  //
8  // https://www.apache.org
9  //
10 // Unless required by ap
11 // distributed under the
12 // WITHOUT WARRANTIES OR
13 // See the License for t
14 // limitations under the
15 //
16
17 import UIKit
18
19 class ViewController:  UIV
20
21     /// An image picker for accessi
22     private var imagePicker
23
24     /// Image counter.
25     private var currentImage
26
27     /// AutoML image classifier wra
28     private lazy var classif
29
30     // MARK: - IBOutlets
31
      @IBOutlet fileprivate we
      @IBOutlet fileprivate we
      @IBOutlet fileprivate we
      @IBOutlet fileprivate we
36
37     // MARK: - UIViewControl
38
39     override func viewDidLoa
```

Carrier 🤎 10:38 PM

Next image

Source: Local model
Latency: 342.0ms
Label: dandelion, Confidence: 0.8509804

Part 2: Time Series

- Is there a difference in ridership between the weekday and weekends?
- Is the mix of bus vs rail ridership changing over time?

```
[15]: # Initialize plotting

register_matplotlib_converters() # Addresses a warning
sns.set(rc={'figure.figsize':(16,4)})
```

```
[16]: # Explore total rides over time

sns.lineplot(data=df, x=df.index, y=df[target]).set_title('Total Rides')
fig = plt.show()
```
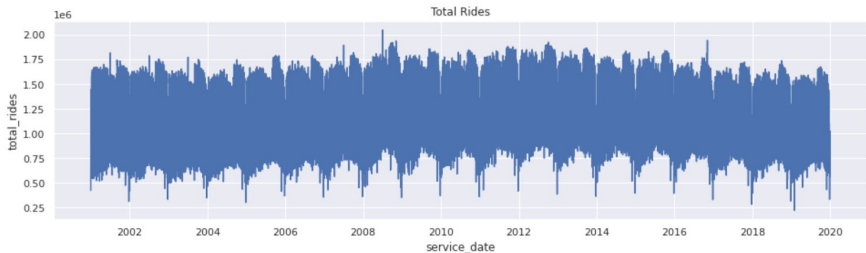


```
[17]: # Explore rides by day type: Weekday (W), Saturday (A), Sunday/Holiday (U)

sns.lineplot(data=df, x=df.index, y=df[target], hue=df['day_type']).set_title('Total Rides by Day Type')
fig = plt.show()
```



```
[18]: # Explore rides by transportation type
```

BigQuery

Q SQL workspace

⇄ Data transfers

🕐 Scheduled queries

⊞ Reservations

⚙ BI Engine

ⓘ FEATURES & INFO   ⌨ SHORTCUT   👁 HIDE PREVIEW FEATURES

Explorer   + ADD DATA

Q Type to search   ❓

Viewing pinned projects.

▼ ⁑ round-dreamer-304721
  ▶ ⊞ demo
    MORE RESULTS

Ⓠ EDITOR 2 ▾ ✕   ⁑ ROUND-... ▾ ✕   ⊞ DEMO ▾ ✕   ⊞ DEMO ▾ ✕

round-dreamer-304721:demo

⊕ CREATE TABLE   📇 SHARE DATASET   ☰ AUTHORIZE ROUTINES   📋 COPY DATASET   🗑 DELETE DATASET

Description ✏   Labels ✏
None   None

Dataset info ✏

Dataset ID	round-dreamer-304721:demo
Created	Feb 19, 2021, 8:16:49 PM
Default table expiration	5 days 0 hr
Last modified	Feb 19, 2021, 8:16:49 PM
Data location	US

JOB HISTORY   QUERY HISTORY   SAVED QUERIES   ⌄

Job history   ↻ REFRESH

Personal history   Project history

≡ Filter queries   ❓

Today

8:17 PM   ✓ Load uploaded file to round-dreamer-304721:demo.cta_ridership

+ COMPOSE NEW QUERY

BigQuery

ⓘ FEATURES & INFO   ⌨ SHORTCUT   ⊘ HIDE PREVIEW FEATURES

Explorer   + ADD DATA

EDITOR 2 ▼ ✕ | ⁘ ROUND-... ▼ ✕ | ▦ DEMO ▼ ✕ | ▦ DEMO ▼ ✕ | ▦ CTA_RID... ▼ ✕ | ⓠ *UNSAVE... 3 ▼ ✕ | ▦ CTA_RID... ▼ ✕ | CTA_RID... | ❯ | ⊞ COMPOSE NEW QUERY

🔍 Type to search   ❓

Viewing pinned projects.

▶ ⁘ round-dreamer-304721
  ▼ ▦ demo
      ▦ cta_ridership
      ▦ cta_ridership_model
    MORE RESULTS
  MORE RESULTS

▶ RUN   💾 SAVE ▼   ⏱ SCHEDULE   ⚙ MORE ▼

✅ This query will process 108.4 KiB (ML) when run.

