

# CMPE-258 Deep Learning

## Assignment – 2

By,

Sheema Murugesh Babu  
(SJSU ID: 015217176)

# Part 2: AutoML Models

# TIME SERIES

 AI Platform

## Notebooks

 NEW INSTANCE REFRESH START STOP RESET UPGRADE DELETE

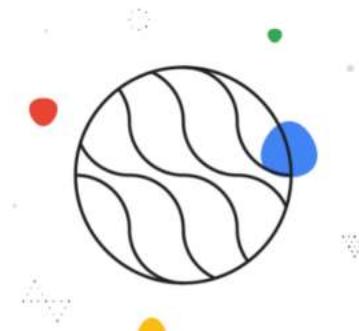
HIDE INFO PANEL

 Dashboard

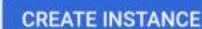
Create and use Jupyter Notebooks with a notebook instance. Notebook instances have JupyterLab pre-installed and are configured with GPU-enabled machine learning frameworks. [Learn more](#)

 AI Hub Data Labeling Notebooks Pipelines Jobs Models Filter Enter property name or value

 Instance name		Zone	Environment	Machine type	GPUs
---	---	------	-------------	--------------	------



You don't have any notebook instances in this project yet

 CREATE INSTANCE

## Info panel

DOCUMENTATION

LABELS

[Notebook instances](#)[Notebook API](#)

Google Cloud Platform time-series ▾

Search products and resources

AI Platform Notebooks NEW INSTANCE REFRESH START STOP RESET UPGRADE DELETE SHOW INFO PANEL

Dashboard Create and use Jupyter Notebooks with a notebook instance. Notebook instances have JupyterLab pre-installed and are configured with GPU-enabled machine learning frameworks. [Learn more](#)

AI Hub

Data Labeling

Filter Enter property name or value

Notebooks

	Instance name	Zone	Environment	Machine type	GPUs	Permission	Labels
<input type="checkbox"/>	tensorflow-2-3-20210305-005633	us-west1-b	TensorFlow:2.3	4 vCPUs, 15 GB RAM	None	Service account	goog-caip-notebook

Pipelines

Jobs

Models

<



File Edit View Run Kernel Git Tabs Settings Help AI Platform Notebooks



Launcher

Name ▾ Last Modified

- src 3 minutes ago
- tutorials 3 minutes ago

Notebook



Python 3



Python [conda  
env:root] \*

Console



Python 3



Python [conda  
env:root] \*

\$\_ Other



Terminal



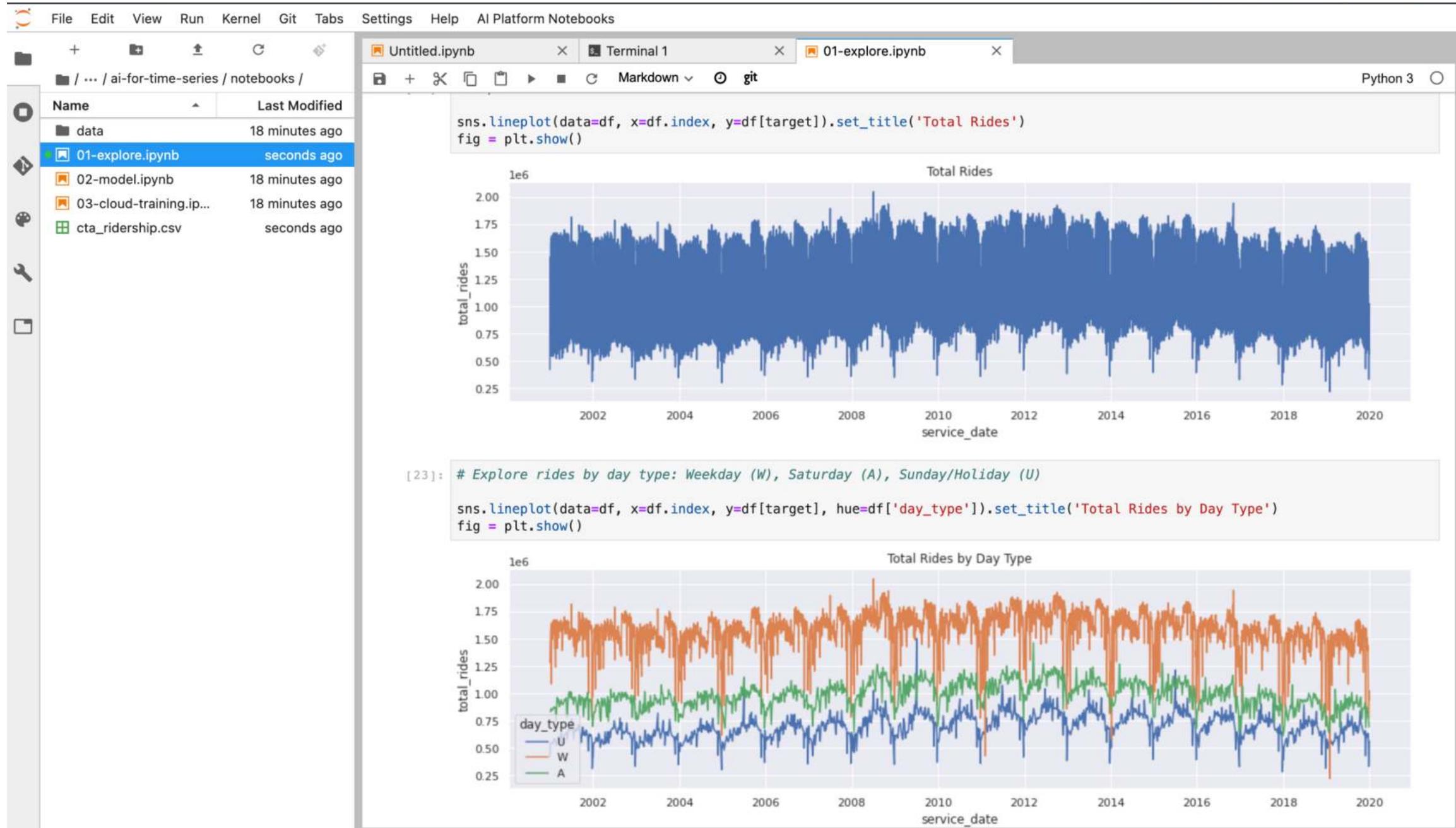
Text File



Markdown File



Show  
Contextual Help





File Edit View Run Kernel Git Tabs Settings Help AI Platform Notebooks

Untitled.ipynb Terminal 1 01-explore.ipynb

Name Last Modified

- data 18 minutes ago
- 01-explore.ipynb a minute ago
- 02-model.ipynb 18 minutes ago
- 03-cloud-training.ip... 18 minutes ago
- cta\_ridership.csv a minute ago

Python 3

### TODO 3: Explore seasonality

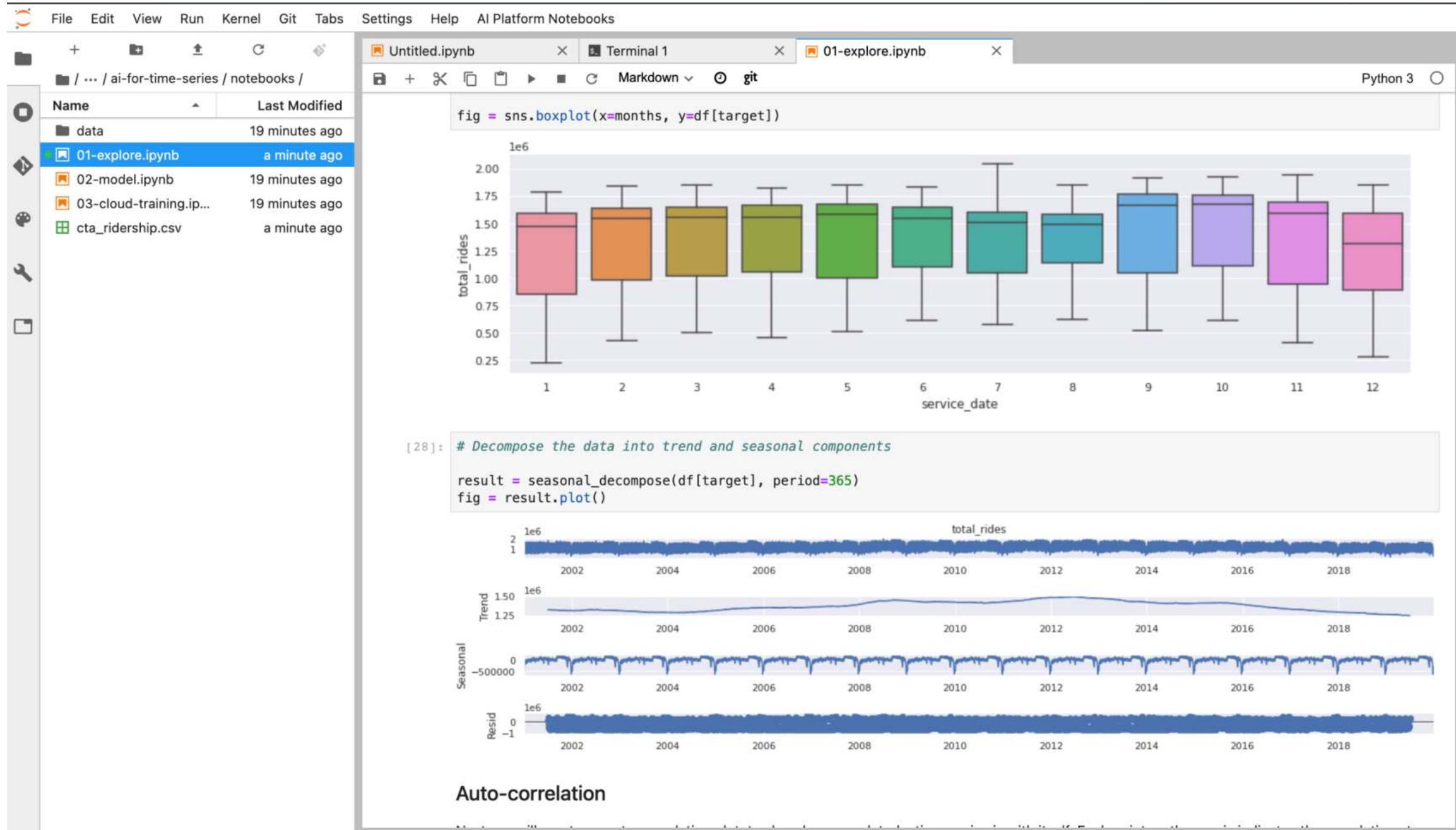
- Is there much difference between months?
- Can you extract the trend and seasonal pattern from the data?

```
[26]: # Show the distribution of values for each day of the week in a boxplot:  
# Min, 25th percentile, median, 75th percentile, max  
  
daysofweek = df.index.to_series().dt.dayofweek  
  
fig = sns.boxplot(x=daysofweek, y=df[target])
```

A boxplot titled 'total rides' on the y-axis (ranging from 0.25 to 2.00) and 'service\_date' on the x-axis (labeled 0, 1, 2, 3, 4, 5, 6). The plot shows seven distinct groups of boxplots, one for each day of the week. The colors of the boxes are blue, orange, green, red, purple, brown, and pink respectively. Each boxplot displays the median (horizontal line inside the box), the interquartile range (the box itself), and the full range of the data (the whiskers). Outliers are represented by individual black dots.

```
[27]: # Show the distribution of values for each month in a boxplot:  
  
months = df.index.to_series().dt.month  
  
fig = sns.boxplot(x=months, y=df[target])
```

A boxplot titled 'total rides' on the y-axis (ranging from 1.50 to 2.00) and 'months' on the x-axis (labeled 1 through 12). The plot shows twelve distinct groups of boxplots, one for each month. The colors of the boxes are pink, orange, yellow, light green, medium green, teal, light blue, medium blue, purple, magenta, light pink, and pink respectively. Each boxplot displays the median (horizontal line inside the box), the interquartile range (the box itself), and the full range of the data (the whiskers). Outliers are represented by individual black dots.



File Edit View Run Kernel Git Tabs Settings Help AI Platform Notebooks

Untitled.ipynb Terminal 1 01-explore.ipynb Python 3

Name Last Modified

- data 19 minutes ago
- 01-explore.ipynb a minute ago
- 02-model.ipynb 19 minutes ago
- 03-cloud-training.ip... 19 minutes ago
- cta\_ridership.csv a minute ago

**Auto-correlation**

Next, we will create an auto-correlation plot, to show how correlated a time-series is with itself. Each point on the x-axis indicates the correlation at a given lag. The shaded area indicates the confidence interval.

Note that the correlation gradually decreases over time, but reflects weekly seasonality (e.g. t-7 and t-14 stand out).

```
[29]: plot_acf(df[target])
fig = plt.show()
```

Autocorrelation

Lag	Correlation (approx.)
0	1.00
1	0.40
2	-0.10
3	-0.15
4	-0.15
5	-0.15
6	0.35
7	0.85
8	0.35
9	-0.10
10	-0.15
11	-0.15
12	-0.10
13	0.35
14	0.85
15	0.35
16	-0.15
17	-0.15
18	-0.15
19	-0.15
20	0.35
21	0.85
22	0.35
23	-0.15
24	-0.15
25	-0.15
26	-0.15
27	0.35
28	0.85
29	0.35
30	-0.15
31	-0.15
32	-0.15
33	-0.15
34	0.35
35	0.85
36	0.35
37	-0.15
38	-0.15
39	-0.15
40	0.00

**Export data**

This will generate a CSV file, which you will use in the next labs of this quest. Inspect the CSV file to see what the data looks like.

```
[30]: df[[target]].to_csv(processed_file, index=True, index_label=ts_col)
```

**Conclusion**

You've successfully completed the exploration and visualization lab. You've learned how to:

Google Cloud Platform time-series ▾

Search products and resources

BigQuery

FEATURES & INFO SHORTCUT HIDE PREVIEW FEATURES

SQL workspace

Explorer + ADD DATA

\*UNSAVED TIME-SE... DEMO COMPOSE NEW QUERY

Type to search

Viewing pinned projects.

time-series-306705

demo

cta\_ridership

MORE RESULTS

Release Notes

JOB HISTORY QUERY HISTORY SAVED QUERIES

```
1 CREATE OR REPLACE MODEL
2   `demo.cta_ridership` 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`
```

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

Google Cloud Platform time-series

Search products and resources

BigQuery

FEATURES & INFO SHORTCUT HIDE PREVIEW FEATURES

SQL workspace

Explorer + ADD DATA

\*UNSAVE... TIME-SE... DEMO COMPOSE NEW QUERY

Type to search

Viewing pinned projects.

time-series-306705

demo

cta\_ridership

cta\_ridership\_model

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 (36.8 sec elapsed, 4.4 MB (ML) processed)

Job information Results Execution details

This statement will create a new model named time-series-306705:demo.cta\_ridership\_model. Depending on the type of model, this may take several hours to complete.

Go to model

Release Notes

JOB HISTORY QUERY HISTORY SAVED QUERIES

Google Cloud Platform time-series ▾

Search products and resources

BigQuery FEATURES & INFO SHORTCUT HIDE PREVIEW FEATURES

SQL workspace Explorer + ADD DATA DEMO CTA\_RID... CTA\_RID... COMPOSE NEW QUERY

Type to search

Viewing pinned projects.

time-series-306705 demo cta\_ridership cta\_ridership\_model

MORE RESULTS

ctaridership\_model

QUERY MODEL DELETE MODEL EXPORT MODEL

DETAILS TRAINING EVALUATION SCHEMA

Model type ARIMA Data location US

### Model Details EDIT

Model ID	time-series-306705:demo.cta_ridership_model
Description	
Labels	
Date created	Friday, March 5, 2021 at 1:32:32 AM GMT-05:00
Model expiration	Never
Date modified	Friday, March 5, 2021 at 1:32:33 AM GMT-05:00
Data location	US
Model type	ARIMA

### Training Options

Training options are the optional parameters that were added in the script to create this model.

