

Time Series Forecasting with the Cloud AI Platform and BQML

126 mins remaining English R

2. Introduction to Time-Series Forecasting

The focus of this codelab is on how to apply time-series forecasting techniques using the Google Cloud Platform. It isn't a general time-series forecasting course, but a brief tour of the concepts may be helpful for our users.

Time Series Data

First, what is a time series? It's a dataset with data recorded at regular time intervals. A time-series dataset contains both time and at least one variable that is dependent on time.

Temperature over time in regions of the American West

Date	City (K)	Forest (K)	Desert (K)
Apr 2013	290	260	280
May 2013	290	270	290
Jun 2013	270	290	310
Jul 2013	270	290	310
Aug 2013	300	290	310
Sep 2013	290	270	300
Oct 2013	270	260	290
Nov 2013	270	260	280
Dec 2013	260	270	250
Jan 2014	270	270	250

Components

A time-series can be decomposed into components:

- Trend: moves up or down in a reasonably predictable pattern
- Seasonal: repeats over a specific period such as a day, week, month, season, etc.
- Random: residual fluctuations

There can be multiple layers of seasonality. For example, a call center might see a pattern in call volume on certain days of the week as well as on given months. The residual might be able to be explained by other variables besides

Next

Time Series Forecasting with the Cloud AI Platform and BQML

121 mins remaining English R

3. Setup your Notebook environment

Now that we have gone through a brief introduction to the data, let's now set up our model development environment.

Step 1: Enable APIs

The BigQuery connector uses the BigQuery Storage API. Search for the **BigQuery Storage API** in the console and enable the API if it is currently disabled.

Step 2: Create an AI Platform Notebooks instance

Navigate to the [AI Platform Notebooks section](#) of your Cloud Console and click **New Instance**. Then select the latest TensorFlow Enterprise 2.x instance type without GPUs.

Use the default options and then click **Create**. Once the instance has been created, select **Open JupyterLab**.

Next

console.cloud.google.com/marketplace/product/google/bigquerystorage.googleapis.com?q=search&referrer=search&authuser=...

Apps Docs | Jérôme Jag... CatsWhoCode.com SOA Governance JREAM | JQuery V... Watch Live Indian... Times Now Live | ... Zoom TV Live | W... Suvarna News 24...

Google Cloud Platform LegalPA

BigQuery Storage API

Google

MANAGE API Enabled

OVERVIEW PRICING DOCUMENTATION

Overview

About Google

Google's mission is to organize the world's information and make it universally accessible and useful. Through products and platforms like Search, Maps, Gmail, Android, Google Play, Chrome and YouTube, Google plays a meaningful role in the daily lives of billions of people.

Additional details

Type: APIs & services
Last updated: 12/9/19
Service name: bigquerystorage.googleapis.com

console.cloud.google.com/ai-platform/notebooks/list/instances?utm_campaign=CDR_kwe_aiml_time-series-forecastin...

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Filter Enter property

R 3.6 Includes basic R packages, scikit-learn, pandas, NLTK and more

Python 3 Includes scikit-learn, pandas and more

Python 3 (CUDA Toolkit 11.0) Optimized for NVIDIA GPUs

TensorFlow Enterprise 1.15 Includes Keras, scikit-learn, pandas, NLTK and more

TensorFlow Enterprise 2.1 Includes Keras, scikit-learn, pandas, NLTK and more

TensorFlow Enterprise 2.3 Includes Keras, scikit-learn, pandas, NLTK and more

TensorFlow 2.4 Includes Keras, scikit-learn, pandas, NLTK and more

PyTorch 1.7 Includes scikit-learn, pandas, NLTK and more

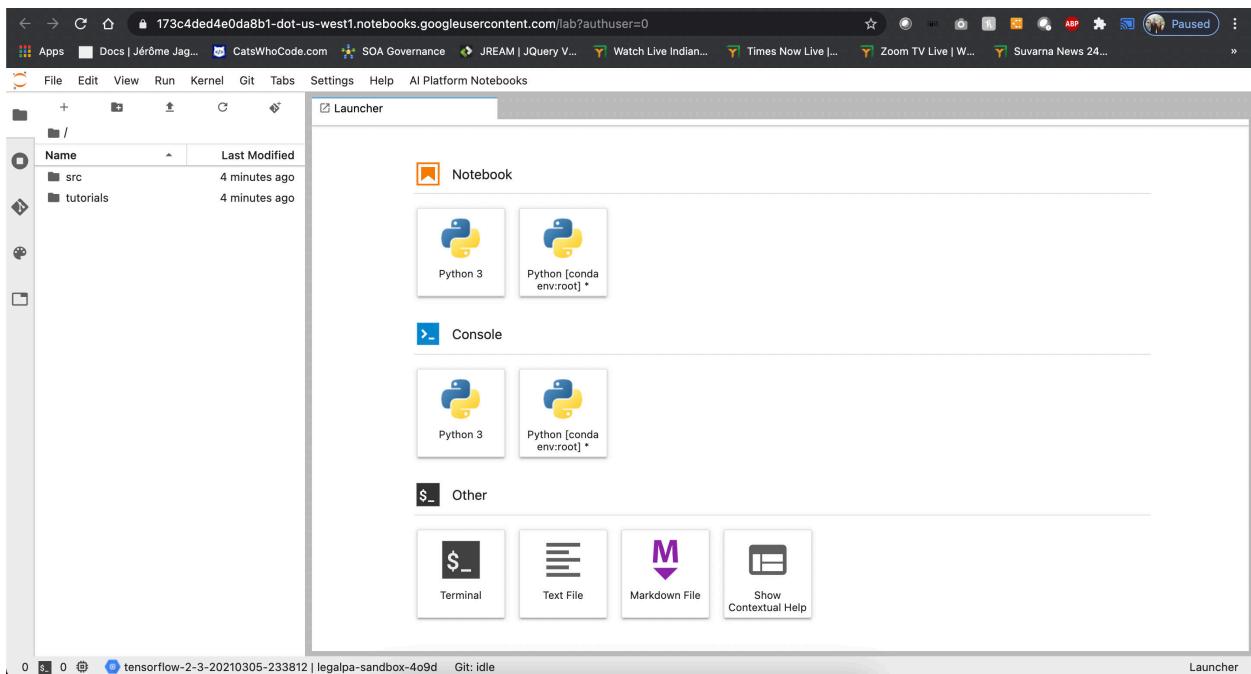
RAPIDS XGBoost [EXPERIMENTAL] Optimized for NVIDIA GPUs

Kaggle Python [BETA] Python image for Kaggle Notebooks, supporting hundreds of machine learning libraries popular on Kaggle

Smart Analytics Frameworks Bioconductor, Apache Beam, Apache Code, Apache Hadoop, and more

INFO PANEL DOCUMENTATION LABELS

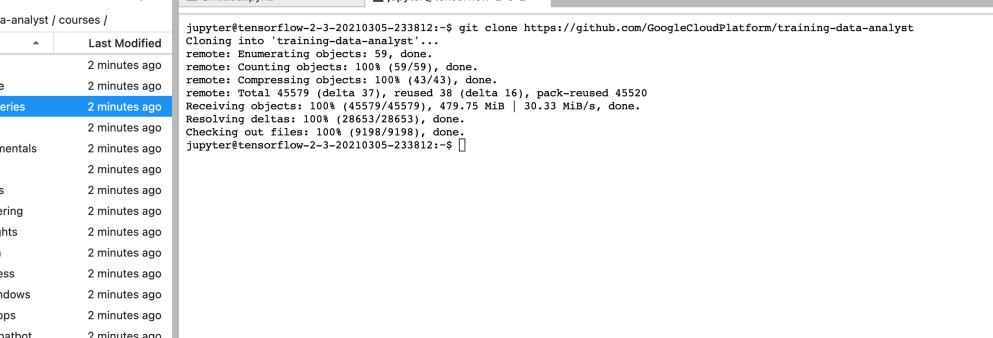
Notebook instances [Notebook API](#)



This screenshot shows a Google Cloud Codelab for 'Time Series Forecasting with the Cloud AI Platform and BQML'. The left sidebar lists steps from 1 to 9: Overview, Introduction to Time-Series Forecasting, Setup your Notebook environment, Explore and Visualize Data (which is currently selected), Create a Model with BigQuery Time Series Forecasting, Build a Custom Forecasting Model, Train and Predict in the Cloud, Challenge, and Cleanup. The main content area is titled '4. Explore and Visualize Data' and contains instructions for creating a query, filling missing values, visualizing data, and decomposing time-series into trend and seasonal components. It also provides a 'Step 1' section with instructions to navigate to a notebook and run cells. A 'Back' button is at the bottom left and a 'Next' button is at the bottom right. A timer in the top right corner shows '116 mins remaining'.

A screenshot of a Jupyter Notebook interface. On the left is a sidebar with a file tree showing a directory structure with 'src' and 'tutorials' folders and an 'Untitled.ipynb' file. The main area shows a terminal window with the command: `jupyter@tensorflow-2-3-20210305-233812:~$ git clone https://github.com/GoogleCloudPlatform/training-data-analyst`. At the bottom, there are tabs for 'tensorflow-2-3-20210305-233812 | legalpa-sandbox-409d' and 'Git: idle'.

A screenshot of a Google Cloud Platform tutorial page titled "Time Series Forecasting with the Cloud AI Platform and BQML". The left sidebar lists steps: 1. Overview, 2. Introduction to Time-Series Forecasting, 3. Setup your Notebook environment, 4. Explore and Visualize Data, 5. Create a Model with BigQuery Time Series Forecasting (which is currently selected), 6. Build a Custom Forecasting Model, 7. Train and Predict in the Cloud, 8. Challenge, and 9. Cleanup. The main content area is titled "5. Create a Model with BigQuery Time Series Forecasting". It includes a sub-section "Step 1" with instructions to import data into a BigQuery table, create a model using BQML syntax, evaluate parameters, and forecast. It also includes "Step 2" instructions to upload CSV data to BigQuery. A screenshot of the Google Cloud Platform interface shows the search bar with "bigquery" and a "Next" button. The top right corner shows a timer for "101 mins remaining" and a language dropdown set to "English".