```
1  CREATE OR REPLACE MODEL
2    `demo.cta_ridership_model` OPTIONS(MODEL_TYPE='ARIMA',
3      TIME_SERIES_TIMESTAMP_COL='service_date',
4      TIME_SERIES_DATA_COL='total_rides',
5      HOLIDAY_REGION='us') AS
6  SELECT
7    service_date, total_rides
8  FROM
9    `demo.cta_ridership`
```

Query results

Query complete (39.9 sec elapsed, 4.4 MB (ML) processed)

Job information   Results   Execution details

ⓘ This statement will create a new model named round-dreamer-304721:demo.cta_ridership_model. Depending on the type of model, this may take several hours to complete.   Go to model

BigQuery

- SQL workspace
- Data transfers
- Scheduled queries
- Reservations
- BI Engine

ⓘ FEATURES & INFO   ⌨ SHORTCUT   ◎ HIDE PREVIEW FEATURES

Explorer   + ADD DATA

🔍 Type to search

Viewing pinned projects.

- round-dreamer-304721
  - demo
    - cta_ridership
    - cta_ridership_model
    - **MORE RESULTS**
  - **MORE RESULTS**

Tabs: 2 ▼ ✕ | ⬡ ROUND-... ▼ ✕ | ▦ DEMO ▼ ✕ | ▦ DEMO ▼ ✕ | ▦ CTA_RID... ▼ ✕ | *UNSAVE... 3 ▼ ✕ | ▦ CTA_RID... ▼ ✕ | CTA_RID... ▼ ✕ | ▶ | ⊞ COMPOSE NEW QUERY

cta_ridership_model

🔍 QUERY MODEL   🗑 DELETE MODEL   ⬆ EXPORT MODEL

DETAILS   TRAINING   **EVALUATION**   SCHEMA

Non Seasonal P ❓	Non Seasonal D ❓	Non Seasonal Q ❓	Has Drift	Log Likelihood	AIC	Variance	Seasonal Period
1	1	4	True	-84,343.913	168,701.826	2,121,476,632.467	Weekly, Yearly
1	1	4	False	-84,345.763	168,703.526	2,122,628,259.179	Weekly, Yearly
4	1	1	True	-84,346.869	168,707.738	2,123,285,308.131	Weekly, Yearly
1	1	3	True	-84,347.973	168,707.946	2,123,959,900.714	Weekly, Yearly
4	1	1	False	-84,348.833	168,709.666	2,124,511,101.972	Weekly, Yearly
1	1	3	False	-84,349.844	168,709.688	2,125,133,805.121	Weekly, Yearly
3	1	2	True	-84,349.466	168,712.932	2,124,875,662.833	Weekly, Yearly
2	1	2	True	-84,351.446	168,714.892	2,126,093,471.221	Weekly, Yearly
2	1	2	False	-84,352.879	168,715.758	2,126,992,389.241	Weekly, Yearly
0	1	5	True	-84,351.067	168,716.134	2,125,867,126.489	Weekly, Yearly
0	1	5	False	-84,352.172	168,716.343	2,126,558,119.381	Weekly, Yearly
3	1	2	False	-84,352.526	168,717.053	2,126,777,555.452	Weekly, Yearly
2	1	3	True	-84,354.875	168,723.749	2,128,191,178.209	Weekly, Yearly
2	1	3	False	-84,357.564	168,727.128	2,129,867,036.91	Weekly, Yearly
3	1	1	True	-84,366.456	168,744.913	2,135,328,985.565	Weekly, Yearly
3	1	1	False	-84,367.982	168,745.963	2,136,287,297.784	Weekly, Yearly
2	1	1	False	-84,407.403	168,822.807	2,160,766,577.274	Weekly, Yearly
2	1	1	True	-84,406.65	168,823.3	2,160,286,811.78	Weekly, Yearly
0	1	4	False	-84,416.093	168,842.186	2,166,260,904.36	Weekly, Yearly
0	1	4	True	-84,415.732	168,843.463	2,166,031,399.586	Weekly, Yearly
0	1	3	False	-84,433.324	168,874.648	2,177,098,384.353	Weekly, Yearly
0	1	3	True	-84,433.107	168,876.215	2,176,960,425.757	Weekly, Yearly

BigQuery

SQL workspace

Data transfers

Scheduled queries

Reservations

BI Engine

ⓘ FEATURES & INFO   ▣ SHORTCUT   HIDE PREVIEW FEATURES

ROUND-...   DEMO   DEMO   CTA_RID...   *UNSAVE... 3   CTA_RID...   CTA_RID...   COMPOSE NEW QUERY

▶ RUN   💾 SAVE ▾   ⏱ SCHEDULE   ⚙ MORE ▾

✓ This query will process 0 B when run.