Actual iterations	1
Auto Arima	true
Data Frequency	Auto Frequency
Holiday Region	US

JOB HISTORY QUERY HISTORY SAVED QUERIES

Google Cloud Platform time-series ▾

Search products and resources

BigQuery

FEATURES & INFO SHORTCUT HIDE PREVIEW FEATURES

SQL workspace

Explorer + ADD DATA DEMO CTA\_RID... CTA\_RID... COMPOSE NEW QUERY

Type to search

Data transfers

Scheduled queries

Reservations

BI Engine

Viewing pinned projects.

time-series-306705

demo

cta\_ridership

cta\_ridership\_model

MORE RESULTS

ctaridership\_model

QUERY MODEL DELETE MODEL EXPORT MODEL

DETAILS TRAINING EVALUATION SCHEMA

View as

Graphs (selected)

Table

Loss

Duration (seconds)

Iteration

Iteration

JOB HISTORY QUERY HISTORY SAVED QUERIES

Release Notes

Google Cloud Platform time-series ▾

Search products and resources

BigQuery

FEATURES & INFO SHORTCUT HIDE PREVIEW FEATURES

SQL workspace

Explorer + ADD DATA DEMO CTA\_RID... CTA\_RID... COMPOSE NEW QUERY

Data transfers

Scheduled queries

Type to search ?

Reservations

Viewing pinned projects.

BI Engine

time-series-306705

demo

cta\_ridership

cta\_ridership\_model

MORE RESULTS

ctaridership\_model

QUERY MODEL DELETE MODEL

EVALUATION DETAILS TRAINING SCHEMA

Non Seasonal P	Non Seasonal D	Non Seasonal Q	Has Drift	Log Likelihood	AIC	Variance
1	1	4	True	-84,343.913	168,701.826	2,121,476,632.467
1	1	4	False	-84,345.763	168,703.526	2,122,628,259.179
4	1	1	True	-84,346.869	168,707.738	2,123,285,308.131
1	1	3	True	-84,347.973	168,707.946	2,123,959,900.714
4	1	1	False	-84,348.833	168,709.666	2,124,511,101.972
1	1	3	False	-84,349.844	168,709.688	2,125,133,805.121
3	1	2	True	-84,349.466	168,712.932	2,124,875,662.833
2	1	2	True	-84,351.446	168,714.892	2,126,093,471.221
2	1	2	False	-84,352.879	168,715.758	2,126,992,389.241
0	1	5	True	-84,351.067	168,716.134	2,125,867,126.489
0	1	5	False	-84,352.172	168,716.343	2,126,558,119.381
3	1	2	False	-84,352.526	168,717.053	2,126,777,555.452
2	1	3	True	-84,354.875	168,723.749	2,128,191,178.209
2	1	3	False	-84,357.564	168,727.128	2,129,867,036.91
3	1	1	True	-84,366.456	168,744.913	2,135,328,985.565
3	1	1	False	-84,367.982	168,745.963	2,136,287,297.784
2	1	1	False	-84,407.403	168,822.807	2,160,766,577.274

JOB HISTORY QUERY HISTORY SAVED QUERIES

Google Cloud Platform time-series ▾

Search products and resources

BigQuery

FEATURES & INFO SHORTCUT HIDE PREVIEW FEATURES

SQL workspace Explorer DEMO CTA\_RID... CTA\_RID... \*UNSAVE... 2 COMPOSE NEW QUERY

RUN SAVE SCHEDULE MORE

This query will process 0 B when run.

SELECT \* FROM ML.EVALUATE(MODEL `demo.cta\_ridership\_model`)

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
2	1	1	4	false	-84345.76278035615	168703.5255607123	2.1226282591786644E9	WEEKLY
3	4	1	1	true	-84346.86918283005	168707.7383656601	2.1232853081307085E9	WEEKLY
4	1	1	3	true	-84347.97278479983	168707.94556959966	2.1239599007139666E9	WEEKLY
5	4	1	1	false	-84348.83291975319	168709.66583950637	2.12451101972134E9	WEEKLY
6	1	1	2	false	-84349.94201557062	168710.60702115024	2.1251229051212925E9	WEEKLY

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

JOB HISTORY QUERY HISTORY SAVED QUERIES

Google Cloud Platform time-series Search products and resources

BigQuery

SQL workspace

DATA TRANSFERS

SCHEDULED QUERIES

RESERVATIONS

BI ENGINE

FEATURES & INFO

SHORTCUT

HIDE PREVIEW FEATURES

Explorer

E... DEMO CTA\_RID... CTA\_RID... \*UNSAVE... 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 (0.3 sec elapsed, 23.4 KB processed)

Job information Results JSON Execution details

MORE

Row	forecast_timestamp	forecast_value	standard_error	confidence_level	prediction_interval_lower_bound	prediction_interval_upper_bound	confidence_interval
1	2020-01-01 00:00:00 UTC	662436.4424369269	46059.49014554253	0.95	572322.980240453	752549.9046334007	57232
2	2020-01-02 00:00:00 UTC	1029641.4669424891	46276.328347693256	0.95	939103.76989082	1120179.1639941582	9391
3	2020-01-03 00:00:00 UTC	1201660.2034356925	47233.43871922012	0.95	1109249.9600529654	1294070.4468184195	1109249
4	2020-01-04 00:00:00 UTC	651095.9776391207	48157.99332862347	0.95	556876.8819095747	745315.0733686666	556876
5	2020-01-05 00:00:00 UTC	467394.91846646497	48621.50963880497	0.95	372268.97250121285	562520.8644317171	372268!
6	2020-01-06 00:00:00 UTC	1158999.319539823	48869.23710364581	0.95	1063388.705171438	1254609.9339082083	106338
7	2020-01-07 00:00:00 UTC	1127789.5651062205	49011.66149084522	0.95	1031900.3033930386	1223678.8268194026	1031900

"anon8c0606767bcf17cd9caaee914b109173eb24b5425" created. Go to table

JOB HISTORY QUERY HISTORY SAVED QUERIES

File Edit View Run Kernel Git Tabs Settings Help AI Platform Notebooks

Untitled.ipynb Terminal 1 01-explore.ipynb 02-model.ipynb Python 3

Name Last Modified

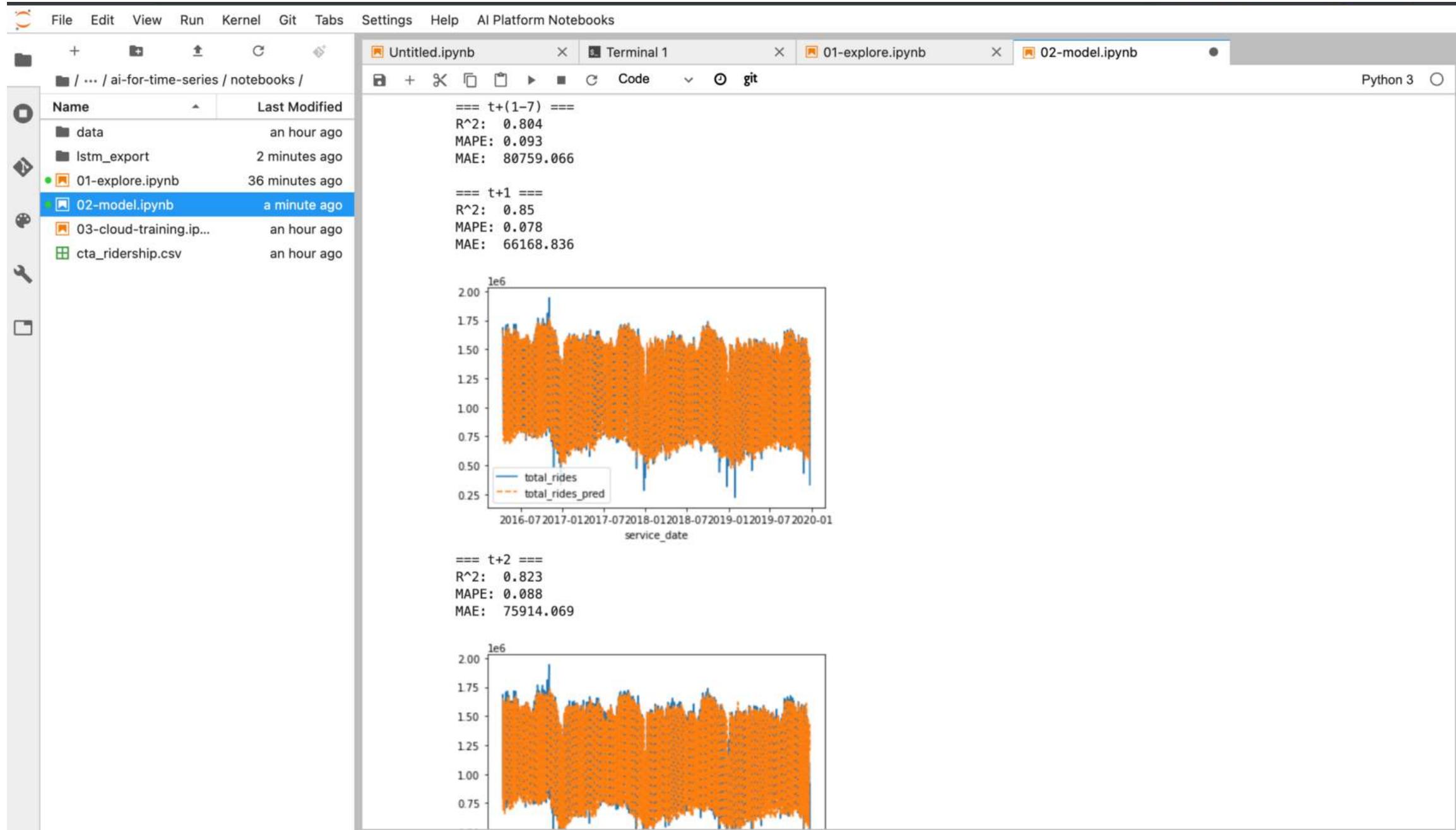
- data an hour ago
- lstm\_export a minute ago
- 01-explore.ipynb 36 minutes ago
- 02-model.ipynb a minute ago
- 03-cloud-training.ip... an hour ago
- cta\_ridership.csv an hour ago

**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.

```
[72]: # 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])  
  
Epoch 1/1000  
173/173 [=====] - 6s 36ms/step - loss: 0.6863 - val_loss: 0.5092  
Epoch 2/1000  
173/173 [=====] - 4s 24ms/step - loss: 0.3529 - val_loss: 0.2498  
Epoch 3/1000  
173/173 [=====] - 4s 22ms/step - loss: 0.2403 - val_loss: 0.2319  
Epoch 4/1000  
173/173 [=====] - 5s 29ms/step - loss: 0.2293 - val_loss: 0.2329  
Epoch 5/1000  
173/173 [=====] - 4s 22ms/step - loss: 0.2236 - val_loss: 0.2405  
Epoch 6/1000  
173/173 [=====] - 4s 22ms/step - loss: 0.2195 - val_loss: 0.2453  
Epoch 7/1000  
173/173 [=====] - 5s 29ms/step - loss: 0.2134 - val_loss: 0.2244  
Epoch 8/1000  
173/173 [=====] - 6s 32ms/step - loss: 0.2106 - val_loss: 0.2241  
Epoch 9/1000  
173/173 [=====] - 6s 37ms/step - loss: 0.2064 - val_loss: 0.2254  
Epoch 10/1000  
173/173 [=====] - 4s 25ms/step - loss: 0.2054 - val_loss: 0.2296  
Epoch 11/1000  
173/173 [=====] - 4s 22ms/step - loss: 0.2035 - val_loss: 0.2128  
Epoch 12/1000  
173/173 [=====] - 4s 22ms/step - loss: 0.2015 - val_loss: 0.2098  
Epoch 13/1000
```



File Edit View Run Kernel Git Tabs Settings Help AI Platform Notebooks

Untitled.ipynb Terminal 1 01-explore.ipynb 02-model.ipynb Python 3

Name Last Modified

- data an hour ago
- lstm\_export 4 minutes ago
- 01-explore.ipynb 39 minutes ago
- 02-model.ipynb seconds ago
- 03-cloud-training.ip... an hour ago
- cta\_ridership.csv an hour ago

**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.

```
[75]: # 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(70, 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])  
  
Epoch 1/1000  
173/173 [=====] - 7s 42ms/step - loss: 0.6462 - val_loss: 0.4083  
Epoch 2/1000  
173/173 [=====] - 6s 36ms/step - loss: 0.3126 - val_loss: 0.2532  
Epoch 3/1000  
173/173 [=====] - 6s 34ms/step - loss: 0.2368 - val_loss: 0.2513  
Epoch 4/1000  
173/173 [=====] - 5s 32ms/step - loss: 0.2259 - val_loss: 0.2263  
Epoch 5/1000  
173/173 [=====] - 4s 23ms/step - loss: 0.2225 - val_loss: 0.2241  
Epoch 6/1000  
173/173 [=====] - 6s 34ms/step - loss: 0.2178 - val_loss: 0.2266  
Epoch 7/1000  
173/173 [=====] - 5s 31ms/step - loss: 0.2127 - val_loss: 0.2221  
Epoch 8/1000  
173/173 [=====] - 6s 33ms/step - loss: 0.2095 - val_loss: 0.2213  
Epoch 9/1000  
173/173 [=====] - 6s 33ms/step - loss: 0.2064 - val_loss: 0.2111  
Epoch 10/1000  
173/173 [=====] - 5s 30ms/step - loss: 0.2039 - val_loss: 0.2088  
Epoch 11/1000  
173/173 [=====] - 5s 27ms/step - loss: 0.2027 - val_loss: 0.2143  
Epoch 12/1000  
173/173 [=====] - 6s 34ms/step - loss: 0.2001 - val_loss: 0.2106
```

File Edit View Run Kernel Git Tabs Settings Help AI Platform Notebooks

Untitled.ipynb Terminal 1 01-explore.ipynb 02-model.ipynb Python 3

Name Last Modified

- data an hour ago
- lstm\_export seconds ago
- 01-explore.ipynb 40 minutes ago
- 02-model.ipynb seconds ago
- 03-cloud-training.ip... an hour ago
- cta\_ridership.csv an hour ago

```
[INFO]: tensorflow:Assets written to: ./lstm_export/assets
```

```
[77]: # 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: 0.805
MAPE: 0.094
MAE: 81756.44

== t+1 ==
R^2: 0.856
MAPE: 0.081
MAE: 68995.976
```

```
[Figure]: A line plot titled 'total_rides' and 'total_rides_pred'. The x-axis is labeled 'service_date' and spans from July 2016 to January 2020. The y-axis ranges from 0.25 to 2.00, with a multiplier of 1e6. The blue line represents the actual total rides, and the orange dashed line represents the predicted total rides. The plot shows a clear seasonal pattern with peaks and troughs.
```

```
[78]: == t+2 ==
R^2: 0.815
MAPE: 0.091
MAE: 78130.804
```

File Edit View Run Kernel Git Tabs Settings Help AI Platform Notebooks

Untitled.ipynb Terminal 1 01-explore.ipynb 02-model.ipynb Python 3

Name Last Modified

- data an hour ago
- lstm\_export 2 minutes ago
- 01-explore.ipynb 42 minutes ago
- 02-model.ipynb a minute ago
- 03-cloud-training.ip... an hour ago
- cta\_ridership.csv an hour ago

## Convolutional Neural Network (CNN)

### TODO 3: Update the CNN architecture

Try adjusting the # of filters (pattern types) and kernel size (size of the sliding window)

```
[78]: from tensorflow.keras.layers import AveragePooling1D

# TODO: Try adjusting the # of filters (pattern types) and kernel size (size of the sliding window)
model = Sequential([
    Conv1D(filters=32, kernel_size=3, input_shape=[n_input_steps, n_features]),
    Flatten(),
    Dense(n_output_steps)])

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

early_stopping = EarlyStopping(monitor='val_loss', patience=5)
_ = model.fit(x=X_train, y=y_train, validation_data=(X_test, y_test), epochs=epochs, callbacks=[early_stopping])
```