The screenshot shows a Jupyter Notebook interface with a terminal window open. The terminal window title is "Untitled.ipynb" and the tab title is "jupyter@tensorflow-2-3-2". The terminal output shows the process of cloning a GitHub repository:

```
jupyter@tensorflow-2-3-20210305-233812:~$ git clone https://github.com/GoogleCloudPlatform/training-data-analyst
Cloning into 'training-data-analyst'...
remote: Enumerating objects: 59, done.
remote: Counting objects: 100% (59/59), done.
remote: Compressing objects: 100% (43/43), done.
remote: Total 45579 (delta 37), reused 38 (delta 16), pack-reused 45520
Receiving objects: 100% (45579/45579), 479.75 MiB | 30.33 MiB/s, done.
Resolving deltas: 100% (28653/28653), done.
Checking out files: 100% (9198/9198), done.
jupyter@tensorflow-2-3-20210305-233812:~$
```

The screenshot shows a Jupyter Notebook interface with the following details:

- Header:** The URL is `173c4ded40da8b1-dot-us-west1.notebooks.googleusercontent.com/lab?authuser=0`. The browser tabs include "Apps", "Docs | Jérôme Jag...", "CatsWhoCode.com", "SOA Governance", "JREAM | JQuery V...", "Watch Live Indian...", "Times Now Live | ...", "Zoom TV Live | W...", and "Suvarna News 24...".
- Left Sidebar:** Shows a file tree under `/.../ai-for-time-series / notebooks /`. The files listed are `Name` and `Last Modified`:
 - `data` 7 minutes ago
 - `01-explore.ipynb` a minute ago
 - `02-model.ipynb` 7 minutes ago
 - `03-cloud-training.ip...` 7 minutes ago
 - `cta_ridership.csv` seconds ago
- Kernel:** TensorFlow 2.3-rc1
- Code Editor:** The notebook contains the following code cells:
 - [3]:

```
from pandas.plotting import register_matplotlib_converters
from statsmodels.graphics.tsplots import plot_acf
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.tsa.stattools import grangercausalitytests

import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
```
 - [4]:

```
# Enter your project and region. Then run the cell to make sure the
# Cloud SDK uses the right project for all the commands in this notebook.

PROJECT = 'LegalPA' # REPLACE WITH YOUR PROJECT NAME
REGION = 'us-central-1' # REPLACE WITH YOUR REGION e.g. us-central

#Don't change the following command - this is to check if you have changed the project name above.
assert PROJECT != 'your-project-name', 'Don't forget to change the project variables!'
```
 - [5]:

```
target = 'total_rides' # The variable you are predicting
target_description = 'Total Rides' # A description of the target variable
features = {'day_type': 'Day Type'} # Weekday = W, Saturday = A, Sunday/Holiday = U
ts_col = 'service_date' # The name of the column with the date field
```

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

Untitled.ipynb x jupyter@tensorflow-2-3-2 x 01-explore.ipynb x Python 3

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

[12]: # Explore total rides over time
sns.lineplot(data=df, x=df.index, y=df[target]).set_title('Total Rides')
fig = plt.show()
```

```
[13]: # Explore rides by day type: Weekday (W), Saturday (A), Sunday/Holiday (U)
sns.lineplot(data=df, x=df.index, y=df[target], hue=df['day_type']).set_title('Total Rides by Day Type')
fig = plt.show()
```

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

Untitled.ipynb x jupyter@tensorflow-2-3-2 x 01-explore.ipynb x Python 3

TODO 2: Review summary statistics

- How many records are in the dataset?
- What is the average # of riders per day?

```
[15]: df[target].describe().apply(lambda x: round(x))

[15]: count    6939
       mean    1368761
       std     391443
       min     222071
       25%    1005394
       50%    1548343
       75%    2049517
       max    2849519
Name: total_rides, dtype: int64
```

TODO 3: Explore seasonality

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

```
[16]: # 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])

[16]: 1.00
      1.25
      1.50
      1.75
      2.00
```

Untitled.ipynb jupyter@tensorflow-2-3-2 01-explore.ipynb Python 3

```
[17]: # 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])

[18]: # Decompose the data into trend and seasonal components
result = seasonal_decompose(df[target], period=365)
fig = result.plot()
```

Untitled.ipynb jupyter@tensorflow-2-3-2 01-explore.ipynb Python 3

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

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).

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.

```
[20]: 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:

- Create a query that groups data into a time series
- Visualize data
- Decompose time series into trend and seasonal components

Creating the data set

Google Cloud Platform - LegalPA

Search products and resources

FEATURES & INFO SHORTCUT HIDE PREVIEW FEATURES

Explorer + ADD DATA

Type to search

Viewing pinned projects.

legalpa-sandbox-4o9d

Resources in this project

Use the Explorer panel to view your data, or create a new Dataset option above.

Dataset ID: legalpa-sandbox-4o9d

Data location (Optional): Default

Default table expiration: Never

Encryption: Google-managed key

Create dataset Cancel

ct_a_ridership.csv Show All

This screenshot shows the Google Cloud Platform BigQuery interface. On the left, the 'Explorer' panel is visible, showing a pinned project 'legalpa-sandbox-4o9d'. In the center, a modal window titled 'Create dataset' is open, allowing the user to define a dataset ID ('legalpa-sandbox-4o9d'), data location ('Default'), and default table expiration ('Never'). The encryption section shows 'Google-managed key' selected. At the bottom right of the modal are 'Create dataset' and 'Cancel' buttons. Below the modal, a file named 'ct_a_ridership.csv' is listed in the main pane, along with a 'Show All' button.

Create a new table

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Explorer + ADD DATA

Type to search

Viewing pinned projects.

legalpa-sandbox-4o9d:demo

Description: None

Dataset info

Dataset ID	legalpa-sandbox-4o9d:demo
Created	Mar 6, 2021, 12:00:13 AM
Default table expiration	Never
Last modified	Mar 6, 2021, 12:00:13 AM
Data location	US

Create table

Source: Create table from: Empty table

Destination: Search for a project: LegalPA Project name: LegalPA Dataset name: demo Table type: Native table

Table name: Letters, numbers, and underscores allowed

Schema: Edit as text

+ Add field

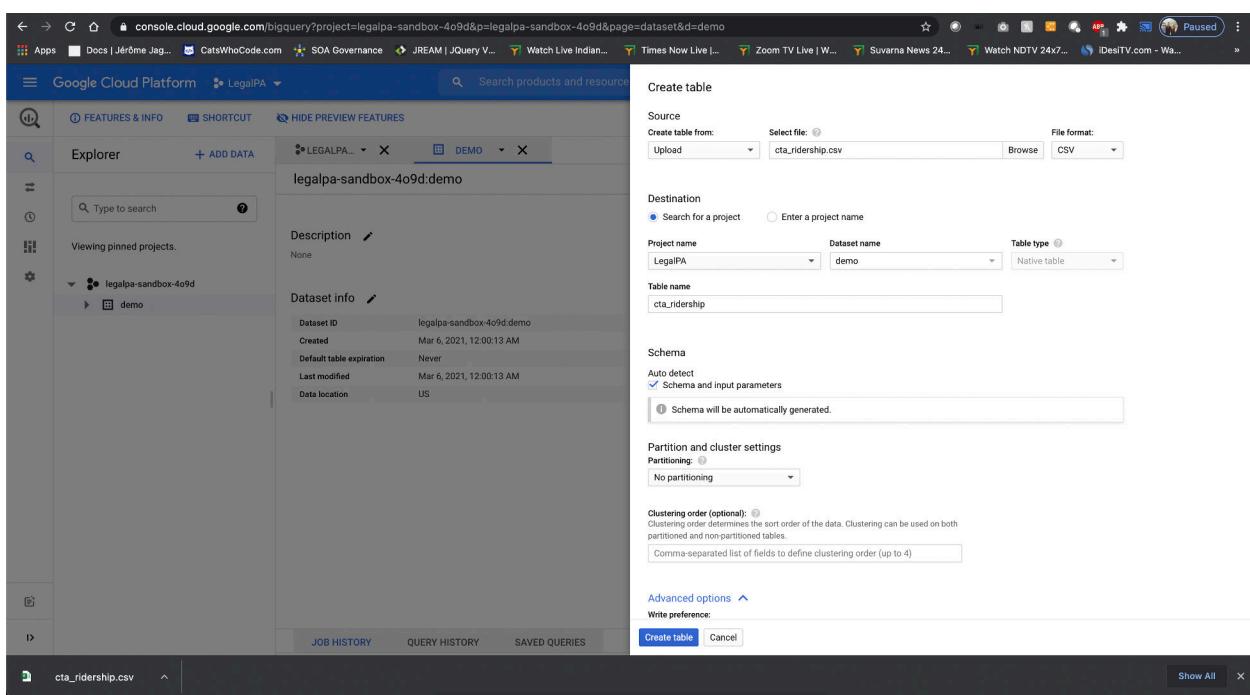
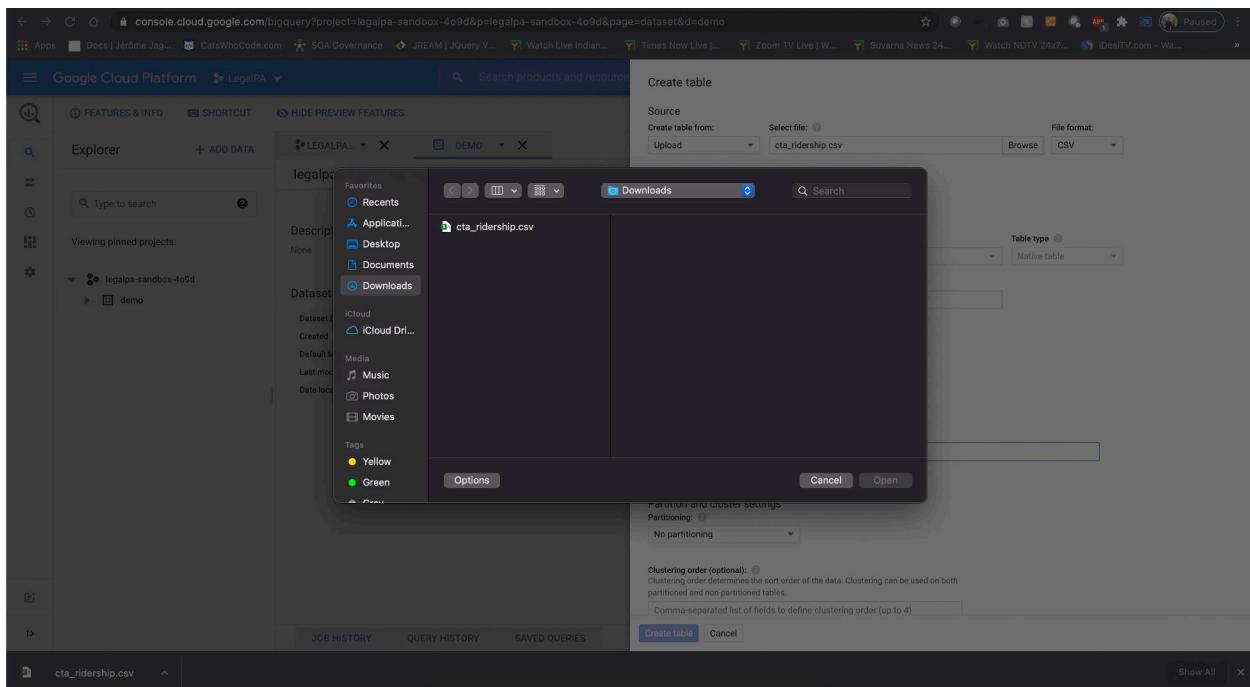
Partition and cluster settings: Partitioning: No partitioning

Clustering order (optional): Comma-separated list of fields to define clustering order (up to 4)

Create table Cancel

ct_a_ridership.csv Show All

This screenshot shows the Google Cloud Platform BigQuery interface. On the left, the 'Explorer' panel is visible, showing a pinned project 'legalpa-sandbox-4o9d' and a dataset 'demo' within it. In the center, a modal window titled 'Create table' is open, allowing the user to define the source ('Empty table'), destination ('Search for a project: LegalPA'), table name ('demo'), and schema ('Edit as text'). The 'Partition and cluster settings' section shows 'No partitioning'. At the bottom right of the modal are 'Create table' and 'Cancel' buttons. Below the modal, a file named 'ct_a_ridership.csv' is listed in the main pane, along with a 'Show All' button.