```
1  SELECT
2    *
3  FROM
4    ML.EVALUATE(MODEL `demo.cta_ridership_model`)
```

Explorer   + ADD DATA

🔍 Type to search

Viewing pinned projects.

▾ round-dreamer-304721
  ▾ demo
    cta_ridership
    cta_ridership_model
    MORE RESULTS
  MORE RESULTS

Query results   📤 SAVE RESULTS   📊 EXPLORE DATA ▾

Query complete (0.2 sec elapsed, 0 B processed)

Job information   Results   JSON   Execution details

Row	non_seasonal_p	non_seasonal_d	non_seasonal_q	has_drift	log_likelihood	AIC	variance	seasonal_periods
1	1	1	4	true	-84343.91298029698	168701.82596059397	2.1214766324672794E9	WEEKLY
								YEARLY
2	1	1	4	false	-84345.76278035615	168703.5255607123	2.1226282591786644E9	WEEKLY
								YEARLY
3	4	1	1	true	-84346.86918283005	168707.7383656601	2.1232853081307085E9	WEEKLY
								YEARLY
4	1	1	3	true	-84347.97278479983	168707.94556959966	2.1239599007139666E9	WEEKLY
								YEARLY
5	4	1	1	false	-84348.83291975319	168709.66583950637	2.124511101972134E9	WEEKLY
								YEARLY
6	1	1	3	false	-84349.84391557962	168709.68783115924	2.1251338051213825E9	WEEKLY

Rows per page: 100 ▾   1 - 42 of 42   First page |< < > >| Last page

"anon04fe69279440cfb354852927cb6abdacf03ee851" created. Go to table ✕

BigQuery

SQL workspace

Data transfers

Scheduled queries

Reservations

BI Engine

Explorer   + ADD DATA

FEATURES & INFO   SHORTCUT   HIDE PREVIEW FEATURES

Type to search

Viewing pinned projects.

round-dreamer-304721
  demo
    cta_ridership
    cta_ridership_model
  MORE RESULTS
MORE RESULTS

2   ROUND-...   DEMO   DEMO   CTA_RID...   *UNSAVE... 3   CTA_RID...   CTA_RID...   + COMPOSE NEW QUERY

RUN   SAVE   SCHEDULE   MORE

This query will process 23.4 KiB when run.

```
1  SELECT
2    *
3  FROM
4    ML.FORECAST(MODEL `demo.cta_ridership_model`,
5      STRUCT(7 AS horizon))
```

Query results   SAVE RESULTS   EXPLORE DATA

Query complete (0.2 sec elapsed, 23.4 KB processed)

Job information   Results   JSON   Execution details

Row	forecast_timestamp	forecast_value	standard_error	confidence_level	prediction_interval_lower_bound	prediction_interval_upper_bound	confidence_interval_lower_bound	confidence_interval_upper_bound
1	2020-01-01 00:00:00 UTC	662436.4424369269	46059.49014554253	0.95	572322.980240453	752549.9046334007	572322.980240453	752549.9046334007
2	2020-01-02 00:00:00 UTC	1029641.4669424891	46276.328347693256	0.95	939103.76989082	1120179.1639941582	939103.76989082	1120179.1639941582
3	2020-01-03 00:00:00 UTC	1201660.2034356925	47233.43871922012	0.95	1109249.9600529654	1294070.4468184195	1109249.9600529654	1294070.4468184195
4	2020-01-04 00:00:00 UTC	651095.9776391207	48157.99332862347	0.95	556876.8819095747	745315.0733686666	556876.8819095747	745315.0733686666
5	2020-01-05 00:00:00 UTC	467394.91846646497	48621.50963880497	0.95	372268.97250121285	562520.8644317171	372268.97250121285	562520.8644317171
6	2020-01-06 00:00:00 UTC	1158999.319539823	48869.23710364581	0.95	1063388.705171438	1254609.9339082083	1063388.705171438	1254609.9339082083
7	2020-01-07 00:00:00 UTC	1127789.5651062205	49011.66149084522	0.95	1031900.3033930386	1223678.8268194026	1031900.3033930386	1223678.8268194026

In this section, you will build models using popular neural network architectures for time-series data.

Long Short Term Memory (LSTM)

```
[45]:  # Reshape test data to match model inputs and outputs

       X_train = X_train_reframed.values.reshape(-1, n_input_steps, n_features)
       X_test = X_test_reframed.values.reshape(-1, n_input_steps, n_features)
       y_train = y_train_reframed.values.reshape(-1, n_output_steps, 1)
       y_test = y_test_reframed.values.reshape(-1, n_output_steps, 1)
```

TODO 2: Update the LSTM architecture

Try increasing and decreasing the number of LSTM units and see if you notice any accuracy improvements.

You can use hyper-parameter tuning to search for optimal values, but that's outside the scope of this lab.