Epoch 1/1000  
173/173 [=====] - 1s 4ms/step - loss: 0.2974 - val\_loss: 0.2548  
Epoch 2/1000  
173/173 [=====] - 0s 2ms/step - loss: 0.2503 - val\_loss: 0.2505  
Epoch 3/1000  
173/173 [=====] - 0s 2ms/step - loss: 0.2478 - val\_loss: 0.2512  
Epoch 4/1000  
173/173 [=====] - 0s 2ms/step - loss: 0.2466 - val\_loss: 0.2481  
Epoch 5/1000  
173/173 [=====] - 0s 2ms/step - loss: 0.2457 - val\_loss: 0.2484  
Epoch 6/1000  
173/173 [=====] - 0s 2ms/step - loss: 0.2451 - val\_loss: 0.2475  
Epoch 7/1000  
173/173 [=====] - 0s 2ms/step - loss: 0.2454 - val\_loss: 0.2467  
Epoch 8/1000  
173/173 [=====] - 0s 2ms/step - loss: 0.2442 - val\_loss: 0.2467  
Epoch 9/1000  
173/173 [=====] - 0s 3ms/step - loss: 0.2442 - val\_loss: 0.2468  
Epoch 10/1000  
173/173 [=====] - 1s 3ms/step - loss: 0.2441 - val\_loss: 0.2447  
Epoch 11/1000  
173/173 [=====] - 1s 3ms/step - loss: 0.2438 - val\_loss: 0.2469  
Epoch 12/1000

File Edit View Run Kernel Git Tabs Settings Help AI Platform Notebooks

Untitled.ipynb Terminal 1 01-explore.ipynb 02-model.ipynb Python 3

Name Last Modified

- cnn\_export seconds ago
- data an hour ago
- lstm\_export 3 minutes ago
- 01-explore.ipynb 43 minutes ago
- 02-model.ipynb a minute ago
- 03-cloud-training.ip... an hour ago
- cta\_ridership.csv an hour ago

```
[80]: preds = model.predict(X_test)
y_pred_cnn = inverse_scale(preds)

evaluate(y_pred_cnn)

==== t+1 ====
R^2: 0.765
MAPE: 0.106
MAE: 97795.296

==== t+1 ====
R^2: 0.802
MAPE: 0.095
MAE: 89388.89
```

```
==== t+2 ====
R^2: 0.766
MAPE: 0.105
MAE: 97860.081
```

File Edit View Run Kernel Git Tabs Settings Help AI Platform Notebooks

Untitled.ipynb Terminal 1 01-explore.ipynb 02-model.ipynb Python 3

Name Last Modified

- cnn\_export 2 minutes ago
- data an hour ago
- Lstm\_export 4 minutes ago
- 01-explore.ipynb 44 minutes ago
- 02-model.ipynb seconds ago
- 03-cloud-training.ip... an hour ago
- cta\_ridership.csv an hour ago

## Convolutional Neural Network (CNN)

### TODO 3: Update the CNN architecture

Try adjusting the # of filters (pattern types) and kernel size (size of the sliding window)

```
[81]: from tensorflow.keras.layers import AveragePooling1D

# TODO: Try adjusting the # of filters (pattern types) and kernel size (size of the sliding window)
model = Sequential([
    Conv1D(filters=40, kernel_size=4, input_shape=[n_input_steps, n_features]),
    Flatten(),
    Dense(n_output_steps)])

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

early_stopping = EarlyStopping(monitor='val_loss', patience=5)
_ = model.fit(x=X_train, y=y_train, validation_data=(X_test, y_test), epochs=epochs, callbacks=[early_stopping])
```

Epoch 1/1000  
173/173 [=====] - 1s 5ms/step - loss: 0.2934 - val\_loss: 0.2558  
Epoch 2/1000  
173/173 [=====] - 0s 2ms/step - loss: 0.2505 - val\_loss: 0.2483  
Epoch 3/1000  
173/173 [=====] - 0s 2ms/step - loss: 0.2482 - val\_loss: 0.2475  
Epoch 4/1000  
173/173 [=====] - 0s 2ms/step - loss: 0.2468 - val\_loss: 0.2500  
Epoch 5/1000  
173/173 [=====] - 0s 2ms/step - loss: 0.2461 - val\_loss: 0.2469  
Epoch 6/1000  
173/173 [=====] - 0s 2ms/step - loss: 0.2461 - val\_loss: 0.2451  
Epoch 7/1000  
173/173 [=====] - 0s 2ms/step - loss: 0.2455 - val\_loss: 0.2475  
Epoch 8/1000  
173/173 [=====] - 0s 2ms/step - loss: 0.2446 - val\_loss: 0.2484  
Epoch 9/1000  
173/173 [=====] - 0s 3ms/step - loss: 0.2450 - val\_loss: 0.2473  
Epoch 10/1000  
173/173 [=====] - 1s 3ms/step - loss: 0.2442 - val\_loss: 0.2476  
Epoch 11/1000  
173/173 [=====] - 1s 4ms/step - loss: 0.2450 - val\_loss: 0.2487

File Edit View Run Kernel Git Tabs Settings Help AI Platform Notebooks

Untitled.ipynb Terminal 1 01-explore.ipynb 02-model.ipynb Python 3

Name Last Modified

- cnn\_export seconds ago
- data an hour ago
- lstm\_export 5 minutes ago
- 01-explore.ipynb 44 minutes ago
- 02-model.ipynb a minute ago
- 03-cloud-training.ip... an hour ago
- cta\_ridership.csv an hour ago

```
[83]: preds = model.predict(X_test)
y_pred_cnn = inverse_scale(preds)

evaluate(y_pred_cnn)

== t+(1-7) ==
R^2: 0.763
MAPE: 0.105
MAE: 97976.89

== t+1 ==
R^2: 0.805
MAPE: 0.094
MAE: 89624.479
```

A line plot comparing actual total rides (blue line) with predicted total rides (orange line) over time. The x-axis represents the service date from July 2016 to January 2020. The y-axis represents the number of rides in millions, ranging from 0.25 to 2.00. The plot shows a highly seasonal pattern with significant weekly fluctuations. The predicted values closely follow the actual values, indicating a good fit.

```
== t+2 ==
R^2: 0.76
MAPE: 0.104
MAE: 97324.473
```

A second line plot comparing actual total rides (blue line) with predicted total rides (orange line) over time. The x-axis represents the service date from July 2016 to January 2020. The y-axis represents the number of rides in millions, ranging from 0.25 to 2.00. The plot shows a highly seasonal pattern with significant weekly fluctuations. The predicted values closely follow the actual values, indicating a good fit.

File Edit View Run Kernel Git Tabs Settings Help AI Platform Notebooks

Untitled.ipynb Terminal 1 01-explore.ipynb 02-model.ipynb Python 3

Name Last Modified

- cnn\_export 3 minutes ago
- data an hour ago
- lstm\_export 8 minutes ago
- 01-explore.ipynb an hour ago
- 02-model.ipynb seconds ago
- 03-cloud-training.ip... an hour ago
- cta\_ridership.csv an hour ago

## Naïve Models

So-called "naïve models" can be surprisingly hard to beat. These can serve as a useful benchmark for your model's performance.

### Random Walk

Assume that future value(s) will be the same as the most recent value.

```
[84]: from statsmodels.tsa.arima.model import ARIMA  
  
hist = df_train[target_col].copy() # Predict based on historical data. Start with the training data  
hist.index.freq = pd.infer_freq(hist.index) # To avoid warnings, explicitly specify the dataframe frequency  
n_pred = len(df_test) + 1 # Number of predictions: 1 on the training set; and then 1 for each additional  
y_pred_rw = np.empty([n_pred,n_output_steps]) # Create an array to hold predictions, with a number of predictions equal to t  
  
for t in range(n_pred):  
    mod = ARIMA(hist, order=(0, 1, 0))  
    res = mod.fit()  
    pred = res.forecast(n_output_steps)  
    y_pred_rw[t] = pred.values  
    if t < n_pred - 1:  
        hist.loc[df_test.iloc[t].name] = df_test[target_col][t] # Append the latest test data row to the history, for fitting  
        hist.index.freq = pd.infer_freq(hist.index)
```

```
[85]: evaluate(y_pred_rw, 0)  
==== t+(1-7) ====  
R^2: -0.834  
MAPE: 0.366  
MAE: 364578.376  
  
==== t+1 ====  
R^2: -0.19  
MAPE: 0.257  
MAE: 269441.826
```



File Edit View Run Kernel Git Tabs Settings Help AI Platform Notebooks

Untitled.ipynb Terminal 1 01-explore.ipynb 02-model.ipynb Python 3

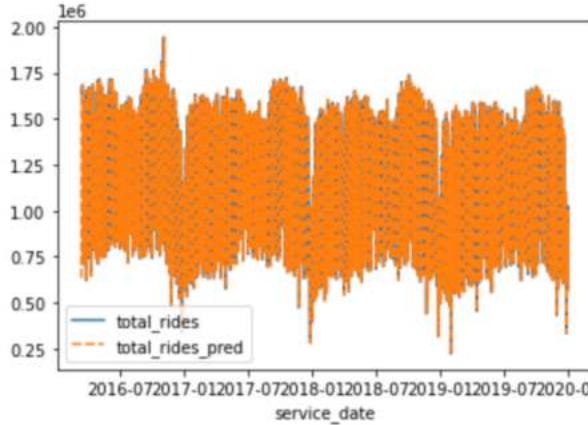
Name Last Modified

- cnn\_export 3 minutes ago
- data an hour ago
- lstm\_export 8 minutes ago
- 01-explore.ipynb an hour ago
- 02-model.ipynb seconds ago
- 03-cloud-training.ip... an hour ago
- cta\_ridership.csv an hour ago

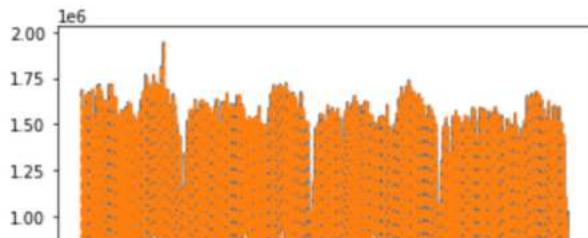
[ 85 ]: evaluate(y\_pred\_rw, 0)

```
==== t+(1-7) ====
R^2: -0.834
MAPE: 0.366
MAE: 364578.376

==== t+1 ====
R^2: -0.19
MAPE: 0.257
MAE: 269441.826
```



==== t+2 ====
R^2: -1.383
MAPE: 0.452
MAE: 451553.613



File Edit View Run Kernel Git Tabs Settings Help AI Platform Notebooks

Untitled.ipynb Terminal 1 01-explore.ipynb 02-model.ipynb

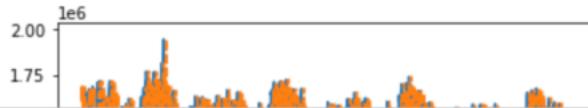
Name Last Modified

- cnn\_export 10 minutes ago
- data 2 hours ago
- lstm\_export 15 minutes ago
- 01-explore.ipynb an hour ago
- 02-model.ipynb 5 minutes ago
- 03-cloud-training.ip... 2 hours ago
- cta\_ridership.csv an hour ago

## Seasonal Naïve

Similar to random walk, but instead of using the previous value, you'll use the value from the previous seasonal period. For example, if you're predicting July's forecast, you'll use last July's value, rather than June's value.

```
[87]: # You will use a walk-forward approach, in which a model is fit on all historical data available.  
# As you progress through the test set to evaluate the model, you will be creating new models for each row in the test set.  
# Each new model will be fit on not only the training data, but on prior test data.  
  
from statsmodels.tsa.statespace.sarimax import SARIMAX  
  
hist = df_train[target_col].copy() # Predict based on historical data. Start with the training data  
hist.index.freq = pd.infer_freq(hist.index) # To avoid warnings, explicitly specify the dataframe frequency  
n_pred = len(df_test) + 1 # Number of predictions: 1 on the training set; and then 1 for each additional  
y_pred_sn = np.empty([n_pred,n_output_steps]) # Create an array to hold predictions, with a number of predictions equal to t  
  
for t in range(n_pred):  
    mod = SARIMAX(hist, order=(0, 0, 0), seasonal_order=(0, 1, 0, n_seasons))  
    res = mod.fit()  
    pred = res.forecast(n_output_steps)  
    y_pred_sn[t] = pred.values  
    if t < n_pred - 1:  
        hist.loc[df_test.iloc[t].name] = df_test[target_col][t] # Append the latest test data row to the history, for fitting  
        hist.index.freq = pd.infer_freq(hist.index)  
  
[88]: evaluate(y_pred_sn, 0)  
==== t+(1-7) ====  
R^2: 0.675  
MAPE: 0.11  
MAE: 108722.34  
  
==== t+1 ====  
R^2: 0.676  
MAPE: 0.11  
MAE: 108556.529
```



File Edit View Run Kernel Git Tabs Settings Help AI Platform Notebooks

Untitled.ipynb Terminal 1 01-explore.ipynb 02-model.ipynb Python 3

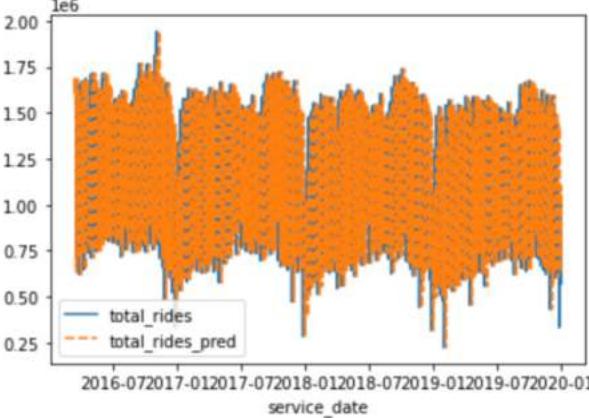
Name Last Modified

- cnn\_export 10 minutes ago
- data 2 hours ago
- lstm\_export 15 minutes ago
- 01-explore.ipynb an hour ago
- 02-model.ipynb 5 minutes ago
- 03-cloud-training.ip... 2 hours ago
- cta\_ridership.csv an hour ago

[ 88 ]: evaluate(y\_pred\_sn, 0)

```
== t+(1-7) ===  
R^2: 0.675  
MAPE: 0.11  
MAE: 108722.34
```

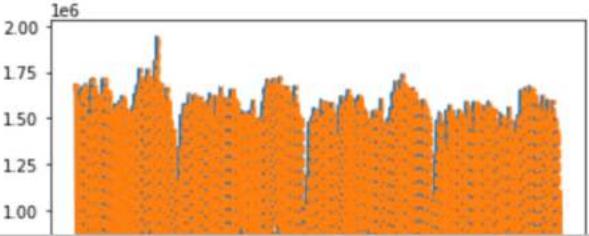
```
== t+1 ===  
R^2: 0.676  
MAPE: 0.11  
MAE: 108556.529
```



total\_rides  
total\_rides\_pred

service\_date

```
== t+2 ===  
R^2: 0.675  
MAPE: 0.11  
MAE: 108611.732
```



File Edit View Run Kernel Git Tabs Settings Help AI Platform Notebooks

Untitled.ipynb Terminal 1 01-explore.ipynb 02-model.ipynb Python 3

Name Last Modified

- cnn\_export 11 minutes ago
- data 2 hours ago
- lstm\_export 16 minutes ago
- 01-explore.ipynb an hour ago
- 02-model.ipynb 6 minutes ago
- 03-cloud-training.ip... 2 hours ago
- cta\_ridership.csv an hour ago

## Statistical Models

You will next implement a popular statistical method for time-series analysis, *exponential smoothing*. Exponential smoothing estimates future data by weighting recent observations more heavily. The [Holt-Winters exponential smoothing](#) method used here uses a "triple" exponential smoothing approach that also considers trend and seasonality.

You can also ensemble classical and machine learning methods for a potentially even more accurate result.