Google Cloud Platform - LegalPA

Search products and resources

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Explorer + ADD DATA

Type to search

Viewing pinned projects.

legalpa-sandbox-409d

demo

cta_ridership

cta_ridership_model

RUN SAVE SCHEDULE MORE

CREATE OR REPLACE MODEL `demo.cta_ridership_model` OPTIONS(MODEL_TYPE='ARIMA', TIME_SERIES_TIMESTAMP_COL='service_date', TIME_SERIES_DATA_COL='total_rides', HOLIDAY_REGION='us') AS

SELECT service_date, total_rides

FROM `demo.cta_ridership`

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

Query results

Query complete (2 min 50 sec elapsed, 4.4 MB (ML) processed)

Job information Results Execution details

Query completed in 2 min 12:05 AM

This query processes ML bytes, and is charged differently than other queries. [Learn more](#)

Open query in editor

JOB HISTORY QUERY HISTORY SAVED QUERIES

cta_ridership.csv Show All

```
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
7   SELECT
8     service_date, total_rides
9   FROM
10    `demo.cta_ridership`
```

Google Cloud Platform - LegalPA

Search products and resources

FEATURES & INFO SHORTCUT HIDE PREVIEW FEATURES

Explorer + ADD DATA

Type to search

Viewing pinned projects.

legalpa-sandbox-409d

demo

cta_ridership

cta_ridership_model

RUN SAVE SCHEDULE MORE

CREATE OR REPLACE MODEL `demo.cta_ridership_model` OPTIONS(MODEL_TYPE='ARIMA', TIME_SERIES_TIMESTAMP_COL='service_date', TIME_SERIES_DATA_COL='total_rides', HOLIDAY_REGION='us') AS

SELECT service_date, total_rides

FROM `demo.cta_ridership`

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

Query results

Query complete (2 min 50 sec elapsed, 4.4 MB (ML) processed)

Job information Results Execution details

Elapsed time	Slot time consumed	Stages	Training Iterations
2 min 50 sec	18 min 55.432 sec	<ul style="list-style-type: none">Preprocess 20.170 secTrain 1 min 23.733 secEvaluate 1 min 5.487 sec	Completed: 1 Planned: 20

Loss Duration (seconds)

JOB HISTORY QUERY HISTORY SAVED QUERIES

cta_ridership.csv Show All

```
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
7   SELECT
8     service_date, total_rides
9   FROM
10    `demo.cta_ridership`
```

Model Details

Model ID	legalpa-sandbox-4o9d.demo.cta_ridership_model
Description	
Labels	
Date created	Saturday, March 6, 2021 at 12:07:58 AM GMT-08:00
Model expiration	Never
Date modified	Saturday, March 6, 2021 at 12:07:58 AM GMT-08:00
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
Auto Arima Max Order	5

Step 4

```

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

Query results

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	2.122628591786644E9	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

Step5:

Google Cloud Platform - LegalPA - console.cloud.google.com/bigquery?project=legalpa-sandbox-409d

Search products and resources

Explorer + ADD DATA

Query results

```

3   FROM
4     ML.EVALUATE(MODEL `demo.cta_ridership_model`);
5
6
7   > SELECT:-
8     FROM
9       ML.PREDICT(MODEL `demo.cta_ridership_model`,
10      STRUCT(7 AS horizon))
11

```

Job information: **Results** JSON Execution details

Row	forecast_timestamp	forecast_value	standard_error	confidence_level	prediction_interval_lower_bound	prediction_interval_upper_bound	confidence_interval_lower_bound	confidence_interval_upper_bound
1	2020-01-01 00:00:00 UTC	662436.4424369269	46059.49014554253	0.95	572322.980240453	752549.9046334007	572322.980240453	752549.9046334007
2	2020-01-02 00:00:00 UTC	1029641.4669424891	46276.328347693256	0.95	939103.76989082	1120179.1639941582	939103.76989082	1120179.1639941582
3	2020-01-03 00:00:00 UTC	1201660.2034356925	47233.43871922012	0.95	1109249.9600529654	1294070.4468184195	1109249.9600529654	1294070.4468184195
4	2020-01-04 00:00:00 UTC	651095.9776391207	48157.99332862347	0.95	556876.881095747	745315.8736866666	556876.881095747	745315.8736866666
5	2020-01-05 00:00:00 UTC	467394.9184664497	48621.5096380497	0.95	372268.97250121285	562520.8644317171	372268.97250121285	562520.8644317171
6	2020-01-06 00:00:00 UTC	1158999.319539823	48869.23710364581	0.95	1063388.705171438	1254609.9339082083	1063388.705171438	1254609.9339082083
7	2020-01-07 00:00:00 UTC	1127789.5651062205	49011.66149084522	0.95	1031900.3033930386	1223678.8268194026	1031900.3033930386	1223678.8268194026

JOB HISTORY QUERY HISTORY SAVED QUERIES

ct_a_ridership.csv

Create a new Bucket

Google Cloud Platform - LegalPA - console.cloud.google.com/storage/browser/legalpa-bucket1;tab=objects?project=legalpa-sandbox-409d&prefix=&forceOnObjectsSortingFiltering=false

Storage

legalpa-bucket1

OBJECTS CONFIGURATION PERMISSIONS RETENTION LIFECYCLE

Buckets > legalpa-bucket1

UPLOAD FILES UPLOAD FOLDER CREATE FOLDER MANAGE HOLDS DOWNLOAD DELETE

Filter by name prefix only ▾ Filter objects and folders

Name	Size	Type	Created time	Storage class	Last modified	Public access	Encryption	Retention expiration date	Holds
No rows to display									

ct_a_ridership.csv

The screenshot shows the Google Cloud Platform Storage interface. On the left, a sidebar lists 'Storage', 'Browser', 'Monitoring', and 'Settings'. The main area is titled 'Bucket details' for 'legalpa-bucket1'. It has tabs for 'OBJECTS', 'CONFIGURATION' (which is selected), 'PERMISSIONS', 'RETENTION', and 'LIFECYCLE'. Under 'CONFIGURATION', there are fields for 'Created' (March 6, 2021 at 12:26:19 AM GMT-8), 'Updated' (March 6, 2021 at 12:26:19 AM GMT-8), 'Location Type' (Region), 'Location' (us-central1 (Iowa)), 'Default storage class' (Standard), 'Encryption type' (Google-managed key), 'Requester pays' (OFF), 'Access control' (Fine-grained), 'Labels' (None), 'Link URL' (https://console.cloud.google.com/storage/browser/legalpa-bucket1), and 'Link for gsutil' (gs://legalpa-bucket1). At the bottom, there's a 'Release Notes' section and a file list containing 'cta_ridership.csv'.

Building a Custom Forecasting Model

The screenshot shows a Jupyter Notebook interface with multiple tabs: 'Untitled.ipynb', 'jupyter@tensorflow-2-3-2', '01-explore.ipynb', and '02-model.ipynb' (selected). The notebook contains the following content:

```

Overview
This notebook demonstrates how to sequence data for a time-series problem, and then how to build deep learning and statistical models.

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
Restarting the kernel may be required to use new packages.

[30]: pip install -U statsmodels scikit-learn --user
Requirement already satisfied: statsmodels in /opt/conda/lib/python3.7/site-packages (0.12.2)
Requirement already satisfied: scikit-learn in /opt/conda/lib/python3.7/site-packages (0.24.1)
Requirement already satisfied: threadpoolctl>=2.0.0 in /opt/conda/lib/python3.7/site-packages (from scikit-learn) (2.1.0)
Requirement already satisfied: numpy==1.13.3 in /opt/conda/lib/python3.7/site-packages (from scikit-learn) (1.19.5)
Requirement already satisfied: scipy==0.19.1 in /opt/conda/lib/python3.7/site-packages (from scikit-learn) (1.6.0)
Requirement already satisfied: joblib==0.11 in /opt/conda/lib/python3.7/site-packages (from scikit-learn) (1.0.1)
Requirement already satisfied: pandas==0.21.2 in /opt/conda/lib/python3.7/site-packages (from statsmodels) (1.2.2)
Requirement already satisfied: python-dateutil>=2.7.3 in /opt/conda/lib/python3.7/site-packages (from pandas>=0.21-->statsmodels) (2.8.1)
Requirement already satisfied: pytz>=2017.3 in /opt/conda/lib/python3.7/site-packages (from pandas>=0.21-->statsmodels) (2021.1)
Requirement already satisfied: six in /opt/conda/lib/python3.7/site-packages (from patsy==0.5-->statsmodels) (1.15.0)
Note: you may need to restart the kernel to use updated packages.

Note: To restart the Kernel, navigate to Kernel > Restart Kernel... on the Jupyter menu.

Import libraries and define constants
[31]: import os

```

At the bottom, it shows 'Mode: Command' and 'Ln 1, Col 1 02-model.ipynb'.

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

Untitled.ipynb x jupyter@tensorflow-2-3-2 x 01-explore.ipynb x 02-model.ipynb Python 3

```

from sklearn.preprocessing import StandardScaler
from statsmodels.tsa.holtwinters import ExponentialSmoothing
from tensorflow.keras import Sequential
from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras.layers import Conv1D, Dense, Dropout, Flatten, LSTM, MaxPooling1D
register_matplotlib_converters() # Address warning

[32]: # Enter your project, region, and a bucket name. Then run the cell to make sure the
# Cloud SDK uses the right project for all the commands in this notebook.

PROJECT = 'legalpa' # REPLACE WITH YOUR PROJECT ID
BUCKET = 'legalpa-bucket1' # REPLACE WITH A UNIQUE BUCKET NAME e.g. your PROJECT NAME
REGION = 'us-central1' # REPLACE WITH YOUR BUCKET REGION e.g. us-central1
BUCKET_URL = 'gs://' + BUCKET

#Don't change the following command - this is to check if you have changed the project name above.
assert PROJECT != 'your-project-name', 'Don''t forget to change the project variables!'