```
[46]:  # Try increasing and decreasing the number of LSTM units and see if you notice any accuracy improvements.
       # Run the next cell to evaluate the results in more detail.

       model = Sequential([
           LSTM(64, input_shape=[n_input_steps, n_features]),
           Dense(n_output_steps)])

       model.compile(optimizer='adam', loss='mae')

       early_stopping = EarlyStopping(monitor='val_loss', patience=patience)
       _ = model.fit(x=X_train, y=y_train, validation_data=(X_test, y_test), epochs=epochs, callbacks=[early_stopping])
```

```
Train on 5515 samples, validate on 1352 samples
Epoch 1/1000
5515/5515 [==============================] - 10s 2ms/sample - loss: 0.6554 - val_loss: 0.4750
Epoch 2/1000
5515/5515 [==============================] - 6s 1ms/sample - loss: 0.3387 - val_loss: 0.2568
Epoch 3/1000
5515/5515 [==============================] - 7s 1ms/sample - loss: 0.2406 - val_loss: 0.2406
Epoch 4/1000
5515/5515 [==============================] - 7s 1ms/sample - loss: 0.2260 - val_loss: 0.2383
Epoch 5/1000
5515/5515 [==============================] - 7s 1ms/sample - loss: 0.2207 - val_loss: 0.2263
Epoch 6/1000
5515/5515 [==============================] - 6s 1ms/sample - loss: 0.2156 - val_loss: 0.2218
Epoch 7/1000
5515/5515 [==============================] - 6s 1ms/sample - loss: 0.2106 - val_loss: 0.2208
Epoch 8/1000
5515/5515 [==============================] - 8s 1ms/sample - loss: 0.2071 - val_loss: 0.2352
Epoch 9/1000
5515/5515 [==============================] - 7s 1ms/sample - loss: 0.2052 - val_loss: 0.2142
Epoch 10/1000
5515/5515 [==============================] - 7s 1ms/sample - loss: 0.2025 - val_loss: 0.2181
Epoch 11/1000
5515/5515 [==============================] - 7s 1ms/sample - loss: 0.2016 - val_loss: 0.2163
```

/ ··· / ai-for-time-series / notebooks /

Name	Last Modified
📁 cnn_export	2 minutes ago
📁 data	19 minutes ago
📁 lstm_export	3 minutes ago
📄 01-explore.ipynb	4 minutes ago
📄 02-model.ipynb	seconds ago
📄 03-cloud-training.ipynb	6 minutes ago
📊 cta_ridership.csv	17 minutes ago

Untitled.ipynb   Terminal 1   01-explore.ipynb   02-model.ipynb   03-cloud-training.ipynb

Markdown   git

```
[47]: model.save('./lstm_export/')
```

```
WARNING:tensorflow:From /opt/conda/lib/python3.7/site-packages/tensorflow_core/python/ops/resource_variable_ops.py:1786: calling Ba
constraint is deprecated and will be removed in a future version.
Instructions for updating:
If using Keras pass *_constraint arguments to layers.
INFO:tensorflow:Assets written to: ./lstm_export/assets
```
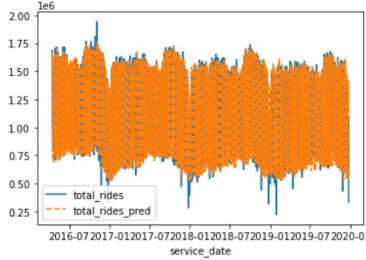
```
[48]: # Predict the results, and then reverse the transformation that scaled all values to a mean of 0 and std. dev. of 1
preds = model.predict(X_test)
y_pred_lstm = inverse_scale(preds)

# Evaluate the overall results and for each time step
evaluate(y_pred_lstm)

# The plot will show the R^2 value (0 lowest -> 1 highest) and the MAE (mean absolute error) for the entire prediction window.
# It will also show individual plots for 1 day out, 2 days out, etc. comparing the actual vs the predicted value.
```
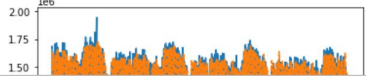
```
=== t+(1-7) ===
R^2:  0.812
MAPE: 0.092
MAE:  81117.131

=== t+1 ===
R^2:  0.858
MAPE: 0.079
MAE:  69010.06
```



```
=== t+2 ===
R^2:  0.827
MAPE: 0.089
MAE:  78629.465
```