## Exponential Smoothing

```
[89]: import warnings

with warnings.catch_warnings():
    warnings.simplefilter("ignore", category=ConvergenceWarning)
```

-----

```
NameError: Traceback (most recent call last)
<ipython-input-89-8daf53ffe6e4> in <module>
      2
      3 with warnings.catch_warnings():
----> 4     warnings.simplefilter("ignore", category=ConvergenceWarning)

NameError: name 'ConvergenceWarning' is not defined
```

```
[ *]: # You will use a walk-forward approach, in which a model is fit on all historical data available.
# As you progress through the test set to evaluate the model, you will be creating new models for each row in the test set.
# Each new model will be fit on not only the training data, but on prior test data.

hist = df_train[target_col].copy() # Predict based on historical data. Start with the training data
hist.index.freq = pd.infer_freq(hist.index) # To avoid warnings, explicitly specify the dataframe frequency
n_pred = len(df_test) + 1 # Number of predictions: 1 on the training set; and then 1 for each additional
y_pred_es = np.empty([n_pred,n_output_steps]) # Create an array to hold predictions, with a number of predictions equal to t

for t in range(n_pred):
    mod = ExponentialSmoothing(hist, seasonal_periods=n_seasons, trend='add', seasonal='add', damped_trend=True, use_boxcox=True)
    res = mod.fit(method='L-BFGS-B') # Use a different minimizer to avoid convergence warnings
    pred = res.forecast(n_output_steps)
    y_pred_es[t] = pred.values
    if t < n_pred - 1:
```

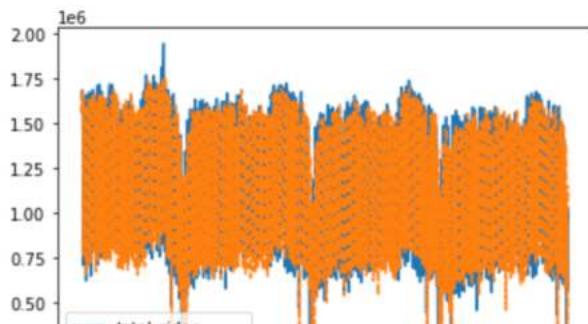
File Edit View Run Kernel Git Tabs Settings Help AI Platform Notebooks

Untitled.ipynb Terminal 1 01-explore.ipynb 02-model.ipynb Python 3

Name Last Modified

- cnn\_export 39 minutes ago
- data 2 hours ago
- lstm\_export 43 minutes ago
- 01-explore.ipynb an hour ago
- 02-model.ipynb 19 minutes ago
- 03-cloud-training.ip... 2 hours ago
- cta\_ridership.csv 2 hours ago

```
[90]: # You will use a walk-forward approach, in which a model is fit on all historical data available.  
# As you progress through the test set to evaluate the model, you will be creating new models for each row in the test set.  
# Each new model will be fit on not only the training data, but on prior test data.  
  
hist = df_train[target_col].copy() # Predict based on historical data. Start with the training data  
hist.index.freq = pd.infer_freq(hist.index) # To avoid warnings, explicitly specify the dataframe frequency  
n_pred = len(df_test) + 1 # Number of predictions: 1 on the training set; and then 1 for each additional  
y_pred_es = np.empty([n_pred,n_output_steps]) # Create an array to hold predictions, with a number of predictions equal to t  
  
for t in range(n_pred):  
    mod = ExponentialSmoothing(hist, seasonal_periods=n_seasons, trend='add', seasonal='add', damped_trend=True, use_boxcox=False)  
    res = mod.fit(method='L-BFGS-B') # Use a different minimizer to avoid convergence warnings  
    pred = res.forecast(n_output_steps)  
    y_pred_es[t] = pred.values  
    if t < n_pred - 1:  
        hist.loc[df_test.iloc[t].name] = df_test[target_col][t] # Append the latest test data row to the history, for fitting  
        hist.index.freq = pd.infer_freq(hist.index)  
  
[91]: evaluate(y_pred_es, 0)  
==== t+(1-7) ====  
R^2: 0.787  
MAPE: 0.107  
MAE: 99395.043  
  
==== t+1 ====  
R^2: 0.834  
MAPE: 0.095  
MAE: 86633.491
```



File Edit View Run Kernel Git Tabs Settings Help AI Platform Notebooks

Untitled.ipynb Terminal 1 01-explore.ipynb 02-model.ipynb Python 3

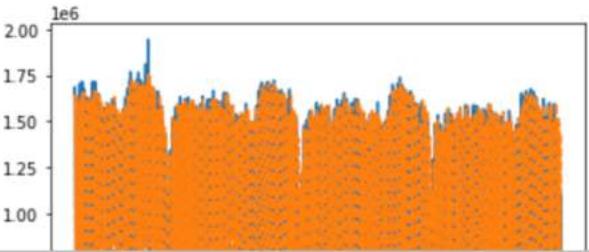
Name Last Modified

- cnn\_export 39 minutes ago
- data 2 hours ago
- lstm\_export 44 minutes ago
- 01-explore.ipynb an hour ago
- 02-model.ipynb 20 minutes ago
- 03-cloud-training.ip... 2 hours ago
- cta\_ridership.csv 2 hours ago

## Ensemble ML and Statistical Models

If the performance of the ML and statistical models are similar, ensembling them can be helpful, because their approaches are quite different.

```
[92]: # Start by adjusting the sizes of the prediction arrays to match.  
# Some methods predict the initial timesteps of the test set.  
# Others start after the first sequence length.  
# So, you will remove the test data that doesn't exist in both sets.  
  
def trunc(df, test_set=df_test, n_input_steps = n_input_steps, n_output_steps = n_output_steps):  
    return df[n_input_steps: -n_output_steps]  
  
y_pred_es_trunc = trunc(y_pred_es)  
y_true_trunc = trunc(df_test)  
  
[93]: models = [y_pred_lstm, y_pred_cnn, y_pred_es_trunc]  
weights = [2, 1, 1]  
  
y_pred_ensemble = np.average( np.array(models), axis=0, weights=weights)  
  
evaluate(y_pred_ensemble, 0, y_true_trunc)  
==== t+(1-7) ====  
R^2: 0.815  
MAPE: 0.089  
MAE: 80804.535  
  
==== t+1 ====  
R^2: 0.858  
MAPE: 0.078  
MAE: 70066.568
```



File Edit View Run Kernel Git Tabs Settings Help AI Platform Notebooks

Untitled.ipynb Terminal 1 01-explore.ipynb 02-model.ipynb Python 3

Name Last Modified

- cnn\_export 39 minutes ago
- data 2 hours ago
- lstm\_export 44 minutes ago
- 01-explore.ipynb an hour ago
- 02-model.ipynb 20 minutes ago
- 03-cloud-training.ip... 2 hours ago
- cta\_ridership.csv 2 hours ago

== t+(1-7) ==  
R^2: 0.815  
MAPE: 0.089  
MAE: 80804.535

== t+1 ==  
R^2: 0.858  
MAPE: 0.078  
MAE: 70066.568

A line plot comparing actual total rides (blue line) with predicted total rides (orange dashed line). The y-axis is labeled '1e6' and ranges from 0.25 to 2.00. The x-axis is labeled 'service\_date' and shows dates from July 2016 to January 2020. The plot displays a highly seasonal pattern with significant weekly fluctuations. The blue line represents the actual data, and the orange dashed line represents the model's prediction.

== t+2 ==  
R^2: 0.824  
MAPE: 0.087  
MAE: 77289.138

A second line plot comparing actual total rides (blue line) with predicted total rides (orange dashed line). The axes and data series are identical to the first plot, showing the same seasonal pattern and model performance metrics.

File Edit View Run Kernel Git Tabs Settings Help AI Platform Notebooks

Untitled.ipynb X Terminal 1 X 01-explore.ipynb X 02-model.ipynb X 03-cloud-training.ipynb Python 3

Name Last Modified

- cnn\_export 42 minutes ago
- data 2 hours ago
- lstm\_export an hour ago
- 01-explore.ipynb an hour ago
- 02-model.ipynb 3 minutes ago
- 03-cloud-training.ip... 2 hours ago
- cta\_ridership.csv 2 hours ago

```
[1]: # Copyright 2020 Google LLC
#
# Licensed under the Apache License, Version 2.0 (the "License");
# you may not use this file except in compliance with the License.
# You may obtain a copy of the License at
#
#     https://www.apache.org/licenses/LICENSE-2.0
#
# Unless required by applicable law or agreed to in writing, software
# distributed under the License is distributed on an "AS IS" BASIS,
# WITHOUT WARRANTIES OR CONDITIONS OF ANY KIND, either express or implied.
# See the License for the specific language governing permissions and
# limitations under the License.
```

## Overview

In this notebook, you'll learn how to submit a job to AI Platform Training. In the job you'll train your TensorFlow 2 model and export the saved model to Cloud Storage.

## Dataset

CTA - Ridership - Daily Boarding Totals: This dataset shows systemwide boardings for both bus and rail services provided by Chicago Transit Authority, dating back to 2001.

## Objective

The goal is to forecast future transit ridership in the City of Chicago, based on previous ridership.

## Install packages and dependencies

### Import libraries and define constants

```
[2]: import datetime
import googleapiclient.discovery
import os
import time
```

File Edit View Run Kernel Git Tabs Settings Help AI Platform Notebooks

Untitled.ipynb Terminal 1 01-explore.ipynb 02-model.ipynb 03-cloud-training.ipynb Python 3

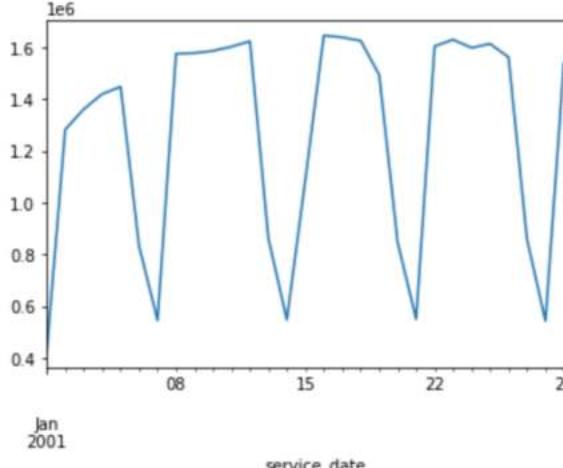
Name Last Modified

- cnn\_export 43 minutes ago
- data 2 hours ago
- lstm\_export an hour ago
- 01-explore.ipynb an hour ago
- 02-model.ipynb 3 minutes ago
- 03-cloud-training.ip... seconds ago
- cta\_ridership.csv 2 hours ago

## Load and preview the data

Pre-processing on the original dataset has been done for you and made available on Cloud Storage.

```
[9]: processed_file = 'cta_ridership.csv' # Which file to save the results to  
  
if os.path.exists(processed_file):  
    input_file = processed_file # File created in previous lab  
else:  
    input_file = f'data/{processed_file}'  
  
[10]: df = pd.read_csv(input_file, index_col=ts_col, parse_dates=True)  
  
# Plot 30 days of ridership  
_ = df[target_col][:30].plot()
```



```
[ ]: # Define some characteristics of the data that will be used later  
n_features = len(df.columns)  
  
# Index of target column. Used later when creating dataframes.  
target_col_num = df.columns.get_loc(target_col)
```

File Edit View Run Kernel Git Tabs Settings Help AI Platform Notebooks

Untitled.ipynb Terminal 1 01-explore.ipynb 02-model.ipynb 03-cloud-training.ipynb Python 3

Name Last Modified

- cnn\_export 43 minutes ago
- data 2 hours ago
- lstm\_export an hour ago
- 01-explore.ipynb an hour ago
- 02-model.ipynb 4 minutes ago
- 03-cloud-training.ip... seconds ago
- cta\_ridership.csv 2 hours ago

## Process data

```
[12]: # Split data  
size = int(len(df) * train_split)  
df_train, df_test = df[0:size].copy(deep=True), df[size:len(df)].copy(deep=True)  
  
df_train.head()
```

```
[12]: total_rides  
service_date  
2001-01-01 423647  
2001-01-02 1282779  
2001-01-03 1361355  
2001-01-04 1420032  
2001-01-05 1448343
```

```
[13]: _ = df_train.plot()
```

1e6

2.00  
1.75  
1.50  
1.25  
1.00  
0.75  
0.50  
0.25

2002 2004 2006 2008 2010 2012 2014 2016

service\_date

total\_rides

Scale values

File Edit View Run Kernel Git Tabs Settings Help AI Platform Notebooks

Untitled.ipynb Terminal 1 01-explore.ipynb 02-model.ipynb

/ ... / ai-for-time-series / notebooks /

Name Last Modified

- cnn\_export an hour ago
- data an hour ago
- Istm\_export an hour ago
- 01-explore.ipynb an hour ago
- 02-model.ipynb seconds ago
- 03-cloud-training.ipynb an hour ago

## Statistical Models

You will next implement a popular statistical method for time-series analysis, *exponential smoothing*. Exponential smoothing estimates future data by weighting recent observations more heavily. The [Holt-Winters exponential smoothing](#) method used here uses a "triple" exponential smoothing approach that also considers trend and seasonality.

You can also ensemble classical and machine learning methods for a potentially even more accurate result.

## Exponential Smoothing

```
[32]: import warnings
from sklearn.exceptions import ConvergenceWarning

with warnings.catch_warnings():
    warnings.simplefilter("ignore", category=ConvergenceWarning)

[33]: # You will use a walk-forward approach, in which a model is fit on all historical data available.
# As you progress through the test set to evaluate the model, you will be creating new models for each row in the test set.
# Each new model will be fit on not only the training data, but on prior test data.

hist = df_train[target_col].copy() # Predict based on historical data. Start with the training data
hist.index.freq = pd.infer_freq(hist.index) # To avoid warnings, explicitly specify the dataframe frequency
n_pred = len(df_test) + 1 # Number of predictions: 1 on the training set; and then 1 for each additional
y_pred_es = np.empty([n_pred,n_output_steps]) # Create an array to hold predictions, with a number of predictions equal to the test set size, each containing the # of tim

for t in range(n_pred):
    mod = ExponentialSmoothing(hist, seasonal_periods=n_seasons, trend='add', seasonal='add', damped_trend=True, use_boxcox=False, initialization_method='heuristic')
    res = mod.fit(method='L-BFGS-B') # Use a different minimizer to avoid convergence warnings
    pred = res.forecast(n_output_steps)
    y_pred_es[t] = pred.values
    if t < n_pred - 1:
        hist.loc[df_test.iloc[t].name] = df_test[target_col][t] # Append the latest test data row to the history, for fitting the next model
        hist.index.freq = pd.infer_freq(hist.index)

[34]: evaluate(y_pred_es, 0)

    == t+(1-7) ==
R^2: 0.787
MAPE: 0.107
MAE: 99395.043

    == t+1 ==
R^2: 0.834
MAPE: 0.095
MAE: 86633.491
```

1 \$ 3 @ tensorflow-2-1-20210305-143944 | time-series-306705 Git: refreshing... Python 3 | Idle Mode: Command ⚙ Ln 1, Col 1 02-model.ipynb



AI Platform

Jobs

+ NEW TRAINING JOB

REFRESH

CANCEL

SHOW INFO PANEL

Filter Filter by prefix...

?