[33]: # Dataset parameters

target_col = 'total_rides' # The variable you are predicting
ts_col = 'service_date' # The name of the column with the date field

[34]: # Model parameters

freq = 'D' # Daily frequency
n_input_steps = 30 # Lookback window
n_output_steps = 7 # How many steps to predict forward
n_seasons = 7 # Monthly periodicity

train_split = 0.8 # % Split between train/test data
epochs = 1000 # How many passes through the data (early-stopping will cause training to stop before this)
patience = 5 # Terminate training after the validation loss does not decrease after this many epochs

```

Create a Cloud Storage bucket

The following steps are required, regardless of your notebook environment.

When you submit a training job using the Cloud SDK, you upload a Python package containing your training code to a Cloud Storage bucket. AI Platform runs the code from this package. In this tutorial, AI Platform also saves the trained model that results from your job in the same bucket. You can then create an AI Platform model version based on this output in order to

Mode: Command L1, Col 1 02-model.ipynb

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```

Load data

[36]: 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}'

[37]: # Read data

df = pd.read_csv(input_file, index_col=ts_col, parse_dates=True)
df.index.freq = freq
df.head()

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

[38]: # 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)

[39]: # 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()

[39]: total_rides

```

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TODO 1: Remove outliers

- Sometimes, you can improve the accuracy of the model by removing outliers.
- In this lab, you'll simply remove some extremely high values.
- You can also apply techniques such as smoothing or resampling the frequency to reduce the impact of outliers.

```
[40]: df_train
[40]: total_rides
service_date
2001-01-01 423647
2001-01-02 1282779
2001-01-03 1361355
2001-01-04 1420032
2001-01-05 1448343
...
2016-03-09 1650991
2016-03-10 1668771
2016-03-11 1684576
2016-03-12 1147428
2016-03-13 635332
5551 rows × 1 columns
```

```
[41]: # Look at the highest peak. What level could you set a threshold that would clip this off?
sns.lineplot(data=df_train[target_col])
```

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```
[42]: service_date
2008-07-03 2049519
2016-11-04 1945417
2008-11-04 1938738
2012-10-03 1926454
2008-10-01 1922280
Name: total_rides, dtype: int64
```

```
[49]: # TODO: Update the threshold below to remove the outliers
threshold = 3052280 # Set this just below the level you are seeing peaks. It will flag any values above it.
assert threshold != -1, 'Set the threshold to the minimum that will eliminate outlier(s)'

# Set any values above the threshold to NaN (not a number)
df_train.loc[df_train[target_col] > threshold, target_col] = np.nan

# Interpolate the missing values (e.g. [3, NaN, 5] becomes [3, 4, 5])
df_train = df_train.interpolate()
```

```
[50]: # Review the updated chart to see if outliers still exist
# NOTE: If you set the threshold too low, rerun starting from the
sns.lineplot(data=df_train[target_col])
```

Mode: Command ↻ Ln 1, Col 1 02-model.ipynb

Scale the inputs and outputs

```
[51]: # For neural networks to converge quicker, it is helpful to scale the values.
# For example, each feature might be transformed to have a mean of 0 and std. dev. of 1.
#
# You are working with a mix of features, input timesteps, output horizon, etc.
# which don't work out-of-the-box with common scaling utilities.
# So, here are a couple wrappers to handle scaling and inverting the scaling.

feature_scaler = StandardScaler()
target_scaler = StandardScaler()

def scale(df,
          fit=True,
          target_col=target_col,
          feature_scaler=feature_scaler,
          target_scaler=target_scaler):
    """
    Scale the input features, using a separate scaler for the target.

    Parameters:
    df (pd.DataFrame): Input dataframe
    fit (bool): Whether to fit the scaler to the data (only apply to training data)
    target_col (pd.Series): The column that is being predicted
    feature_scaler (StandardScaler): Scaler used for features
    target_scaler (StandardScaler): Scaler used for target

    Returns:
    df_scaled (pd.DataFrame): Scaled dataframe
    """

    target = df[target_col].values.reshape(-1, 1)
    if fit:
        target_scaler.fit(target)
    target_scaled = target_scaler.transform(target)

    # Select all columns other than target to be features
    features = df.loc[:, df.columns != target_col].values

    if features.shape[1] == 1: # If there are any features
        if fit:
            feature_scaler.fit(features)

    feature_scaler = StandardScaler()
    feature_scaler.fit(features)
```

Create sequences of time-series data

```
[52]: def reframe(data, n_input_steps = n_input_steps, n_output_steps = n_output_steps, target_col = target_col):
    target_col_num = data.columns.get_loc(target_col)

    # Iterate through data and create sequences of features and outputs
    df = pd.DataFrame(data)
    cols = []
    for i in range(n_input_steps, 0, -1):
        cols.append(df.shift(i))
    for i in range(0, n_output_steps):
        cols.append(df.shift(-i))

    # Concatenate values and remove any missing values
    df = pd.concat(cols, axis=1)
    df.dropna(inplace=True)

    # Split the data into feature and target variables
    n_feature_cols = n_input_steps * n_features
    features = df.iloc[:, 0:n_feature_cols]
    target_cols = [i for i in range(n_feature_cols + target_col_num, n_feature_cols + n_output_steps * n_features, n_features)]
    targets = df.iloc[:, target_cols]

    return (features, targets)

X_train_reframed, y_train_reframed = reframe(df_train_scaled)
X_test_reframed, y_test_reframed = reframe(df_test_scaled)
```

Evaluate results

```
[53]: def print_stats(timestep, y_true, y_pred, target_col, chart=True, table=False, dec=3):
    ...
    Helper function to print overall summary statistics and stats for each time step
    ...

    # Print summary statistics
    print('==' + timestep + '===')
    print('R2: ' + str(np.round(r2_score(y_true, y_pred), dec)))
    print('MAPE: ' + str(np.round(mean_absolute_percentage_error(y_true, y_pred), dec)))
    print('MAE: ' + str(np.round(mean_absolute_error(y_true, y_pred), dec)))
    ...
```

ML: Long Short Term Memory (LSTM) Model

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ML Models

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

Long Short Term Memory (LSTM)

```
[54]: # Reshape test data to match model inputs and outputs
X_train = X_train_reframed.values.reshape(-1, n_input_steps, n_features)
X_test = X_test_reframed.values.reshape(-1, n_input_steps, n_features)
y_train = y_train_reframed.values.reshape(-1, n_output_steps, 1)
y_test = y_test_reframed.values.reshape(-1, n_output_steps, 1)
```

TODO 2: Update the LSTM architecture

Try increasing and decreasing the number of LSTM units and see if you notice any accuracy improvements. You can use hyper-parameter tuning to search for optimal values, but that's outside the scope of this lab.

```
[55]: # 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 [=====] - 12s 60ms/step - loss: 0.6372 - val_loss: 0.4089
Epoch 2/1000
173/173 [=====] - 11s 64ms/step - loss: 0.3087 - val_loss: 0.2493
Epoch 3/1000
173/173 [=====] - 10s 60ms/step - loss: 0.2351 - val_loss: 0.2364
Epoch 4/1000
173/173 [=====] - 11s 64ms/step - loss: 0.2259 - val_loss: 0.2335
Epoch 5/1000
173/173 [=====] - 11s 64ms/step - loss: 0.2232 - val_loss: 0.2306
```

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

WARNING:tensorflow:From /opt/conda/lib/python3.7/site-packages/tensorflow/python/training/tracking/tracking.py:111: Model.state_updates (from tensorflow.python.keras.engine.training) is deprecated and will be removed in a future version.
Instructions for updating:
This property should not be used in TensorFlow 2.0, as updates are applied automatically.
WARNING:tensorflow:From /opt/conda/lib/python3.7/site-packages/tensorflow/python/training/tracking/tracking.py:111: Layer.updates (from tensorflow.python.keras.engine.base_layer) is deprecated and will be removed in a future version.
Instructions for updating:
This property should not be used in TensorFlow 2.0, as updates are applied automatically.
INFO:tensorflow:Assets written to: ./lstm_export/assets

```
[57]: # 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(1-7) ===
R^2: 0.79
MAPE: 0.097
MAE: 84497.504

== t+1 ===
R^2: 0.848
MAPE: 0.08
MAE: 66690.304
```

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Convolutional Neural Network (CNN) Model

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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)

```
[58]: 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 5ms/step - loss: 0.3070 - val_loss: 0.2507
Epoch 2/1000
173/173 [=====] - 1s 4ms/step - loss: 0.2487 - val_loss: 0.2540
Epoch 3/1000
173/173 [=====] - 1s 4ms/step - loss: 0.2467 - val_loss: 0.2474
Epoch 4/1000
173/173 [=====] - 1s 4ms/step - loss: 0.2462 - val_loss: 0.2460
Epoch 5/1000
173/173 [=====] - 1s 3ms/step - loss: 0.2451 - val_loss: 0.2486
Epoch 6/1000
173/173 [=====] - 1s 3ms/step - loss: 0.2448 - val_loss: 0.2467
Epoch 7/1000
173/173 [=====] - 1s 3ms/step - loss: 0.2450 - val_loss: 0.2455
Epoch 8/1000
173/173 [=====] - 1s 3ms/step - loss: 0.2443 - val_loss: 0.2467
Epoch 9/1000
173/173 [=====] - 1s 3ms/step - loss: 0.2435 - val_loss: 0.2486
Epoch 10/1000
173/173 [=====] - 1s 4ms/step - loss: 0.2437 - val_loss: 0.2459
Epoch 11/1000
173/173 [=====] - 1s 3ms/step - loss: 0.2438 - val_loss: 0.2496
Epoch 12/1000
173/173 [=====] - 1s 4ms/step - loss: 0.2425 - val_loss: 0.2461

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```
[59]: model.save('./cnn_export/')

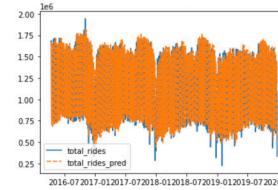
INFO:tensorflow:Assets written to: ./cnn_export/assets
```

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

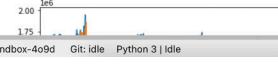
evaluate(y_pred_cnn)
```

==== t+1 ====
R²: 0.767
MAPE: 0.183
MAE: 96931.467

==== t+1 ====
R²: 0.805
MAPE: 0.092
MAE: 89192.999



==== t+2 ====
R²: 0.768
MAPE: 0.101
MAE: 95170.767



Mode: Edit Ln 1, Col 1 02-model.ipynb

Naïve Model

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.

```
[61]: from statsmodels.tsa.arima.model import ARIMA
ist = df_train[target_col].copy() # Predict based on historical data. Start with the training data
ist.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
pred_rw = 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

for t in range(n_pred):
    mod = ARIMA(ist,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 the next model
hist.index.freq = pd.infer_freq(hist.index)

evaluate(y_pred_rw, 0)

```

== t+1-7 ==
R²: -0.034
MAPE: 0.366
MAE: 364578.376

== t+1 ==
R²: -0.19
MAPE: 0.257
MAE: 269441.826



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Seasonal Naïve

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.