 Job ID

Type

HyperTune

HyperTune parameters

Target metric

Create time

Elapsed time

Logs

Labels

 caip\_training\_1614978905

Custom code training

No

Mar 5, 2021, 4:15:11 PM

10 min

View Logs



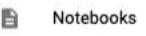
Dashboard



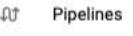
AI Hub



Data Labeling



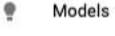
Notebooks



Pipelines



Jobs



Models

AI Platform

 Job Details

[DEPLOY MODEL](#)      [DOWNLOAD MOD](#)

caip\_training\_1614978905

 Succeeded (10 min)

Creation time Mar 5, 2021, 4:15:11 PM

**Start time** Mar 5, 2021, 4:24:10 PM

**End time** Mar 5, 2021, 4:25:11 PM

**Logs**

**TensorBoard** TensorBoard is available from this page only for models trained with built-in TensorFlow algorithm.

**Consumed ML units** 0.0

**Training input**

SHOW ISQ

**Model location:** [/tmp/nccode\\_206705\\_2000](#)

CPL

GPI

## NETWORK

[COLLAPSE ALL](#)

[EXPAND ALL](#)

### Master CPU utilization

### Percent



### Master memory utilization

### Percent



iOS APP

× Create a project (Step 1 of 3)

Let's start with a name for  
your project®

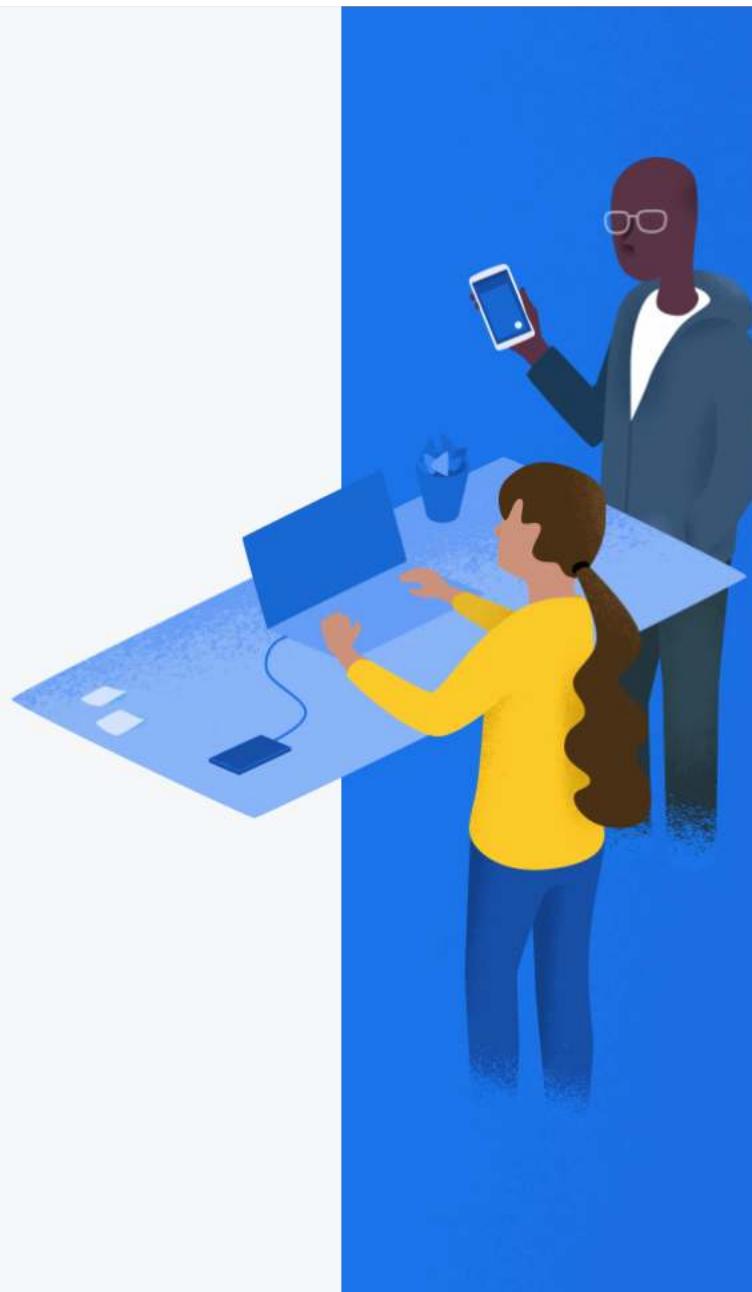
Project name

ML Kit Codelab

 ml-kit-codelab-sheema-2902

 sjsu.edu

Continue



 Create a project (Step 2 of 3)

## Google Analytics for your Firebase project

Google Analytics is a free and unlimited analytics solution that enables targeting, reporting, and more in Firebase Crashlytics, Cloud Messaging, In-App Messaging, Remote Config, A/B Testing, Predictions, and Cloud Functions.

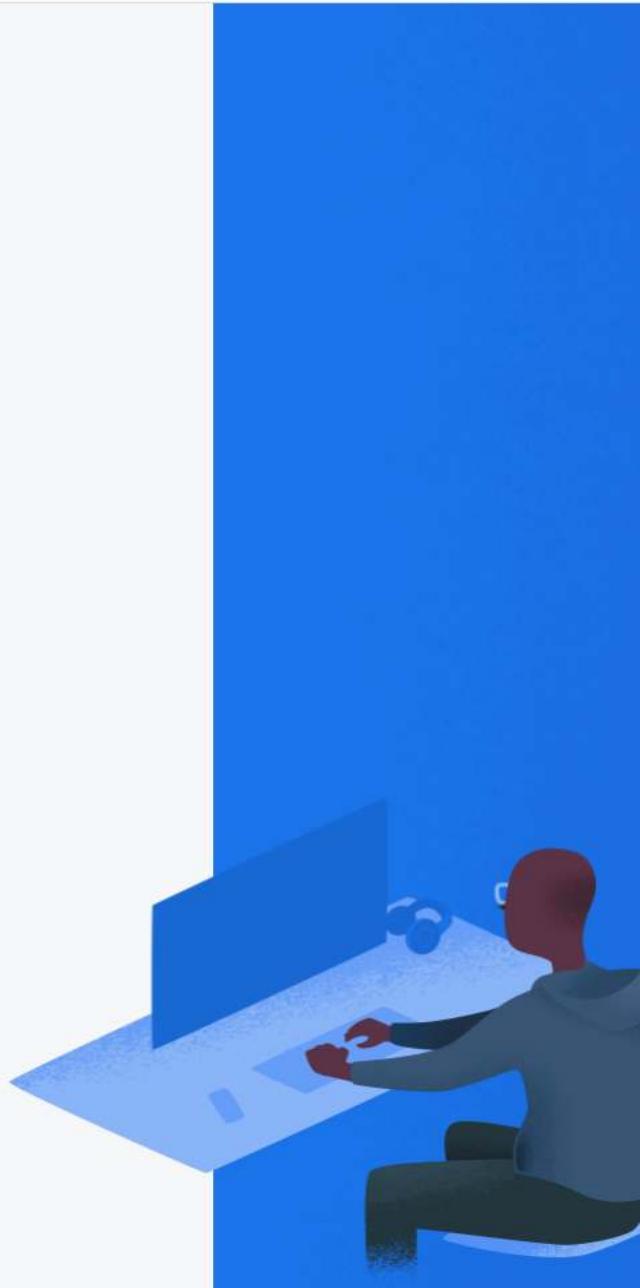
Google Analytics enables:

-  A/B testing [?](#)
-  Crash-free users [?](#)
-  User segmentation & targeting across [?](#)  
Firebase products
-  Event-based Cloud Functions triggers [?](#)
-  Predicting user behavior [?](#)
-  Free unlimited reporting [?](#)

  Enable Google Analytics for this project  
Recommended

[Previous](#)

[Continue](#)



× Create a project (Step 3 of 3)

## Configure Google Analytics

Choose or create a Google Analytics account [?](#)

 Default Account for Firebase [!\[\]\(68a1910447ad5088ad0b81e5d2b246b6\_img.jpg\)](#)

Automatically create a new property in this account [!\[\]\(647e44ea77c89a016b9d36ad68afc84b\_img.jpg\)](#)

Upon project creation, a new Google Analytics property will be created in your chosen Google Analytics account and linked to your Firebase project. This link will enable data flow between the products. Data exported from your Google Analytics property into Firebase is subject to the Firebase terms of service, while Firebase data imported into Google Analytics is subject to the Google Analytics terms of service. [Learn more](#)

[Previous](#)

[Create project](#)





ML Kit Codelab

✓ Your new project is ready

Continue





Firebase

ML Kit Codelab ▾

Go to docs

[Project Overview](#)

## Build

Authentication, Cloud Firestore, Rea...

## Release &amp; Monitor

Crashlytics, Performance, Test Lab, ...

## Analytics

Dashboard, Realtime, Events, Conve...

## Engage

Predictions, A/B Testing, Cloud Mes...

## Extensions

## Spark

Free \$0/month

[Upgrade](#)

## ML Kit Codelab

Spark plan

# Get started by adding Firebase to your app

[Add an app to get started](#)

Store and sync app data in milliseconds



## Authentication

Authenticate and manage users



## Cloud Firestore

Realtime updates, powerful queries, and automatic scaling

 Add Firebase to your iOS app

1 Register app

iOS bundle ID ?

com.google.firebaseio.codelab.mlkit.automl

App nickname (optional) ?

Sheema iOS App

App Store ID (optional) ?

123456789

**Register app**

2 Download config file

3 Add Firebase SDK

4 Add initialization code

5 Next steps



## Add Firebase to your iOS app

### Register app

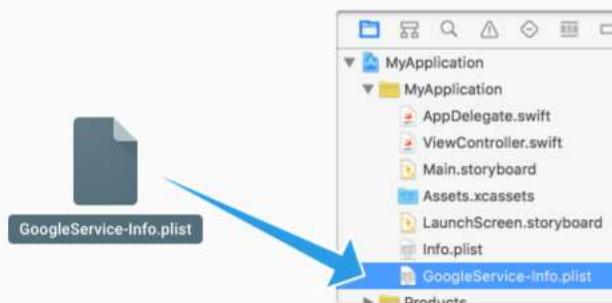
iOS bundle ID: com.google.firebaseio.codelab.mlkit.automl, App nickname: Sheema iOS App

### Download config file

Instructions for Xcode below | [Unity](#) [C++](#)

 [Download GoogleService-Info.plist](#)

Move the GoogleService-Info.plist file you just downloaded into the root of your Xcode project and add it to all targets.



[Next](#)

### Add Firebase SDK

### Add initialization code

### Next steps



## Add Firebase to your iOS app

### Register app

iOS bundle ID: com.google.firebaseio.codelab.mlkit.automl, App nickname: Sheema iOS App

### Download config file

### 3 Add Firebase SDK

Instructions for CocoaPods | [Download ZIP](#) [Unity](#) [C++](#)

Google services use [CocoaPods](#) to install and manage dependencies. Open a terminal window and navigate to the location of the Xcode project for your app.

Create a Podfile if you don't have one:

```
$ pod init
```



Open your Podfile and add:

```
# add the Firebase pod for Google Analytics
pod 'Firebase/Analytics'
# add pods for any other desired Firebase products
# https://firebase.google.com/docs/ios/setup#available-pods
```



Save the file and run:

```
$ pod install
```



This creates an .xcworkspace file for your app. Use this file for all future development on your application.

[Previous](#)

[Next](#)

### 4 Add initialization code

[Next step](#)



MLVisionExample > iPod touch (7th generation) MLVisionExample: Ready | Today at 12:07 PM

Show the Issue navigator

GoogleService-Info.plist

MLVisionExample > MLVisionExample > GoogleService-Info.plist > No Selection

Key Type Value

Information Property List Dictionary (14 items)

Key	Type	Value
CLIENT_ID	String	14596468043-fj2ud0ufddj7chf80aivph7jhcnchdp.apps.googleusercontent.com
REVERSED_CLIENT_ID	String	com.googleusercontent.apps.14596468043-fj2ud0ufddj7chf80aivph7jhcnchd
API_KEY	String	AlzaSyDMoUzyCbXX_r1tG2K9daUUQJ8TL3mLCY
GCM_SENDER_ID	String	14596468043
PLIST_VERSION	String	1
BUNDLE_ID	String	com.google.firebaseio.codelab.mlkit.automl
PROJECT_ID	String	ml-kit-codelab-sheema-2902
STORAGE_BUCKET	String	ml-kit-codelab-sheema-2902.appspot.com
IS_ADS_ENABLED	Boolean	0
IS_ANALYTICS_ENABLED	Boolean	0
IS_APPINVITE_ENABLED	Boolean	1
IS_GCM_ENABLED	Boolean	1
IS_SIGNIN_ENABLED	Boolean	1
GOOGLE_APP_ID	String	1:14596468043:ios:0a11c49f1e9139b85accce

Identity and Type

Name GoogleService-Info.plist

Type Default - Property List XML

Location Relative to Group ..../GoogleService-Info.plist

Full Path /Users/sheemamb/ Documents/Masters/ Spring\_2021/ CMPE\_258\_Deep\_Learning/ HW\_2/automl-vision-edge-in-mlkit-master/ GoogleService-Info.plist

On Demand Resource Tags

Tags

Localization

Localize...

Target Membership

MLVisionExample

+ Filter

```
automl-vision-edge-in-mlkit-master -- zsh -- 146x38
(base) sheemamb@Sheemas-MacBook-Pro automl-vision-edge-in-mlkit-master % brew install cocoapods
Updating Homebrew...
==> Auto-updated Homebrew!
Updated 1 tap (homebrew/core).
==> New Formulae
cyrus-sasl          gopass-jsonapi      klee           python-tabulate      tomcat@9          wllvm
==> Updated Formulae
Updated 135 formulae.

Warning: cocoapods 1.10.1 is already installed and up-to-date.
To reinstall 1.10.1, run:
  brew reinstall cocoapods
(base) sheemamb@Sheemas-MacBook-Pro automl-vision-edge-in-mlkit-master %
```

```
mlkit-automl — vim Podfile — 146x38
source 'https://github.com/CocoaPods/Specs.git'

platform :ios, '9.0'
use_frameworks!

target 'MLVisionExample' do
  pod 'FirebaseMLVision', '0.16.0'
  pod 'FirebaseMLCommon', '0.16.0'
  pod 'FirebaseMLVisionAutoML', '0.16.0'
  pod 'Firebase/Analytics'
end
~
```

```
(base) sheemamb@Sheemas-MacBook-Pro mlkit-automl % vim Podfile
(base) sheemamb@Sheemas-MacBook-Pro mlkit-automl % pod 'Firebase/Analytics'
[!] Unknown command: 'Firebase/Analytics'
Did you mean: deintegrate?

Usage:

$ pod COMMAND

CocoaPods, the Cocoa library package manager.

Commands:

+ cache      Manipulate the CocoaPods cache
+ deintegrate Deintegrate CocoaPods from your project
+ env         Display pod environment
+ init        Generate a Podfile for the current directory
+ install     Install project dependencies according to versions from a
              Podfile.lock
+ ipc         Inter-process communication
+ lib         Develop pods
+ list        List pods
+ outdated   Show outdated project dependencies
+ plugins    Show available CocoaPods plugins
+ repo       Manage spec-repositories
+ search     Search for pods
+ setup      Setup the CocoaPods environment
+ spec       Manage pod specs
+ trunk      Interact with the CocoaPods API (e.g. publishing new specs)
+ try        Try a Pod!
+ update     Update outdated project dependencies and create new Podfile.lock

Options:

--allow-root  Allows CocoaPods to run as root
--silent     Show nothing
--version    Show the version of the tool
--verbose    Show more debugging information
```

```
mlkit-automl -- zsh -- 146x38

--allow-root    Allows CocoaPods to run as root
--silent        Show nothing
--version       Show the version of the tool
--verbose       Show more debugging information
--no-ansi       Show output without ANSI codes
--help          Show help banner of specified command
(base) sheemamb@Sheemas-MacBook-Pro mlkit-automl % pod install
Analyzing dependencies
Downloading dependencies
Installing Firebase (6.0.0)
Installing FirebaseAnalytics (6.0.0)
Installing FirebaseCore (6.0.0)
Installing FirebaseInstanceID (4.0.0)
Installing FirebaseMLCommon (0.16.0)
Installing FirebaseMLVision (0.16.0)
Installing FirebaseMLVisionAutoML (0.16.0)
Installing GTMSessionFetcher (1.2.1)
Installing GoogleAPIClientForREST (1.3.8)
Installing GoogleAppMeasurement (6.0.0)
Installing GoogleMobileVision (1.6.0)
Installing GoogleToolboxForMac (2.2.0)
Installing GoogleUtilities (6.0.0)
Installing Protobuf (3.7.0)
Installing TensorFlowLite (1.13.1)
Installing nanopb (0.3.9011)
Generating Pods project
Integrating client project

[!] Please close any current Xcode sessions and use `MLVisionExample.xcworkspace` for this project from now on.
Pod installation complete! There are 4 dependencies from the Podfile and 16 total pods installed.

[!] FirebaseMLCommon has been deprecated
[!] FirebaseMLVision has been deprecated
[!] FirebaseMLVisionAutoML has been deprecated in favor of MLKitImageLabelingAutoML
(base) sheemamb@Sheemas-MacBook-Pro mlkit-automl %
```