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.

```
[63]: from statsmodels.tsa.statespace.sarimax import SARIMAX
ist = df_train[target_col].copy() # Predict based on historical data. Start with the training data
ist.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
pred_sn = 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

for t in range(n_pred):
    mod = SARIMAX(ist,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 the next model
hist.index.freq = pd.infer_freq(hist.index)

evaluate(y_pred_sn, 0)

```

== t+1-7 ==
R²: 0.675
MAPE: 0.11
MAE: 188722.34

== t+1 ==
R²: 0.676
MAPE: 0.11
MAE: 188556.529



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Exponential Smoothing

Exponential Smoothing

```
[67]: #import warnings
#with warnings.catch_warnings():
#    warnings.simplefilter("ignore", category=ConvergenceWarning)
import warnings
from statsmodels.tools.sm_exceptions import ConvergenceWarning
warnings.simplefilter('ignore', ConvergenceWarning)

# 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 datframe 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

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='h'
    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 = hist.append(df_test.iloc[t].name) # Append the latest test data row to the history, for fitting the next model
        hist.index.freq = pd.infer_freq(hist.index)

[68]: evaluate(y_pred_es, 0)

    == t+1 ==
R^2: 0.767
MAPE: 0.107
MAE: 99483.059

    == t+1 ==
R^2: 0.834
MAPE: 0.095
MAE: 86649.592

1e6
```

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Ensemble ML and Statistical Models

Ensemble ML and Statistical Models

```
[69]: # 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)

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 ==
R^2: 0.811
MAPE: 0.091
MAE: 81367.169

    == t+1 ==
R^2: 0.854
MAPE: 0.078
MAE: 69923.56
```

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Training and Prediction in Cloud

```

import datetime
import googleapiclient.discovery
import os
import time

import numpy as np
import pandas as pd
import tensorflow as tf

from google.api_core.client_options import ClientOptions
from google.cloud import storage
from sklearn.preprocessing import StandardScaler

# Check the TensorFlow version installed
tf.__version__

```

```

2.3.2

```

```

# Enter your project, region, and a bucket name. Then run the cell to make sure the
# Cloud SDK uses the right project for all the commands in this notebook.

PROJECT = 'your-project-name' # REPLACE WITH YOUR PROJECT ID
BUCKET = 'your-bucket-name' # REPLACE WITH A UNIQUE BUCKET NAME e.g. your PROJECT NAME
REGION = 'us-central1' # REPLACE WITH YOUR BUCKET REGION e.g. us-central1
BUCKET_URL = 'gs://' + BUCKET

#Don't change the following command - this is to check if you have changed the project name above.
assert PROJECT != 'your-project-name', 'Don''t forget to change the project variables!'

```

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Name Last Modified

- cnn_export an hour ago
- data 2 hours ago
- Istn_export an hour ago
- trainer 3 minutes ago
- 01-explore.ipynb 2 hours ago
- 02-model.ipynb 23 minutes ago
- 03-cloud-training.ipynb** a minute ago
- cta_ridership.csv 2 hours ago

Create a Cloud Storage bucket

The following steps are required, regardless of your notebook environment.

When you submit a training job using the Cloud SDK, you upload a Python package containing your training code to a Cloud Storage bucket. AI Platform runs the code from this package. In this tutorial, AI Platform also saves the trained model that results from your job in the same bucket. You can then create an AI Platform model version based on this output in order to serve online predictions.

```
[7]: # Training parameters
MODEL_NAME = 'cta_ridership'
FRAMEWORK='TENSORFLOW'
RUNTIME_VERSION = '1.2.3'
PYTHON_VERSION = '3.7'
PREDICTIONS_FILE = 'predictions.json'
```

```
[8]: storage_client = storage.Client()
try:
    bucket = storage_client.get_bucket(BUCKET)
    print('Bucket exists, let''s not recreate it.')
except:
    bucket = storage_client.create_bucket(BUCKET)
    print('Created bucket: ' + BUCKET)
```

Bucket exists, lets not recreate it.

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)
```

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Name Last Modified

- cnn_export an hour ago
- data 2 hours ago
- Istn_export an hour ago
- trainer 3 minutes ago
- 01-explore.ipynb 2 hours ago
- 02-model.ipynb 23 minutes ago
- 03-cloud-training.ipynb** a minute 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
```

service_date	total_rides
2001-01-01	423647
2001-01-02	1282779
2001-01-03	1361355
2001-01-04	1420032
2001-01-05	1448343

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

1 4 tensorflow-2-3-20210305-233812 | legalpa-sandbox-4o9d Git: refreshing... Python 3 | Busy Mode: Command ↻ Ln 1, Col 1 03-cloud-training.ipynb

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

Untitled.ipynb jupyter@tensorflow-2-3-2 01-explore.ipynb 02-model.ipynb 03-cloud-training.ipynb

Scale values

```
[14]: # Review original values
df_train.head()

[14]:
total_rides
service_date
2001-01-01    423647
2001-01-02    1282779
2001-01-03    1361355
2001-01-04    1420032
2001-01-05    1448343

[15]: # For neural networks to converge quicker, it is helpful to scale the values.
# For example, each feature might be transformed to have a mean of 0 and std. dev. of 1.
#
# You are working with a mix of features, input timesteps, output horizon, etc.
# which don't work out-of-the-box with common scaling utilities.
# So, here are a couple wrappers to handle scaling and inverting the scaling.

feature_scaler = StandardScaler()
target_scaler = StandardScaler()

def scale(df,
          fit=True,
          target_col=target_col,
          feature_scaler=feature_scaler,
          target_scaler=target_scaler):
    """
    Scale the input features, using a separate scaler for the target.

    Parameters:
    df (pd.DataFrame): Input dataframe
    fit (bool): Whether to fit the scaler to the data (only apply to training data)
    target_col (pd.Series): The column that is being predicted
    feature_scaler (StandardScaler): Scaler used for features
    target_scaler (StandardScaler): Scaler used for target
    """

    return (df, target_col)
```

1 4 tensorflow-2-3-20210305-233812 | legalpa-sandbox-4o9d Git: idle Python 3 | Busy Mode: Command Ln 1, Col 1 03-cloud-training.ipynb

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

Untitled.ipynb jupyter@tensorflow-2-3-2 01-explore.ipynb 02-model.ipynb 03-cloud-training.ipynb

Create sequences of time series data

```
[17]: def reframe(data, n_input_steps = n_input_steps, n_output_steps = n_output_steps, target_col = target_col):
    target_col_num = data.columns.get_loc(target_col)

    # Iterate through data and create sequences of features and outputs
    df = pd.DataFrame(data)
    cols = []
    for i in range(n_input_steps, 0, -1):
        cols.append(df.shift(i))
    for i in range(0, n_output_steps):
        cols.append(df.shift(-1))

    # Concatenate values and remove any missing values
    df = pd.concat(cols, axis=1)
    df.dropna(inplace=True)

    # Split the data into feature and target variables
    n_feature_cols = n_input_steps * n_features
    features = df.iloc[:, 0:n_feature_cols]
    target_cols = [for i in range(n_feature_cols + target_col_num, n_feature_cols + n_output_steps * n_features, n_features)]
    targets = df.iloc[:, target_col]

    return (features, targets)

X_train_reframed, y_train_reframed = reframe(df_train_scaled)
X_test_reframed, y_test_reframed = reframe(df_test_scaled)
```

Build a model and submit your training job to AI Platform

The model you're building here trains pretty fast so you could train it in this notebook, but for more computationally expensive models, it's useful to train them in the Cloud. To use AI Platform Training, you'll package up your training code and submit a training job to the AI Platform Prediction service.

In your training script, you'll also export your trained `SavedModel` to a Cloud Storage bucket.

Prepare test data

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

1 4 tensorflow-2-3-20210305-233812 | legalpa-sandbox-4o9d Git: refreshing... Python 3 | Busy Mode: Command Ln 1, Col 1 03-cloud-training.ipynb

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

Untitled.ipynb jupyter@tensorflow-2-3-2 01-explore.ipynb 02-model.ipynb 03-cloud-training.ipynb

Prepare test data

```
[18]: # Reshape test data to match model inputs and outputs
X_train = X_train_reframed.values.reshape(-1, n_input_steps, n_features)
X_test = X_test_reframed.values.reshape(-1, n_input_steps, n_features)
y_train = y_train_reframed.values.reshape(-1, n_output_steps)
y_test = y_test_reframed.values.reshape(-1, n_output_steps)

[19]: # Specify directories to be used later
TRAINER_DIR = 'trainer'
EXPORT_DIR = 'tf_export'

[20]: # Create trainer directory if it doesn't already exist
!mkdir $TRAINER_DIR
!touch $TRAINER_DIR/_init__.py

[21]: # Copy numpy arrays to npy files
np.save(TRAINER_DIR + '/x_train.npy', X_train)
np.save(TRAINER_DIR + '/x_test.npy', X_test)
np.save(TRAINER_DIR + '/y_train.npy', y_train)
np.save(TRAINER_DIR + '/y_test.npy', y_test)
```

Prepare model code

```
[22]: # Write training code out to a file that will be submitted to the training job
# Note: f-strings are supported in Python 3.6 and above

model_template = """import argparse
import numpy as np
import os
import tempfile

from google.cloud import storage
from tensorflow import keras
from tensorflow.keras import Sequential
from tensorflow.keras.layers import Dense, LSTM"""

[23]: # Copy the model and training data files to a GCS bucket
!gsutil -m cp -r trainer $BUCKET_URI
```

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

Untitled.ipynb jupyter@tensorflow-2-3-2 01-explore.ipynb 02-model.ipynb 03-cloud-training.ipynb

Copy the model and training data files to a GCS bucket

```
[23]: # Copy the model and training data files to a GCS bucket
!gsutil -m cp -r trainer $BUCKET_URI

Copying file://trainer/_init_.py [Content-Type=text/x-python]...
Copying file://trainer/model.py [Content-Type=text/x-python]...
Copying file://trainer/x_train.npy [Content-Type=application/octet-stream]...
Copying file://trainer/x_test.npy [Content-Type=application/octet-stream]...
Copying file://trainer/y_train.npy [Content-Type=application/octet-stream]...
Copying file://trainer/y_test.npy [Content-Type=application/octet-stream]...
- [6/6 files] 1.9 MiB/ 1.9 MiB 100% Done
Operation completed over 6 objects/1.9 MiB.
```

List the contents of the bucket to ensure they were copied properly

```
[24]: # List the contents of the bucket to ensure they were copied properly
!gsutil ls $BUCKET_URI/TRAINER_DIR
```

Submit training job

```
[25]: # Re-run this if you need to create a new training job
timestamp = str(datetime.datetime.now().time())
JOB_NAME = 'cap_training_' + str(int(time.time()))

[26]: # Set training job parameters
MODULE_NAME = TRAINER_DIR + '.model'
TRAIN_DIR = os.getcwd() + '/' + TRAINER_DIR
JOB_DIR = BUCKET_URI
```

Submit the training job

```
[27]: # Submit the training job
!gcloud ai-platform jobs submit training $JOB_NAME \
--scale-tier basic \
--package-path $TRAIN_DIR \
```

Google Cloud Platform - LegalPA

Storage Bucket details

legalpa-bucket1

OBJECTS CONFIGURATION PERMISSIONS RETENTION LIFECYCLE

Buckets > legalpa-bucket1 > trainer

UPLOAD FILES UPLOAD FOLDER CREATE FOLDER MANAGE HOLDS DOWNLOAD DELETE

Filter by name prefix only Filter objects and folders

Name	Size	Type	Created time	Storage class	Last modified	Public access	Encryption	Retention expiration date	Holds
__init__.py	0 B	text/x-python	Mar 6, 2021, 1:46...	Standard	Mar 6, 2021, 1:46...	Not public	Google-managed key	—	None
model.py	2.3 KB	text/x-python	Mar 6, 2021, 1:46...	Standard	Mar 6, 2021, 1:46...	Not public	Google-managed key	—	None
x_train.npz	317 KB	application/octet-stream	Mar 6, 2021, 1:46...	Standard	Mar 6, 2021, 1:46...	Not public	Google-managed key	—	None
x_train.n	1.3 MB	application/octet-stream	Mar 6, 2021, 1:46...	Standard	Mar 6, 2021, 1:46...	Not public	Google-managed key	—	None
y_train.npz	74.1 KB	application/octet-stream	Mar 6, 2021, 1:46...	Standard	Mar 6, 2021, 1:46...	Not public	Google-managed key	—	None
y_train.n	301.7 KB	application/octet-stream	Mar 6, 2021, 1:46...	Standard	Mar 6, 2021, 1:46...	Not public	Google-managed key	—	None