mlkit-automl — vim Podfile — 146x38

```
source 'https://github.com/CocoaPods/Specs.git'
```

```
platform :ios, '9.0'  
use_frameworks!
```

```
target 'MLVisionExample' do  
  pod 'FirebaseMLVision', '0.16.0'  
  pod 'FirebaseMLCommon', '0.16.0'  
  pod 'FirebaseMLVisionAutoML', '0.16.0'  
  pod 'Firebase/Analytics'  
  pod 'Firebase/Auth'  
  pod 'Firebase/Firestore'  
end
```

```
mlkit-automl — -zsh — 146x38
```

```
Installing GoogleToolboxForMac (2.2.0)  
Installing GoogleUtilities (6.0.0)  
Installing Protobuf (3.7.0)  
Installing TensorFlowLite (1.13.1)  
Installing nanopb (0.3.9011)  
Generating Pods project  
Integrating client project
```

```
[!] Please close any current Xcode sessions and use `MLVisionExample.xcworkspace` for this project from now on.  
Pod installation complete! There are 4 dependencies from the Podfile and 16 total pods installed.
```

```
[!] FirebaseMLCommon has been deprecated
```

```
[!] FirebaseMLVision has been deprecated
```

```
[!] FirebaseMLVisionAutoML has been deprecated in favor of MLKitImageLabelingAutoML
```

```
(base) sheemamb@Sheemas-MacBook-Pro mlkit-automl % vim Podfile  
(base) sheemamb@Sheemas-MacBook-Pro mlkit-automl % pod install  
Analyzing dependencies  
Downloading dependencies  
Installing BoringSSL-GRPC (0.0.3)  
Installing Firebase 6.0.0  
Installing FirebaseAuth (6.0.0)  
Installing FirebaseAuthInterop (1.1.0)  
Installing FirebaseFirestore (1.3.2)  
Installing gRPC-C++ (0.0.9)  
Installing gRPC-Core (1.21.0)  
Installing leveldb-library (1.22.1)  
Generating Pods project  
Integrating client project
```

```
Pod installation complete! There are 6 dependencies from the Podfile and 23 total pods installed.
```

```
[!] FirebaseMLCommon has been deprecated
```

```
[!] FirebaseMLVision has been deprecated
```

```
[!] FirebaseMLVisionAutoML has been deprecated in favor of MLKitImageLabelingAutoML
```

```
(base) sheemamb@Sheemas-MacBook-Pro mlkit-automl % open MLVisionExample.xcworkspace
```

MLVisionExample > iPod touch (7th generation)

Buildtime (2) Runtime

MLVisionExample project 1 issue 1 warning

Validate Project Settings  
Update to recommended settings  
MLVisionExample.xcodeproj

Pods project 1 issue 1 warning

Validate Project Settings  
Update to recommended settings  
Pods.xcodeproj

Pods.xcodeproj

Buildtime (2) Runtime

MLVisionExample project 1 issue 1 warning

Validate Project Settings  
Update to recommended settings  
MLVisionExample.xcodeproj

Pods project 1 issue 1 warning

Validate Project Settings  
Update to recommended settings  
Pods.xcodeproj

General Signing & Capabilities Resource Tags Info Build Settings Build Phases Build Rules

PROJECT Targets

Identity

Display Name: openssl\_grpc

Bundle Identifier: org.cocoapods.openssl-grpc

Version: 0.0.3

Build: 1

Deployment Info

iOS 8.0: iPhone, iPad

macOS 10.15: Mac, Scale Interface to Match iPad, Show "Designed for iPad" Run Destination

App Extensions: Allow app extension API only

Frameworks and Libraries

Name	Platforms	Embed
Foundation.framework	macOS + iOS	Do Not Embed

Development Assets

Add development assets here

Identity and Type

Name: Pods

Location: Relative to Group  
Full Path: /Users/sheemamb/.../Pods/Pods.xcodeproj

Project Document

Project Format: Xcode 8.0-compatible

Organization:

Class Prefix:

Text Settings

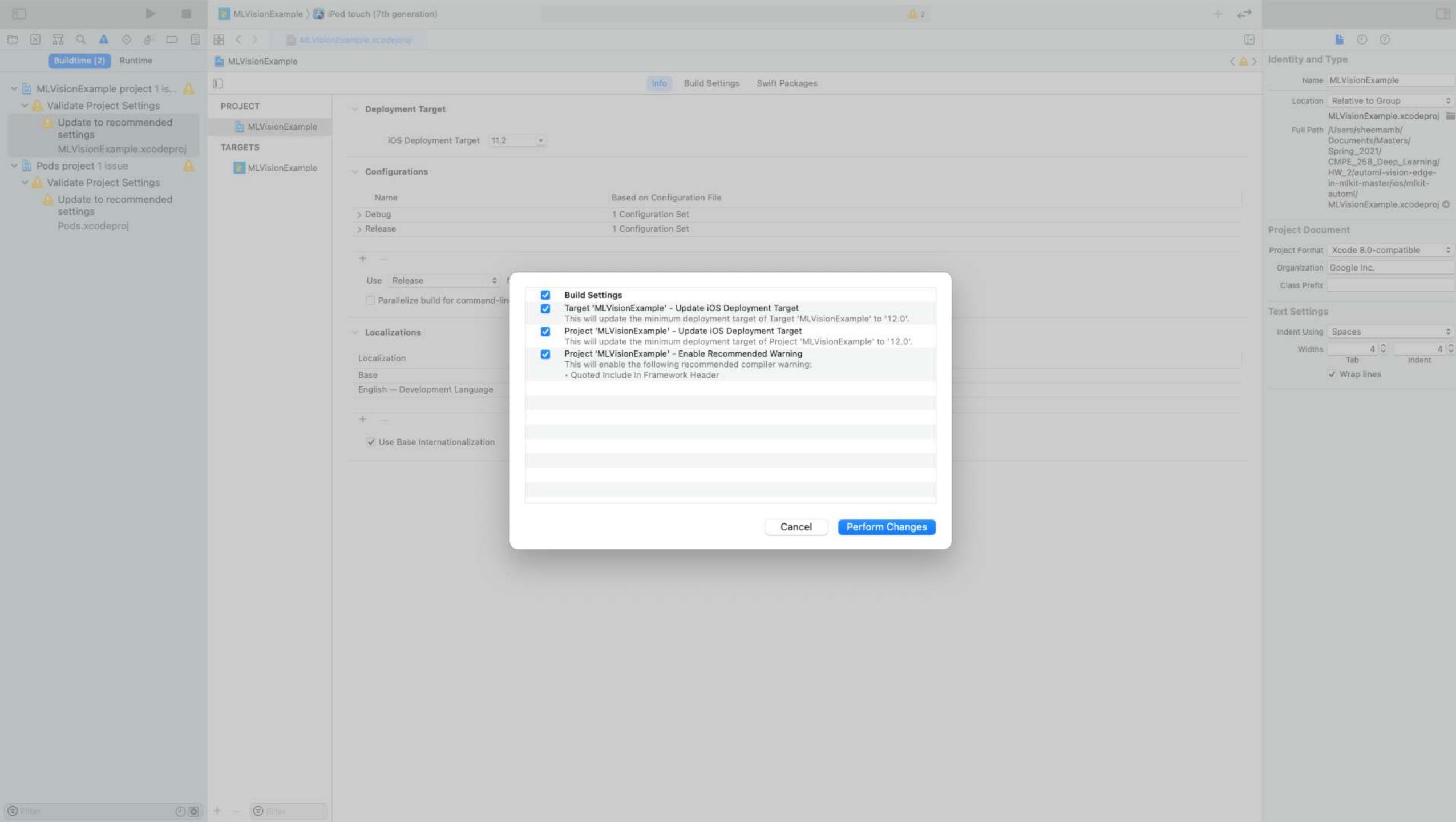
Indent Using: Spaces

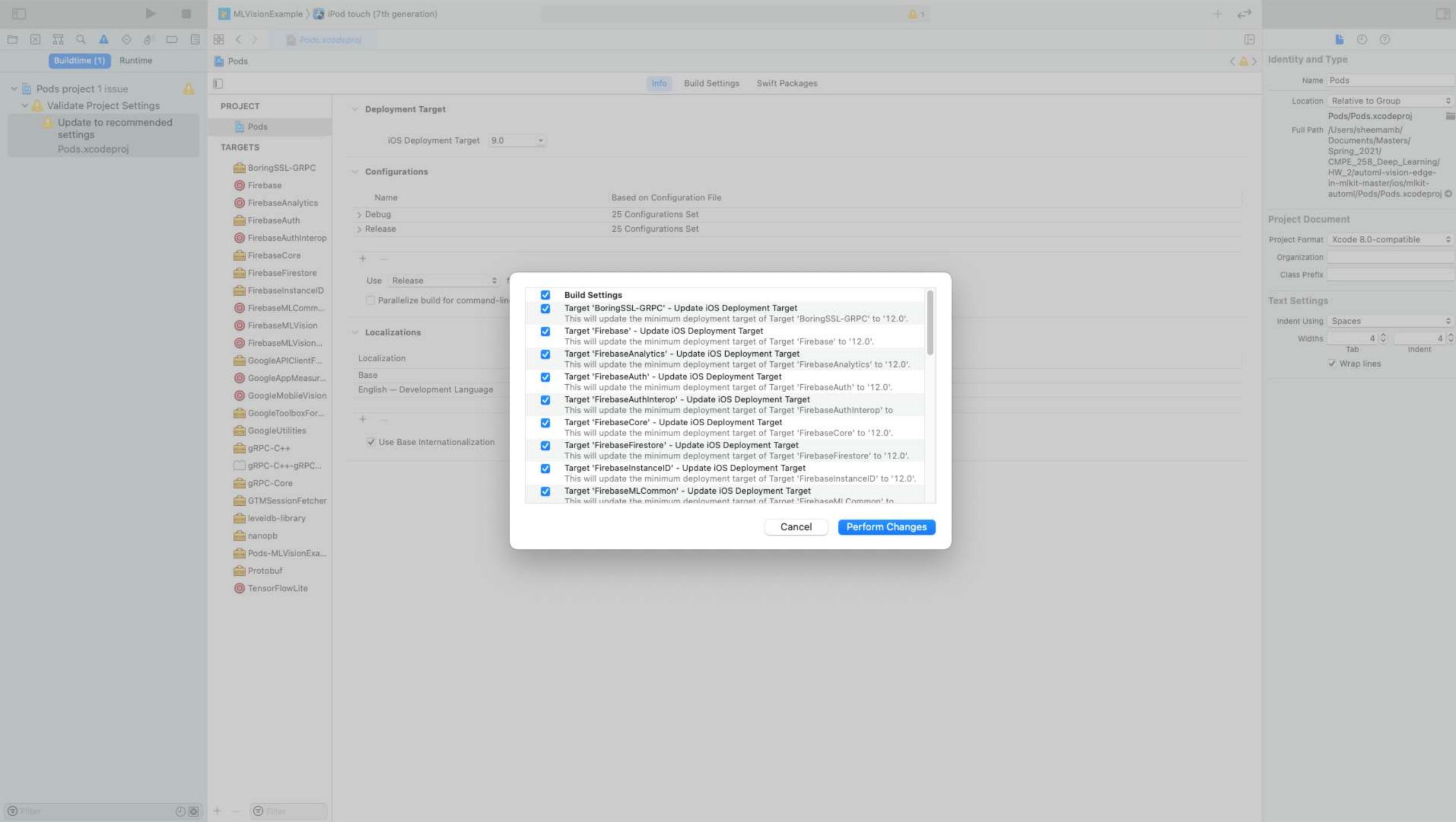
Widths: Tab 4 Indent 4

Wrap lines: checked

Filter

+ - Filter





The screenshot shows the Xcode interface with the following details:

- Project Navigator:** On the left, the project structure for "MLVisionExample" is shown. It includes a main group "MLVisionExample" containing "AppDelegate.swift", "ViewController.swift", "MLKitExtensions.swift", "UIUtilities.swift", and "CameraViewController.swift". Below these are "Supporting Files" (Info.plist, GoogleService-Info.plist), "Resources", "Products", "Pods" (with a Podfile), and "Targets Support Files".
- Editor:** The main editor area displays the content of "AppDelegate.swift". The code starts with an Apache License 2.0 header and then defines an AppDelegate class that conforms to UIResponder and UIApplicationDelegate. It initializes a window and configures Firebase.
- Identity and Type:** A sidebar on the right provides metadata for the selected file:
  - Name: AppDelegate.swift
  - Type: Default - Swift Source
  - Location: Relative to Group
  - Full Path: /Users/sheemamb/.../MLVisionExample/AppDelegate.swift
- On Demand Resource Tags:** A section indicating "Only resources are taggable".
- Target Membership:** Shows that the file is part of the "MLVisionExample" target.
- Text Settings:** Configuration for text encoding, line endings, and indentation (using spaces, width 4, tab width 4, wrap lines checked).

## Add Firebase to your iOS app

### Register app

iOS bundle ID: com.google.firebaseio.codelab.mlkit.automl, App nickname: Sheema iOS App

### Download config file

### Add Firebase SDK

### Add initialization code

### Next steps

You're all set!

Make sure to check out the [documentation](#) to learn how to get started with each Firebase product that you want to use in your app.

You can also explore [sample Firebase apps](#).

Or, continue to the console to explore Firebase.

[Previous](#)

[Continue to console](#)





Firebase

ML Kit Codelab ▾ Project settings

Go to docs



Project Overview



## Build

Authentication, Cloud Firestore, Real...

## Release &amp; Monitor

Crashlytics, Performance, Test Lab, ...

## Analytics

Dashboard, Realtime, Events, Conve...

## Engage

Predictions, A/B Testing, Cloud Mes...

## Extensions

## Spark

Free \$0/month

Upgrade



iOS apps

**iOS Sheema iOS App**  
com.google.firebaseio.codelab.mlkit.automl

Add app

SDK setup and configuration

Need to reconfigure the Firebase SDKs for your app? Revisit the SDK setup instructions or just download the configuration file containing keys and identifiers for your app.