Release Notes

https://console.cloud.google.com/storage/browser/legalpa-bucket1?project=legalpa-sandbox-409d

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

Untitled.ipynb x jupyter+tensorflow-2-3-2 x 01-explore.ipynb x 02-model.ipynb x 03-cloud-training.ipynb x Python 3

Submit training job

```
[25]: # Re-run this if you need to create a new training job
timestamp = str(datetime.datetime.now().time())
JOB_NAME = "caip_training_" + str(int(time.time()))

[26]: # Set training job parameters
MODULE_NAME = TRAINER_DIR + '.model'
TRAIN_DIR = os.getcwd() + '/' + TRAINER_DIR
JOB_DIR = BUCKET_URI

[27]: # Submit the training job
!gcloud ai-platform jobs submit training $JOB_NAME \
--scale-tier BASIC \
--package-path $TRAIN_DIR \
--module-name $MODULE_NAME \
--job-dir $BUCKET_URI \
--region $REGION \
--runtime-version $RUNTIME_VERSION \
--python-version $PYTHON_VERSION

Job [caip_training_1615024010] submitted successfully.
Your job is still active. You may view the status of your job with the command
$ gcloud ai-platform jobs describe caip_training_1615024010
or continue streaming the logs with the command
$ gcloud ai-platform jobs stream-logs caip_training_1615024010
jobId: caip_training_1615024010
state: QUEUED
```

```
[28]: # Check the job status
!gcloud ai-platform jobs describe $JOB_NAME

createTime: '2021-03-06T09:46:54Z'
endTime: '2021-03-06T09:46:54Z'
jobId: caip_training_1615024010
status: UNKNOWN
```

1 2 3 4 tensorflow-2-3-20210305-233812 | legalpa-sandbox-409d Git: refreshing... Python 3 | Busy Mode: Command Ln 1, Col 1 03-cloud-training.ipynb

The screenshot shows the Google Cloud Platform AI Platform Jobs page. A single job is listed:

Job ID	Type	HyperTune	HyperTune parameters	Target metric	Create time	Elapsed time	Logs	Labels
caip_training_1615024010	Custom code training	No			Mar 6, 2021, 1:46:54 AM	10 min 59 sec	View Logs	

The screenshot shows a Jupyter Notebook titled "03-cloud-training.ipynb". The code cell contains the following Python script for deploying a model version:

```

print(MODEL_NAME)
cta_ridership

# Create model if it doesn't already exist
!gcloud ai-platform models create $MODEL_NAME --region $REGION
Using endpoint [https://us-central1-ml.googleapis.com/]
Created ai platform model [projects/legalpa-sandbox-409d/models/cta_ridership].

# Create the model version
export_path = BUCKET_URI + '/' + EXPORT_DIR
version = 'version-' + str(int(time.time()))

!gcloud ai-platform versions create $version \
--model $MODEL_NAME \
--region=$REGION \
--origin $export_path \
--runtime-version=$RUNTIME_VERSION \
--framework $FRAMEWORK \
--python-version=$PYTHON_VERSION
Using endpoint [https://us-central1-ml.googleapis.com/]
Creating version (this might take a few minutes).....done.

!gcloud ai-platform versions list --model $MODEL_NAME --region $REGION
Using endpoint [https://us-central1-ml.googleapis.com/]
NAME          DEPLOYMENT_URL      STATE
version_1615050084 gs://legalpa-bucket1/tf_export READY

!gcloud ai-platform versions describe $version \
--model=$MODEL_NAME --region=$REGION
Using endpoint [https://us-central1-ml.googleapis.com/]
createTime: '2021-03-06T17:01:25Z'
deploymentUri: gs://legalpa-bucket1/tf_export
etag: Ak3nax-xE7w=
framework: TENSORFLOW
isDefault: true

```

Generated Model:

console.cloud.google.com/ai-platform/models?project=legalpa-sandbox-409d

Google Cloud Platform LegalPA

Search products and resources

SHOW INFO PANEL

This is AI Platform (Classic). Migrate your resources to AI Platform (Unified) to get the latest features like data labeling, AutoML-powered training, and endpoint management. [Learn More](#)

GO TO UNIFIED AI PLATFORM

Region: us-central1

Filter by prefix...

Name	Default version	Description	Endpoint	Labels
cta_ridership	version_1615050084		us-central1-ml.googleapis.com	

console.cloud.google.com/ai-platform/models/cta_ridership;region=us-central1/versions?project=legalpa-sandbox-409d

Google Cloud Platform LegalPA

Search products and resources

SHOW INFO PANEL

Model Details

Name: cta_ridership

Default version: version_1615050084

Region: us-central1

Endpoint: us-central1-ml.googleapis.com

VERSIONS EVALUATION BETA

Filter: Filter by prefix...

Name	Create time	Last used	Labels
version_1615050084 (default)	Mar 6, 2021, 9:01:25 AM		

Google Cloud Platform - LegalPA

Version Details

version_1615050084

Description	cta_ridership
Model location	gs://legalpa-bucket/tf_export
Creation time	Mar 6, 2021, 9:01:25 AM
Last use time	
Python version	3.7
Framework	TensorFlow
Framework version	2.3.1
Runtime version	2.3
Machine type	n1-standard-2

PERFORMANCE RESOURCE USAGE EVALUATION TEST & USE

Test your model with sample input data

Request an online prediction by sending your input data instances as a JSON object.

Learn how to format input data ↗

```
{
  "instances": [
    <value>|<simple/nested list>|<object>,
    ...
  ]
}
```

TEST

Prediction of the model

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

Untitled.ipynb x jupyter@tensorflow-2-3-2 x 01-explore.ipynb x 02-model.ipynb x 03-cloud-training.ipynb x Python 3

Get predictions on deployed model

```
[85]: # Initialize client
endpoint = 'https://ml.googleapis.com'
client_options = ClientOptions(api_endpoint=endpoint)
service = googleapiclient.discovery.build('ml', 'v1', client_options=client_options, cache_discovery=False)

print(endpoint)
https://ml.googleapis.com

[86]: service = googleapiclient.discovery.build('ml', 'v1')

[87]: # Helper function to invoke the prediction service from
# https://github.com/GoogleCloudPlatform/python-docs-samples/blob/master/ml_engine/online_prediction/predict.py

def predict_json(project, model, instances, version=None):
    """Send json data to a deployed model for prediction.

    Args:
        project (str): project where the AI Platform Model is deployed.
        model (str): model name.
        instances ([String]): Keys should be the names of Tensors
            your deployed model expects as inputs. Values should be datatypes
            convertible to Tensors, or (potentially nested) lists of datatypes
            convertible to tensors.
        version: str, version of the model to target.

    Returns:
        Mapping[str: Any]: dictionary of prediction results defined by the
            model.

    """
    name = 'projects/{}/models/{}'.format(project, model)

    if version is not None:
        name += '/versions/{}'.format(version)

    response = service.projects().predict(
        name=name,
        body={'instances': instances}
    ).execute()
```

The screenshot shows a Jupyter Notebook interface with several tabs open:

- Untitled.ipynb
- jupyter-on-tensorflow-2-3-2.ipynb
- 01-explore.ipynb
- 02-model.ipynb
- 03-cloud-training.ipynb

The current tab is "03-cloud-training.ipynb". The code in the cell is as follows:

```
# Print prediction and compare to actual value
print('Predicted riders:', int(round(inverse_scale(np.array([pred_val[0][0]]).reshape(1,1))[0][0])))
print('Actual riders:', int(round(inverse_scale(np.array([y_test[0][0]]))[0][0])))

Predicted riders: 1646008
Actual riders: 1647321
```

Below the code cell, there is a section titled "Cleanup" containing the following code:

```
# Delete model version resource
!echo gcloud ai-platform versions delete {version} --model {MODEL_NAME} --quiet

# Delete model resource
!echo gcloud ai-platform models delete {MODEL_NAME} --quiet

gcloud ai-platform versions delete_version_1615050884 --model cta_ridership --quiet
gcloud ai-platform models delete cta_ridership --quiet
```

At the bottom, there is a section titled "Conclusion" with the following text:

In this section, you've learned how to:

- Prepare data and models for training in the cloud
- Train your model and monitor the progress of the job with AI Platform Training
- Predict using the model with AI Platform Predictions

Time Series Forecasting with the Cloud AI Platform and BQML

46 mins remaining English R

8. Challenge

In this section, you will try applying the concepts you learned to a new dataset!

We won't provide detailed instructions, just some hints (if you want them!).

The goal is to predict 311 service requests from the City of New York. These non-emergency requests include noise complaints, street light issues, etc.

Step 1

Let's start by understanding the dataset.

First, access the [City of New York 311 Service Requests](#) dataset.

To get to know the data better, try out a couple of the sample queries listed in the dataset description:

- What is the number of 311 requests related to ice cream trucks?
- What days get the most 311 requests related to parties?

In the BigQuery UI, select [Create Query](#) to see how to access the dataset. Note the select statement is querying from `bigquery-public-data.new_york_311.311_service_requests`.

Step 2

We're ready to get started. In this section, make modifications to the [Explore and Visualize](#) notebook to work with this data.

Hints

- Duplicate the `@1-explore.ipynb` notebook and begin working from it.
- To explore the data, try this query:

Back **Next**

console.cloud.google.com/marketplace/product/city-of-new-york/nyc-311?utm_campaign=CDR_kwe_aism_time-series-forecasting_011521&utm_source=extern...

Google Cloud Platform LegalPA

NYC 311
City of New York

311 Service Requests from 2010 to the present

[VIEW DATASET](#)

OVERVIEW **SAMPLES**

Overview

This data includes all New York City 311 service requests from 2010 to the present, and is updated daily. 311 is a non-emergency number that provides access to non-emergency municipal services.

This public dataset is hosted in Google BigQuery and is included in BigQuery's 1TB/mo of free tier processing. This means that each user receives 1TB of free BigQuery processing every month, which can be used to run queries on this public dataset. Watch this short video to learn how to get started quickly using BigQuery to access public datasets. [What is BigQuery](#)

[About the provider](#)

Additional details

Type: [Datasets](#)
Last updated: 2/7/20
Category: [Public safety](#)
Dataset source: [NYC OpenData](#)
Cloud service: BigQuery
Region: US
Update frequency: Daily

Samples

Now viewing project 'LegalPA' in organization 'cisco.com'

console.cloud.google.com/bigquery?sq=395060689603:9ab043a78b054c35b285476b296f6162&project=legalpa-sandbox-409d

Google Cloud Platform LegalPA

FEATURES & INFO SHORTCUT HIDE PREVIEW FEATURES

Explorer + ADD DATA

Type to search

Viewing pinned projects.

legalpa-sandbox-409d

bigrquery-public-data

EDITOR NYC 311 ...

RUN SAVE SCHEDULE MORE

1 SELECT
2 COUNT(*) AS requests
3 FROM
4 `bigrquery-public-data.new_york.311_service_requests`
5 WHERE
6 LOWER(descriptor) LIKE '%ice cream truck'

COMPOSE NEW QUERY

This query will process 312.7 MiB when run.

Query results

SAVE RESULTS EXPLORE DATA

Query complete (0.4 sec elapsed, 312.7 MB processed)

Job information Results JSON Execution details

Row	requests
1	12659

console.cloud.google.com/bigquery?sq=395060689603:77e9ccf95a02407c8e5db7d853fc3813&project=legalpa-sandbox-409d

Google Cloud Platform LegalPA

FEATURES & INFO SHORTCUT HIDE PREVIEW FEATURES

Explorer + ADD DATA

Type to search

Viewing pinned projects.

legalpa-sandbox-409d

bigrquery-public-data

EDITOR NYC 311 ...

RUN SAVE SCHEDULE MORE

1 SELECT
2 extract(DAYOFWEEK
3 FROM
4 created_date) AS party_day,
5 borough,
6 COUNT(*) AS num_parties
7 FROM
8 `bigrquery-public-data.new_york.311_service_requests`
9 WHERE
10 LOWER(descriptor) LIKE '%party'
11 GROUP BY
12 party_day,
13 borough
14 ORDER BY
15 num_parties DESC

COMPOSE NEW QUERY

This query will process 599.7 MiB when run.

Query results

SAVE RESULTS EXPLORE DATA

Query complete (1.1 sec elapsed, 599.7 MB processed)

Job information Results JSON Execution details

Row	party_day	borough	num_parties
1	1	BROOKLYN	111114
2	7	BROOKLYN	110643
3	7	MANHATTAN	96680
4	1	MANHATTAN	88933
5	1	QUEENS	79136

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

console.cloud.google.com/bigquery?project=legalpa-sandbox-409d

The screenshot shows the Google Cloud Platform BigQuery interface. A query titled "UNSAVE_2" is running, processing 824.1 MiB of data. The query itself is:

```

1 SELECT distinct complaint_type FROM `bigquery-public-data.new_york_311.311_service_requests`
2 where lower(complaint_type) like '%parties%';
3
4
5 SELECT distinct vehicle_type FROM `bigquery-public-data.new_york_311.311_service_requests`;
6
7
8 SELECT
9   COUNT(unique_key) as y,
10  DATE_TRUNC(DATE(created_date), month) as ds
11 FROM `bigquery-public-data.new_york_311.311_service_requests`
12 GROUP by ds ORDER BY ds asc;

```

The results table has three columns: Row, y, and ds. The data is as follows:

Row	y	ds
1	182117	2010-01-01
2	159489	2010-02-01
3	198639	2010-03-01
4	162854	2010-04-01
5	158039	2010-05-01
6	157840	2010-06-01

codelabs.developers.google.com/codelabs/time-series-forecasting-with-cloud-ai-platform#7

This is a step-by-step guide for time series forecasting. Step 2 involves modifying an Explore and Visualize notebook. The sidebar lists steps 1 through 9.

Step 2

We're ready to get started. In this section, make modifications to the **Explore** and **Visualize** notebook to work with this data.

Hints

- Duplicate the `@1-explore.ipynb` notebook and begin working from it.
- To explore the data, try this query:

```

from google.cloud import bigquery as bq

sql = """
SELECT * FROM `bigquery-public-data.new_york_311.311_service_requests` LIMIT 5
"""

client = bq.Client(project=PROJECT)
df = client.query(sql).to_dataframe()
df.head()

```

- To get the counts of incidents by month, use this query:

```

SELECT
  COUNT(unique_key) as y,
  DATE_TRUNC(DATE(created_date), month) as ds
FROM `bigquery-public-data.new_york_311.311_service_requests`
GROUP by ds ORDER BY ds asc

```

- Update the column variables in the constants section. In the query above, the target column is `y`, and the date column is `ds`. There are no additional features.
- Consider changing the file name in which you export the data for the next lab.

Step 2

Back **Next**

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

Untitled.ipynb jupyter@tensorflow-2: ~ 01-explore.ipynb 01-explore-NYC-311.ipynb 02-model.ipynb 03-cloud-training.ipynb 02-model-NYC_311.ipynb

Install packages and dependencies

Restarting the kernel may be required to use new packages.

```
[2]: %pip install -U statsmodels scikit-learn --user
Requirement already satisfied: statsmodels in /opt/conda/lib/python3.7/site-packages (0.12.2)
Requirement already satisfied: scikit-learn in /opt/conda/lib/python3.7/site-packages (0.24.1)
Requirement already satisfied: threadpoolctl==2.0.0 in /opt/conda/lib/python3.7/site-packages (from scikit-learn) (2.1.0)
Requirement already satisfied: joblib==0.11 in /opt/conda/lib/python3.7/site-packages (from scikit-learn) (1.0.1)
Requirement already satisfied: numpy<1.13,!=1.11,!=1.12 in /opt/conda/lib/python3.7/site-packages (from scikit-learn) (1.19.5)
Requirement already satisfied: scipy<1.1.1 in /opt/conda/lib/python3.7/site-packages (from scikit-learn) (1.6.0)
Requirement already satisfied: pandas>=0.21 in /opt/conda/lib/python3.7/site-packages (from statsmodels) (1.2.2)
Requirement already satisfied: patsy>=0.5 in /opt/conda/lib/python3.7/site-packages (from statsmodels) (0.5.1)
Requirement already satisfied: python-dateutil<2.7.3 in /opt/conda/lib/python3.7/site-packages (from pandas>=0.21->statsmodels) (2.8.1)
Requirement already satisfied: pytz>=2017.3 in /opt/conda/lib/python3.7/site-packages (from pandas>=0.21->statsmodels) (2021.1)
Requirement already satisfied: six in /opt/conda/lib/python3.7/site-packages (from patsy>=0.5->statsmodels) (1.15.0)
Note: you may need to restart the kernel to use updated packages.
```

Note: To restart the Kernel, navigate to Kernel > Restart Kernel... on the Jupyter menu.

Import libraries and define constants

```
[3]: from pandas.plotting import register_matplotlib_converters
from statsmodels.graphics.tsaplots import plot_acf
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.tsa.stattools import grangercausalitytests

import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
```

```
[7]: # Enter your project and region. Then run the cell to make sure the
# Cloud SDK uses the right project for all the commands in this notebook.

PROJECT = 'LegalPA' # REPLACE WITH YOUR PROJECT NAME
REGION = 'us-central1' # REPLACE WITH YOUR REGION e.g. us-central1

#Don't change the following command - this is to check if you have changed the project name above.
assert PROJECT != 'your-project-name', 'Don''t forget to change the project variables!'
```

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Untitled.ipynb jupyter@tensorflow-2: ~ 01-explore.ipynb 01-explore-NYC-311.ipynb 02-model.ipynb 03-cloud-training.ipynb 02-model-NYC_311.ipynb

Load data

Do you want to restart to install these updates now or try tonight?

```
[28]: # Import CSV file
from google.cloud import bigquery as bq

sql = """
SELECT
    COUNT(unique_key) as y,
    DATE_TRUNC(DATE(created_date), month) as ds
FROM `bigquery-public-data.new_york_311.311_service_requests`
GROUP BY ds ORDER BY ds asc
"""

client = bq.Client(project=PROJECT)
df = client.query(sql).to_dataframe()

df.head()
```

```
[28]:      y          ds
0  182117  2010-01-01
1  159489  2010-02-01
2  198639  2010-03-01
3  162854  2010-04-01
4  158039  2010-05-01
```

```
[29]: # Drop duplicates
df = df.drop_duplicates()
```

```
[30]: # Sort by date
df = df.sort_index()
```

Explore data

Untitled.ipynb jupyter@tensorflow-2: ~ 01-explore.ipynb x 01-explore-NYC-311.ipynb x 02-model.ipynb x 03-cloud-training.ipynb x 02-model-NYC_311.ipynb x

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

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- cnn_export an hour ago
- data 14 hours ago
- Istm_export an hour ago
- trainer 12 hours ago
- 01-explore-NYC-311...** 20 minutes ago
- 01-explore.ipynb 13 hours ago
- 02-model-NYC_311... 35 minutes ago
- 02-model.ipynb 12 hours ago
- 03-cloud-training.i... 3 hours ago
- CTA_-_Ridership_... an hour ago
- cta_ridership.csv 13 hours ago
- NYC_311_file.csv an hour ago

Explore data

```
[31]: # Print the top 5 rows
df.head()
```

	y	ds
0	182117	2010-01-01
1	159489	2010-02-01
2	198639	2010-03-01
3	162854	2010-04-01
4	158039	2010-05-01

TODO 1: Analyze the patterns

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

```
[32]: # Initialize plotting
register_matplotlib_converters() # Addresses a warning
sns.setrc('figure.figsize':(16,4))
```

```
[33]: # Explore total rides over time
sns.lineplot(data=df, x=df.ds, y=df.y).set_title('Total Rides')
```

Total Rides

Untitled.ipynb jupyter@tensorflow-2: ~ 01-explore.ipynb x 01-explore-NYC-311.ipynb x 02-model.ipynb x 03-cloud-training.ipynb x 02-model-NYC_311.ipynb x

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

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- 03-cloud-training.i... 3 hours ago
- CTA_-_Ridership_... an hour ago
- cta_ridership.csv 13 hours ago
- NYC_311_file.csv an hour ago

Explore data

```
[34]: sns.lineplot(data=df, x=df.ds, y=df.y).set_title('Service Requests')
```

Service Requests

TODO 2: Review summary statistics

- How many records are in the dataset?
- What is the average # of riders per day?

```
[44]: df.y.describe().apply(lambda x: round(x))
```

	count	mean	std	min	25%	50%	75%	max
count	134	186287	33800	192481	195550	179518	205969	309695
mean		186287	33800	192481	195550	179518	205969	309695
std			33800					
min				192481	195550	179518	205969	309695
25%					195550	179518	205969	309695
50%						179518	205969	309695
75%							205969	309695
max								309695
Name	y							
Type								

TODO 3: Explore seasonality

- Is there much difference between months?

Do you want to restart to install these updates now or try tonight?

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).

```
[58]: plot_acf(df['y'])
fig = plt.show()
```

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.

```
[61]: df[['y']].to_csv('NYC_311_file.csv', index=True, index_label='ts_col')
```

Conclusion

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

- Create a query that groups data into a time series

Do you want to restart to install these updates now or try tonight?

Time Series Forecasting with the Cloud AI Platform and BQML

46 mins remaining | English | R

Step 3

Let's now create a time-series model with the daily data.

Hints

- Duplicate the `02-model.ipynb` notebook and begin working from it.
- Change the input file name if you changed it in the previous notebook.
- There doesn't appear to be any obvious outliers in the data, so skip or comment out those cells.
- Adjust the LSTM units and CNN filters and kernel size for this new model.