[See SDK instructions](#) [Download GoogleService-Info.plist](#)

App ID ⓘ  
1:14596468043:ios:0a11c49f1e9139b85accce

Encoded App ID ⓘ  
app-1:14596468043:ios-0a11c49f1e9139b85accce

App nickname  
Sheema iOS App

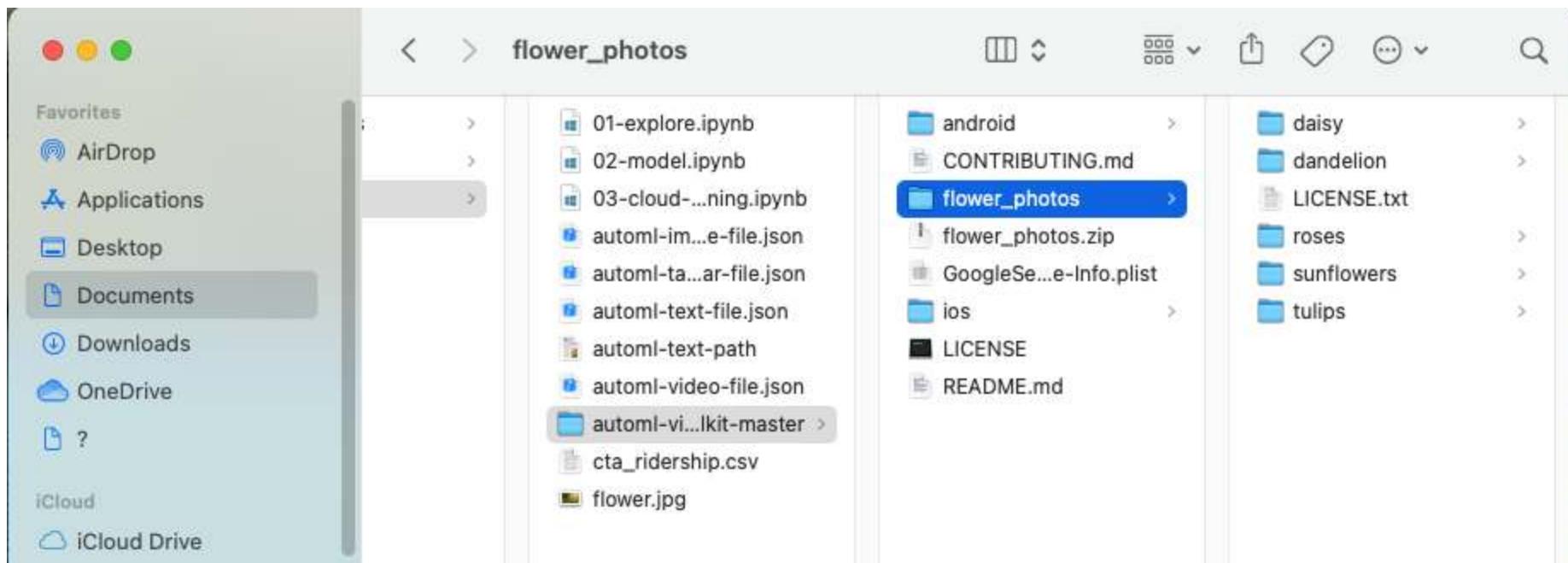
Bundle ID  
com.google.firebaseio.codelab.mlkit.automl

App Store ID ⓘ  
Add an App Store ID

Team ID ⓘ  
Add a Team ID

[Remove this app](#)

Delete project



Apps Others Google Machine Learning... San Jose State Un... nbviewer Datasets MSSE Study mate... Dream Career LAB R Slack | data-gobli... Tableau eLearning CMPE 272 Interview Prep Getting Started Other Bookmarks

**Firebase**

Project Overview

**Build**

- Authentication
- Cloud Firestore
- Realtime Database
- Storage
- Hosting
- Functions
- Machine Learning

**Release & Monitor**  
Crashlytics, Performance, Test Lab, ...

**Analytics**  
Dashboard, Realtime, Events, Conve...

**Engage**  
Predictions, A/B Testing, Cloud Mes...

Extensions

Spark Free \$0/month Upgrade

## ML Kit Codelab

## Machine Learning

APIs Custom AutoML

We've streamlined the AutoML in Firebase experience so you can get all the benefits in one place.

- Models are now trained through the Google Cloud console. This brings the following additional features:
  - Support for both image classification and object detection models.
  - Support for TensorFlow Lite, Core ML, and container export formats.
- You can still distribute AutoML models over-the-air using [Firebase ML Custom Model Deployment](#). Models created using AutoML can now be found there.

[Learn more](#) [Go to Cloud AutoML](#)

## Vision

Dashboard

Datasets

Models

Cloud AI

## Vision

To get started building an AutoML vision classification or object detection model, enable the AutoML API. [Learn more](#)

[ENABLE AUTOML API](#)



● Name Type Total images Labeled images Last updated Status

No rows to display

## Create new dataset

Dataset name \*

Flowers|

Use letters, numbers and underscores up to 32 characters.

Select your model objective



Single-Label Classification

Predict the one correct label that you want assigned to an image.



Multi-Label Classification

Predict all the correct labels that you want assigned to an image.



Object detection

Predict all the locations of objects that you're interested in.

CANCEL

CREATE DATASET



Vision

Flowers

LABEL STATS

EXPORT DATA



Dashboard

IMPORT

IMAGES

TRAIN

EVALUATE

TEST &amp; USE

Single-Label Classification



Datasets

## 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.

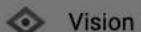
flower\_photos.zip

1 file

[SELECT FILES](#)

gs:// Destination on Cloud Storage

[BROWSE](#)[CONTINUE](#)

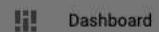


Vision

Flowers

LABEL STATS

EXPORT DATA



Dashboard

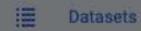
IMPORT

IMAGES

TRAIN

EVALUATE

TEST &amp; USE



Datasets

## 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

gs:// Destination on Cloud Storage

BROWSE

CONTINUE

## Create a bucket

- Name your bucket**

Pick a globally unique, permanent name. [Naming guidelines](#)

flower-bucket-2902

Tip: Don't include any sensitive information

CONTINUE

- Choose where to store your data**

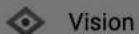
- Choose a default storage class for your data**

- Choose how to control access to objects**

- Advanced settings (optional)**

CREATE

CANCEL

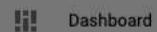


Vision

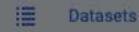
Flowers

LABEL STATS

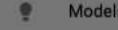
EXPORT DATA



Dashboard



Datasets



Models

## 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**

 gs:// Destination on Cloud Storage

BROWSE

CONTINUE

## Create a bucket

### Name your bucket

### • Choose where to store your data

This permanent choice defines the geographic placement of your data and affects cost, performance, and availability. [Learn more](#)

#### Location type

- Region  
Lowest latency within a single region
- Dual-region  
High availability and low latency across 2 regions
- Multi-region  
Highest availability across largest area

#### Location

us-east1 (South Carolina) 

**CONTINUE**

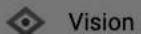
### • Choose a default storage class for your data

### • Choose how to control access to objects

### • Advanced settings (optional)

**CREATE**

CANCEL

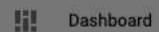


Vision

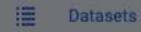
Flowers

LABEL STATS

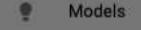
EXPORT DATA



Dashboard



Datasets



Models

## 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

gs:// Destination on Cloud Storage

BROWSE

CONTINUE

## Create a bucket

### Name your bucket

### Choose where to store your data

### • Choose a default storage class for your data

A storage class sets costs for storage, retrieval, and operations. Pick a default storage class based on how long you plan to store your data and how often it will be accessed. [Learn more](#)

 Standard 

Best for short-term storage and frequently accessed data

 Nearline

Best for backups and data accessed less than once a month

 Coldline

Best for disaster recovery and data accessed less than once a quarter

 Archive

Best for long-term digital preservation of data accessed less than once a year

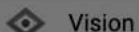
CONTINUE

### • Choose how to control access to objects

### • Advanced settings (optional)

CREATE

CANCEL



Vision

Flowers

LABEL STATS

EXPORT DATA

IMPORT

IMAGES

TRAIN

EVALUATE

TEST &amp; 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

gs:// Destination on Cloud Storage

BROWSE

CONTINUE

## Create a bucket

- Name your bucket
- Choose where to store your data
- Choose a default storage class for your data
- Choose how to control access to objects

### Access control

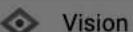
- Fine-grained  
Specify access to individual objects by using object-level permissions (ACLs) in addition to your bucket-level permissions (IAM). [Learn more](#)
- Uniform  
Ensure uniform access to all objects in the bucket by using only bucket-level permissions (IAM). This option becomes permanent after 90 days. [Learn more](#)

CONTINUE

- Advanced settings (optional)

CREATE

CANCEL



Vision

Flowers

LABEL STATS

EXPORT DATA

IMPORT

IMAGES

TRAIN

EVALUATE

TEST &amp; 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

gs:// Destination on Cloud Storage

BROWSE

CONTINUE

## Create a bucket

### Name your bucket

### Choose where to store your data

### Choose a default storage class for your data

### Choose how to control access to objects

### Advanced settings (optional)

#### Encryption

##### Google-managed encryption key

No configuration required

##### Customer-managed encryption key (CMEK)

Manage via Google Cloud Key Management Service

#### Retention policy

Set a retention policy to specify the minimum duration that this bucket's objects must be protected from deletion or modification after they're uploaded. You might set a policy to address industry-specific retention challenges. [Learn more](#)

##### Set a retention policy

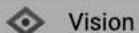
#### Labels

Labels are key:value pairs that allow you to group related buckets together or with other Cloud Platform resources. [Learn more](#)

+ ADD LABEL

CREATE

CANCEL



Vision



Dashboard



Datasets



Models

Flowers

LABEL STATS

EXPORT DATA

IMPORT

IMAGES

TRAIN

EVALUATE

TEST &amp; 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

gs:// Destination on Cloud Storage

BROWSE

CONTINUE

## Select folder

Buckets ▾

flower-bucket-2902



SELECT

CANCEL

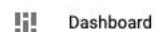


Vision

Flowers

LABEL STATS

EXPORT DATA



Dashboard

IMPORT

IMAGES

TRAIN

EVALUATE

TEST &amp; USE

Single-Label Classification



Datasets

## 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://flower-bucket-2902[BROWSE](#)[CONTINUE](#)

## Vision

[Flowers](#)[LABEL STATS](#)[EXPORT DATA](#)

## Dashboard

[IMPORT](#)[IMAGES](#)[TRAIN](#)[EVALUATE](#)[TEST & USE](#)

Single-Label Classification

## Datasets

## 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://flower-bucket-2902 [BROWSE](#)

IMPORTING IMAGES...

### Uploads and ML Kit Codelab operations

flower\_photos-2021-03-10T18:32:28.413Z.zip

## Vision

## Datasets

[+ NEW DATASET](#)

## Dashboard

## Datasets

## Models

Name	Type	Total images	Labeled images	Last updated	Status	⋮
Flowers ICN1857427532790366208	Single-Label Classification	1,000	1,000	Mar 10, 2021, 1:45:01 PM	Success: Importing images	⋮

## Vision

## Flowers

## LABEL STATS

## EXPORT DATA

IMPORT

IMAGES

TRAIN

EVALUATE

TEST &amp; USE

Single-Label Classification

All images

1,000

Filter Filter images

 Select all

Labeled

1,000

Unlabeled

0

Filter labels

+

⋮

daisy

200



tulips(1)



daisy(1)



dandelion(1)



roses(1)



daisy(1)



dandelion(1)



sunflowers(1)



dandelion(1)

sunflowers

200

tulips

200



tulips(1)



tulips(1)



daisy(1)



daisy(1)



tulips(1)



roses(1)



dandelion(1)



sunflowers(1)

ADD NEW LABEL



sunflowers(1)



sunflowers(1)



daisy(1)



daisy(1)



sunflowers(1)



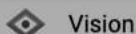
roses(1)



daisy(1)



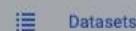
daisy(1)



Vision



Dashboard



Datasets



Models

Flowers

LABEL STATS

EXPORT DATA

IMPORT

IMAGES

TRAIN

EVALUATE

TEST &amp; USE

## You have enough images to start training

Unlabeled images aren't used. Your dataset will be automatically split into [Train, Validation, and Test sets](#).

Ideally, each label should have at least 10 images. Fewer images often result in inaccurate precision and recall. You must also have at least 8, 1, 1 images each assigned to your Train, Validation and Test sets.

Labels	Images	Train	Validation	Test
daisy	<div style="width: 200px;"><div style="width: 160px;"></div></div> 200	160	20	20
dandelion	<div style="width: 200px;"><div style="width: 160px;"></div></div> 200	160	20	20
roses	<div style="width: 200px;"><div style="width: 160px;"></div></div> 200	160	20	20
sunflowers	<div style="width: 200px;"><div style="width: 160px;"></div></div> 200	160	20	20
tulips	<div style="width: 200px;"><div style="width: 160px;"></div></div> 200	160	20	20

[START TRAINING](#)

## Train new model

### 1 Define your model

Model name \*

Flowers\_20210310020954

 Cloud hosted

Host your model on Google Cloud for online predictions

 Edge

Download your model for offline/mobile use

[CONTINUE](#)

### 2 Optimize model for

### 3 Set a node hour budget

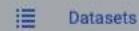
[START TRAINING](#)[CANCEL](#)



Vision



Dashboard



Datasets



Models

Flowers

LABEL STATS

EXPORT DATA

IMPORT

IMAGES

TRAIN

EVALUATE

TEST &amp; USE

## You have enough images to start training

Unlabeled images aren't used. Your dataset will be automatically split into [Train, Validation, and Test sets](#).

Ideally, each label should have at least 10 images. Fewer images often result in inaccurate precision and recall. You must also have at least 8, 1, 1 images each assigned to your Train, Validation and Test sets.

Labels	Images	Train	Validation	Test
daisy	<div style="width: 100%;"><div style="width: 80%;"> </div></div> 200	160	20	20
dandelion	<div style="width: 100%;"><div style="width: 80%;"> </div></div> 200	160	20	20
roses	<div style="width: 100%;"><div style="width: 80%;"> </div></div> 200	160	20	20
sunflowers	<div style="width: 100%;"><div style="width: 80%;"> </div></div> 200	160	20	20
tulips	<div style="width: 100%;"><div style="width: 80%;"> </div></div> 200	160	20	20

**START TRAINING**

## Train new model

### 1 Define your model

### 2 Optimize model for

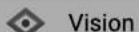
Goal	Package size	Accuracy	Latency for Google Pixel 2
<input type="radio"/>	6 MB	Higher	360 ms
<input type="radio"/>	3.2 MB	Medium	150 ms
<input checked="" type="radio"/>	0.6 MB	Lower	56 ms

Please note that prediction latency estimates are for guidance only. Actual latency will depend on your network connectivity.

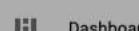
**CONTINUE**

### 3 Set a node hour budget

**START TRAINING****CANCEL**



Vision



Dashboard



Datasets



Models

Flowers

LABEL STATS

EXPORT DATA

IMPORT

IMAGES

TRAIN

EVALUATE

TEST &amp; USE

## You have enough images to start training

Unlabeled images aren't used. Your dataset will be automatically split into [Train, Validation, and Test sets](#).

Ideally, each label should have at least 10 images. Fewer images often result in inaccurate precision and recall. You must also have at least 8, 1, 1 images each assigned to your Train, Validation and Test sets.

Labels	Images	Train	Validation	Test
daisy	<div style="width: 200px;"><div style="width: 160px;"></div></div> 200	160	20	20
dandelion	<div style="width: 200px;"><div style="width: 160px;"></div></div> 200	160	20	20
roses	<div style="width: 200px;"><div style="width: 160px;"></div></div> 200	160	20	20
sunflowers	<div style="width: 200px;"><div style="width: 160px;"></div></div> 200	160	20	20
tulips	<div style="width: 200px;"><div style="width: 160px;"></div></div> 200	160	20	20

[START TRAINING](#)

## Train new model

### 1 Define your model

### 2 Optimize model for

### 3 Set a node hour budget

Enter the maximum number of node hours you want to spend training your model.

We recommend using [3 node hours](#) for your dataset. However, you can train for as little as 1 node hours. You may also eligible to train with free node hours. [Pricing guide](#)

Set your budget \*  node hours

Estimated completion date: Mar 10, 2021 4 PM  
GMT-5

[START TRAINING](#)[CANCEL](#)



Vision

Flowers

LABEL STATS

EXPORT DATA



Dashboard



Datasets



Models

## Models

TRAIN NEW MODEL

## Flowers\_20210310020954

Training may take several hours. This includes node training time as well as infrastructure set up and tear down, which you aren't charged for.

You will be emailed once training completes.

Training model...

CANCEL

## Vision

Flowers

LABEL STATS

EXPORT DATA

IMPORT

IMAGES

TRAIN

EVALUATE

TEST &amp; USE

Single-Label Classification

Datasets

Models

## Models

TRAIN NEW MODEL

Flowers\_20210310020954

⋮

Average precision ⓘ

**0.967**

Precision\* ⓘ

93.48%

Recall\* ⓘ

86%

\* Using a score threshold of 0.5

Model ID ⓘ

ICN1035152814155759616

Created

Mar 10, 2021, 2:14:06 PM

Base model

None

Data

1,000 images

Model type

Mobile Low Latency

Train cost

0.712 node hours

Deployment state

Not deployed

[SEE FULL EVALUATION](#)[RESUME TRAINING](#)

## Vision

## Flowers

## LABEL STATS

## EXPORT DATA

IMPORT

IMAGES

TRAIN

EVALUATE

TEST &amp; USE

Single-Label Classification

## Datasets

Model

Flowers\_20210310020954

Confidence threshold



0.5

Filter labels

## All labels

All labels	0.96742
daisy	0.98021
dandelion	0.99511
roses	0.93840
sunflowers	0.96226
tulips	0.94114

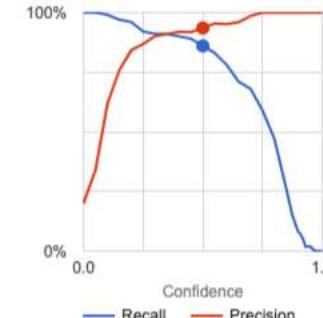
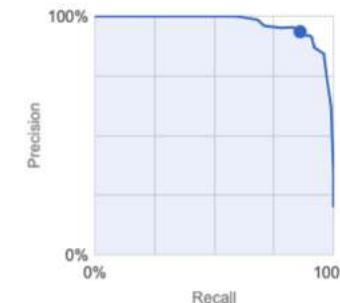
Total images 900

Test items 100

Precision 93.48%

Recall 86%

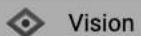
Use the slider to see which confidence threshold works best for your model on the precision-recall tradeoff curve.  
[Learn more about these metrics and graphs.](#)



## Confusion matrix

This table shows how often the model classified each label correctly (in blue), and which labels were most often confused for that label (in gray). Note that this table is limited to the 10 most confused labels. You can download the entire confusion matrix as a CSV file.

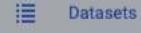
True Label	Predicted Label					
		sunflowers	dandelion	tulips	roses	daisy
sunflowers	95%	-	-	5%	-	
dandelion	5%	95%	-	-	-	
tulips	5%	-	85%	5%	5%	
roses	5%	-	10%	85%	-	
daisy	5%	5%	-	-	90%	



Vision



Dashboard



Datasets



Models

Flowers

LABEL STATS

EXPORT DATA

IMPORT

IMAGES

TRAIN

EVALUATE

TEST &amp; USE

Model

Flowers\_20210310020954

To use online prediction, deploy your model to the cloud. Deployed model charges are per hour and number of machines used. [Pricing guide](#)

Notice for beta users: The v1beta1 API endpoint is scheduled for deletion after GA release. If your beta models have not been [redeployed since October 17, 2019](#), please do so now to

## Use your model



TF Lite

Export your model as a TF Lite package to run your model on edge or mobile devices.



TensorFlow.js

Export your model as a TensorFlow.js package to run your model in the browser and in Node.js.



Core ML

Export a .mlmodel file to run your model on iOS and macOS devices.



Container

Export your model as a TF Saved Model to run on a Docker container.



Coral

Export your model as a TFLite package to run on Coral Dev Board or USB Accelerator.

## Export TF Lite package

The Tensorflow Lite (.tflite) format allows you to run your model on mobile and embedded devices.

1. Export your model as a TF Lite package.

Destination folder on Cloud Storage

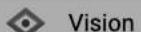
 flower-bucket-2902[BROWSE](#)

[EXPORT](#) [OPEN IN GCS](#)

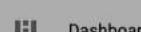
2. After your model finishes exporting, you can copy your package to your computer using this command:

```
$ gsutil cp -r gs://flower-bucket-2902 ./download_dir
```

3. Follow the quickstart to learn how to implement your model on your device.  
[Android quickstart](#) [iOS quickstart](#)



Vision



Dashboard



Datasets



Models

Flowers

LABEL STATS

EXPORT DATA

IMPORT

IMAGES

TRAIN

EVALUATE

TEST &amp; USE

Model

Flowers\_20210310020954

To use online prediction, deploy your model to the cloud. Deployed model charges are per hour and number of machines used. [Pricing guide](#)

Notice for beta users: The v1beta1 API endpoint is scheduled for deletion after GA release. If your beta models have not been [redeployed since October 17, 2019](#), please do so now to

## Use your model



TF Lite

Export your model as a TF Lite package to run your model on edge or mobile devices.



TensorFlow.js

Export your model as a TensorFlow.js package to run your model in the browser and in Node.js.



Core ML

Export a .mlmodel file to run your model on iOS and macOS devices.



Container

Export your model as a TF Saved Model to run on a Docker container.



Coral

Export your model as a TFLite package to run on Coral Dev Board or USB Accelerator.

Export operation finished



## Export TF Lite package

The Tensorflow Lite (.tflite) format allows you to run your model on mobile and embedded devices.

1. Export your model as a TF Lite package.

Destination folder on Cloud Storage

 flower-bucket-demo-2902[BROWSE](#)

[EXPORT](#) [OPEN IN GCS](#)

2. After your model finishes exporting, you can copy your package to your computer using this command:

```
$ gsutil cp -r gs://flower-bucket-demo-2902 ./download
```

3. Follow the quickstart to learn how to implement your model on your device.  
[Android quickstart](#) [iOS quickstart](#)

MLVisionExample > iPod touch (7th generation)

AppDelegate.swift | model.tflite | model-export\_icn\_tflite-Flowers\_20210310020954-2021-03-10T21\_05\_34.372466Z\_model.tflite

MLVisionExample

MLVisionExample

- AppDelegate.swift
- ViewController.swift
- MLKitExtensions.swift
- UIUtilities.swift
- CameraViewController.swift
- ImageClassifier.swift

Supporting Files

- Info.plist
- GoogleService-Info.plist

Resources

automl

- dict.txt
- manifest.json
- model-export\_icn\_tflite-...
  - model.tflite

GoogleService-Info.plist

LaunchScreen.xib

Images.xcassets

flowers

Products

Pods

Frameworks

Pods

- Podfile

Frameworks

Pods

Products

Targets Support Files

MLVisionExample > Resources > automl > model-export\_icn\_tflite-Flowers\_20210310020954-2021-03-10T21\_05\_34.372466Z\_model.tflite > No Selection

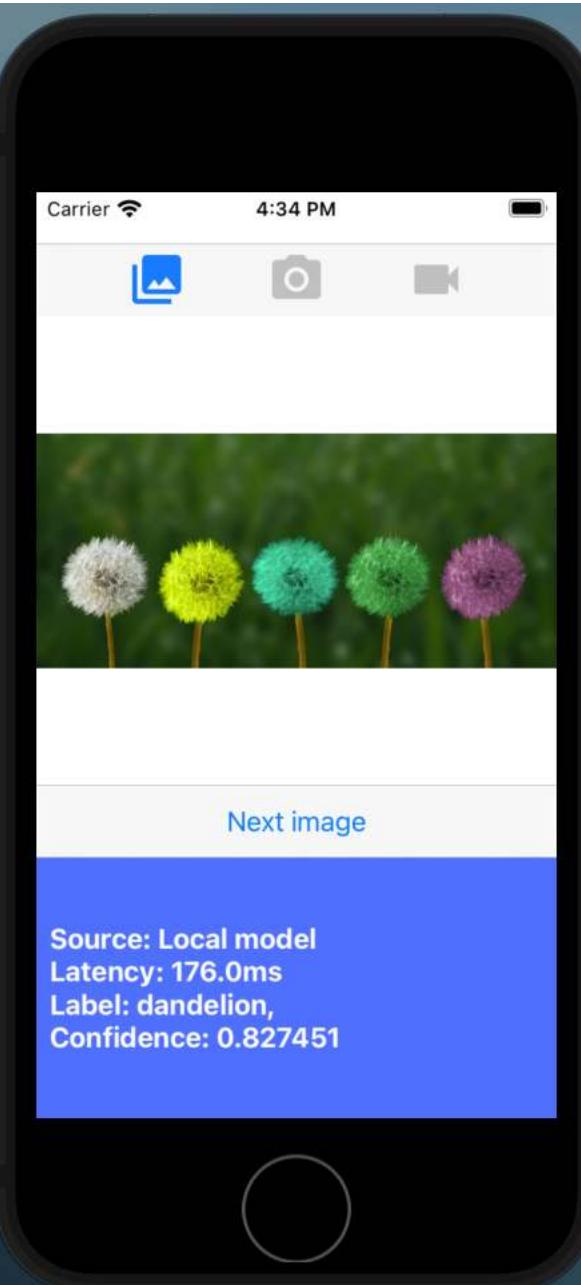
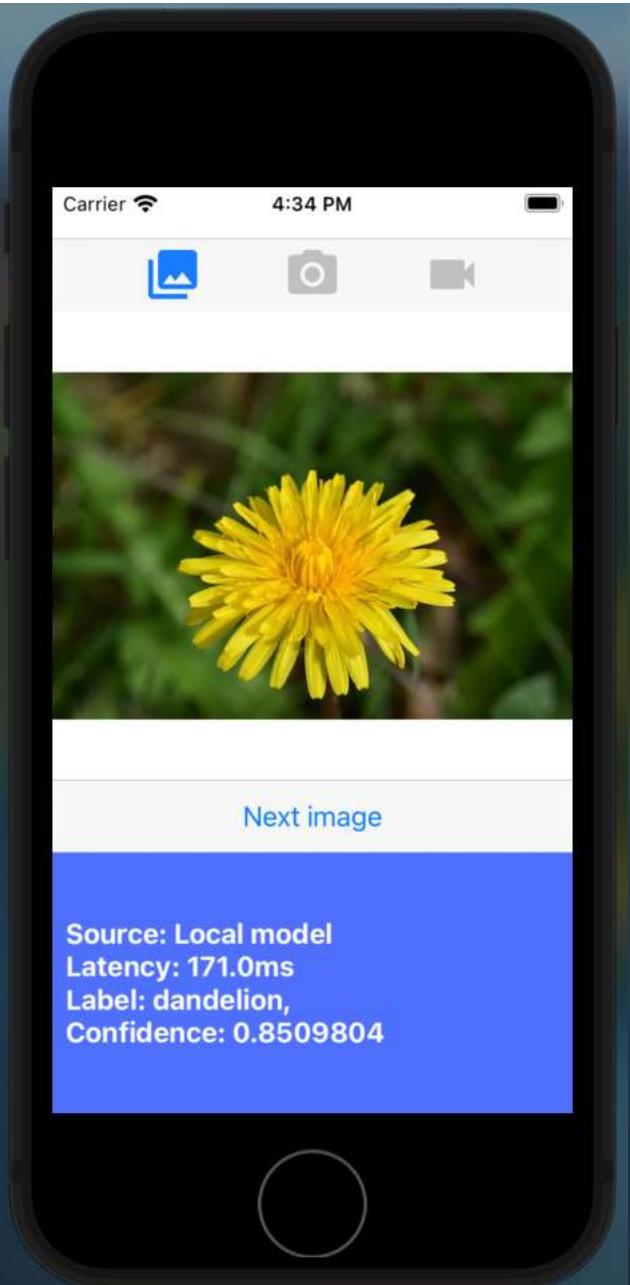
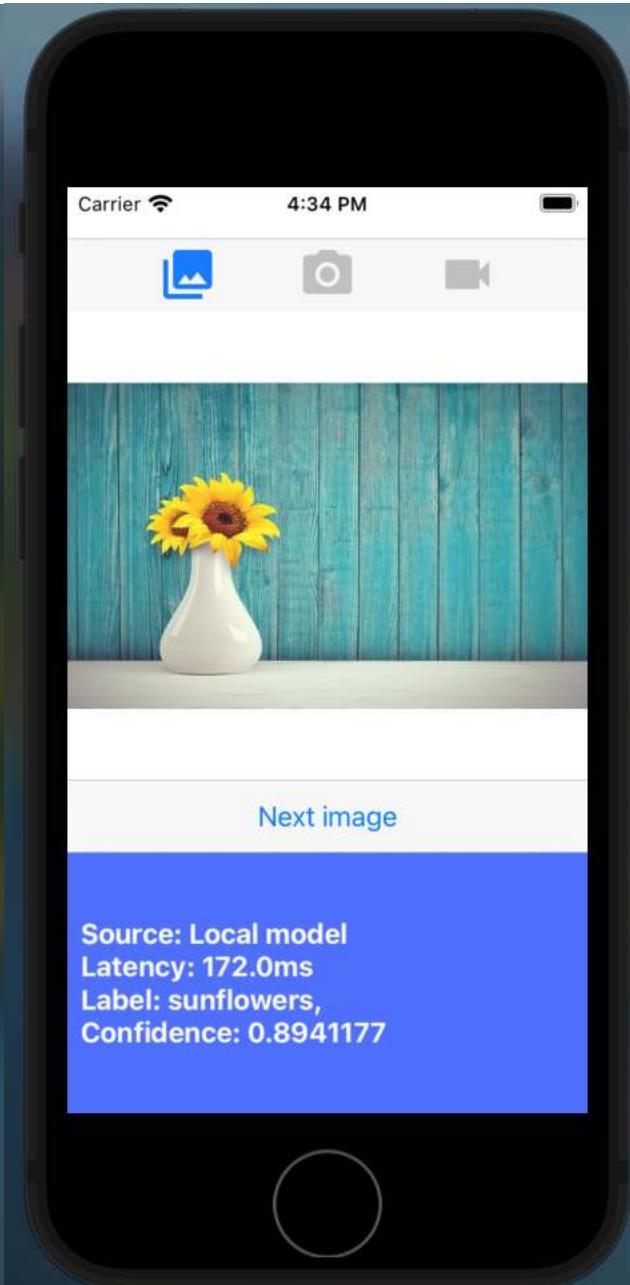
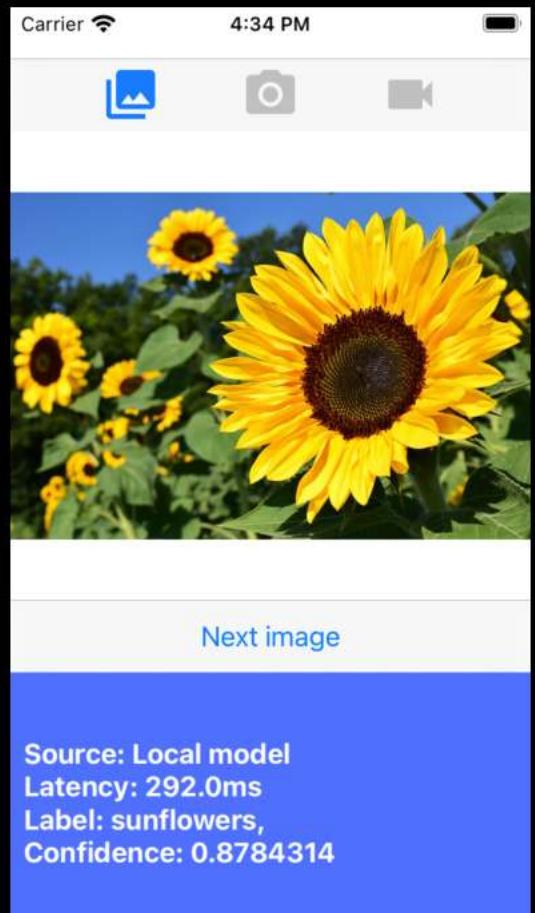
Identity and Type

Name: model-export\_icn\_tflite-Flowers\_20210310020954-2021-03-10T21\_05\_34.372466Z\_model.tflite

Type: Default - Data

Location: Relative to Group

Full Path: /Users/sheemamb/ Documents/Masters/ Spring\_2021/ CMPE\_258\_Deep\_Learning/HW\_2/automl-vision-edge-in-mlkit-master/ios/mlkit-automl/Resources/automl/model-export\_icn\_tflite-Flowers\_20210310020954-2021-03-10T21\_05\_34.372466Z\_model.tflite





THANK YOU!