Step 4

For a final challenge, let's predict with monthly data, which will require several changes to the parameters:

```
n_features = 1 # Holidays aren't included in the monthly data set we created
n_input_steps = 12 # Lookback window of 12 months
n_output_steps = 1 # Predict one month ahead
n_seasons = 12 # For the statistical model, use yearly periodicity (12 months)
```

Hints

- The LSTM model does not perform well with the monthly dataset. More complex architectures such as stacked LSTMs or LSTM-CNN could be investigated.
- The 1-Dimensional CNN architecture does much better using the following parameters (which should be optimized using [hyperparameter tuning](#)): `filters=64` and `kernel_size=12`.
- The exponential smoothing model performs better than the LSTM but worse than the CNN.
- An ensemble of the CNN and exponential smooth models does even better than either model individually. In basic testing, using a weight of 2:1 CNN to ES provided good results. (In this case, the `weights` array would be set to `[2, 1, 1]`).
- Note that you will see slightly different evaluation results when inspecting an ensembled model. The code evaluate an ensemble of models uses the intersection of the test data used between model types. For id

Back **Next**

Untitled.ipynb jupyter@tensorflow-2: ~ 01-explore.ipynb x 01-explore-NYC-311.ip x 02-model.ipynb x 03-cloud-training.ipynb x 02-model-NYC_311.ip

Overview

This notebook demonstrates how to sequence data for a time-series problem, and then how to build deep learning and statistical models.

Dataset

[City of New York 311 Service Requests] (https://console.cloud.google.com/marketplace/details/city-of-new-york/nyc-311?utm_campaign=CDR_kwe_aimi_time-series-forecasting_011521&utm_source=external&utm_medium=web) This dataset includes all New York City 311 service requests from 2010 to the present, and is updated daily. 311 is a non-emergency number that provides access to non-emergency municipal services.

Objective

The goal is to forecast unique 311 service that is being served by city of new york.

Install packages and dependencies

Restarting the kernel may be required to use new packages.

```
[2]: %pip install -U statsmodels scikit-learn -user
Requirement already satisfied: statsmodels in /opt/conda/lib/python3.7/site-packages (0.12.2)
Requirement already satisfied: scikit-learn in /opt/conda/lib/python3.7/site-packages (0.24.1)
Requirement already satisfied: threadpoolctl==2.0.0 in /opt/conda/lib/python3.7/site-packages (from scikit-learn) (2.1.0)
Requirement already satisfied: numpy==1.13.3 in /opt/conda/lib/python3.7/site-packages (from scikit-learn) (1.19.5)
Requirement already satisfied: scipy==0.19.1 in /opt/conda/lib/python3.7/site-packages (from scikit-learn) (1.6.0)
Requirement already satisfied: joblib==0.1.0 in /opt/conda/lib/python3.7/site-packages (from scikit-learn) (1.0.1)
Requirement already satisfied: pandas==0.21.0 in /opt/conda/lib/python3.7/site-packages (from statsmodels) (1.2.2)
Requirement already satisfied: numpy==1.16.2 in /opt/conda/lib/python3.7/site-packages (from statsmodels) (0.6.1)
Requirement already satisfied: python-dateutil==2.7.3 in /opt/conda/lib/python3.7/site-packages (from pandas>=0.21->statsmodels) (2.8.1)
Requirement already satisfied: pytz==2017.3 in /opt/conda/lib/python3.7/site-packages (from pandas>=0.21->statsmodels) (2021.1)
Requirement already satisfied: six in /opt/conda/lib/python3.7/site-packages (from patsy>=0.5->statsmodels) (1.15.0)
Note: you may need to restart the kernel to use updated packages.
```

Note: To restart the Kernel, navigate to Kernel > Restart Kernel... on the Jupyter menu.

Import libraries and define constants

Untitled.ipynb jupyter@tensorflow-2: ~ 01-explore.ipynb x 01-explore-NYC-311.ip x 02-model.ipynb x 03-cloud-training.ipynb x 02-model-NYC_311.ip

Cloud SDK uses the right project for all the commands in this notebook.
REGION = 'us-central1' # REPLACE WITH YOUR REGION e.g. us-central
PROJECT = 'LegalPA' # REPLACE WITH YOUR PROJECT ID
BUCKET = 'legalpa-bucket1' # REPLACE WITH A UNIQUE BUCKET NAME e.g. your PROJECT NAME
BUCKET_URI = "gs://" + BUCKET

#Don't change the following command - this is to check if you have changed the project name above.
assert PROJECT != 'your-project-name', 'Don\'t forget to change the project variables!'

```
[5]: # Dataset parameters
target_col = 'y' # The variable you are predicting
ts_col = 'service_date' # The name of the column with the date field
```

[6]: # Model parameters
freq = 'D' # Daily frequency
n_input_steps = 30 # Lookback window
n_output_step = 7 # How many steps to predict forward
n_seasons = 7 # Monthly periodicity

```
train_split = 0.8 # % Split between train/test data
epochs = 1000 # How many passes through the data (early-stopping will cause training to stop before this)
patience = 5 # Terminate training after the validation loss does not decrease after this many epochs
```

Create a Cloud Storage bucket

The following steps are required, regardless of your notebook environment.

When you submit a training job using the Cloud SDK, you upload a Python package containing your training code to a Cloud Storage bucket. AI Platform runs the code from this package. In this tutorial, AI Platform also saves the trained model that results from your job in the same bucket. You can then create an AI Platform model version based on this output in order to serve online predictions.

```
[7]: storage_client = storage.Client()
try:
    bucket = storage_client.get_bucket(BUCKET)
    print('Bucket exists, let\'s not recreate it.')
except:
    bucket = storage_client.create_bucket(BUCKET)
    print('Created bucket: ' + BUCKET)
```

Untitled.ipynb jupyter@tensorflow-2: ~ 01-explore.ipynb 01-explore-NYC-311.ip 02-model.ipynb 03-cloud-training.ipynb 02-model-NYC_311.ip

Do you want to restart to install these updates now or try tonight?

Load data

```
[8]: processed_file = 'NYC_311_file.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}'

[9]: # Read data

df = pd.read_csv(input_file, index_col='ts_col', parse_dates=True)
df.index.freq = freq

df.head()

[9]:
```

service_date	y
0	182117
1	159469
2	198639
3	162854
4	158039

```
[10]: # Define some characteristics of the data that will be used later
n_features = 1 # Holidays aren't included in the monthly data set we created
n_input_steps = 12 # Lookback window of 12 months
n_output_steps = 1 # Predict one month ahead
n_seasons = 12

# Index of target column. Used later when creating dataframes.
target_col_num = df.columns.get_loc(target_col)

[11]: # 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)
```

Untitled.ipynb jupyter@tensorflow-2: ~ 01-explore.ipynb 01-explore-NYC-311.ip 02-model.ipynb 03-cloud-training.ipynb 02-model-NYC_311.ip

Do you want to restart to install these updates now or try tonight?

Scale the inputs and outputs

```
[17]: # For neural networks to converge quicker, it is helpful to scale the values.
# For example, each feature might be transformed to have a mean of 0 and std. dev. of 1.
#
# You are working with a mix of features, input timesteps, output horizon, etc.
# which don't work out-of-the-box with common scaling utilities.
# So, here are a couple wrappers to handle scaling and inverting the scaling.

feature_scaler = StandardScaler()
target_scaler = StandardScaler()

def scale(df,
          fit=True,
          target_col=target_col,
          feature_scaler=feature_scaler,
          target_scaler=target_scaler):
    """
    Scale the input features, using a separate scaler for the target.

    Parameters:
    df (pd.DataFrame): Input dataframe
    fit (bool): Whether to fit the scaler to the data (only apply to training data)
    target_col (pd.Series): The column that is being predicted
    feature_scaler (StandardScaler): Scaler used for features
    target_scaler (StandardScaler): Scaler used for target

    Returns:
    df_scaled (pd.DataFrame): Scaled dataframe
    """

    target = df[target_col].values.reshape(-1, 1)
    if fit:
        target_scaler.fit(target)
        target_scaled = target_scaler.transform(target)

    # Select all columns other than target to be features
    features = df.loc[:, df.columns != target_col].values

    if features.shape[1]: # If there are any features
        if fit:
            feature_scaler.fit(features)
```

Untitled.ipynb jupyter@tensorflow-2: ~ 01-explore.ipynb x 01-explore-NYC-311.ipc x 02-model.ipynb x 03-cloud-training.ipynb x 02-model-NYC_311.ip

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Create sequences of time-series data

```
[18]: def reframe(data, n_input_steps = n_input_steps, n_output_steps = n_output_steps, target_col = target_col):
    target_col_num = data.columns.get_loc(target_col)

    # Iterate through data and create sequences of features and outputs
    df = pd.DataFrame(data)
    cols=list()
    for i in range(n_input_steps, 0, -1):
        cols.append(df.shift(i))
    for i in range(0, n_output_steps):
        cols.append(df.shift(-i))

    # Concatenate values and remove any missing values
    df = pd.concat(cols, axis=1)
    df.dropna(inplace=True)

    # Split the data into feature and target variables
    n_feature_cols = n_input_steps * n_features
    features = df.iloc[:,0:n_feature_cols]
    target_cols = [i for i in range(n_feature_cols + target_col_num, n_feature_cols + n_output_steps * n_features, n_features)]
    targets = df.loc[:,target_cols]

    return (features, targets)

X_train_reframed, y_train_reframed = reframe(df_train_scaled)
X_test_reframed, y_test_reframed = reframe(df_test_scaled)
```

Evaluate results

```
[19]: def print_stats(timestep, y_true, y_pred, target_col, chart=True, table=False, dec=3):
    ...
    Helper function to print overall summary statistics and stats for each time step
    ...

    # Print summary statistics
    print('==== t' + str(timestep) + ' ====')
    print('R2: ' + str(np.round(r2_score(y_true, y_pred), dec)))
    print('MAPE: ' + str(np.round(mean_absolute_percentage_error(y_true, y_pred), dec)))
    print('MAE: ' + str(np.round(mean_absolute_error(y_true, y_pred), dec)))
```

Untitled.ipynb jupyter@tensorflow-2: ~ 01-explore.ipynb x 01-explore-NYC-311.ipc x 02-model.ipynb x 03-cloud-training.ipynb x 02-model-NYC_311.ip

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Long Short Term Memory (LSTM)

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

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

TODO 2: Update the LSTM architecture

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

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

```
[21]: # 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
3/3 [=====] - 1s 333ms/step - loss: 0.9243 - val_loss: 1.8443
Epoch 2/1000
3/3 [=====] - 0s 39ms/step - loss: 0.8203 - val_loss: 1.8219
Epoch 3/1000
3/3 [=====] - 0s 40ms/step - loss: 0.7385 - val_loss: 1.8052
Epoch 4/1000
3/3 [=====] - 0s 42ms/step - loss: 0.6456 - val_loss: 1.7969
Epoch 5/1000
3/3 [=====] - 0s 45ms/step - loss: 0.5665 - val_loss: 1.8299
Epoch 6/1000
3/3 [=====] - 0s 41ms/step - loss: 0.4644 - val_loss: 1.9126
Epoch 7/1000
3/3 [=====] - 0s 38ms/step - loss: 0.4168 - val_loss: 2.0431
```

Untitled.ipynb jupyter@tensorflow-2: ~ 01-explore.ipynb 01-explore-NYC-311.ip 02-model.ipynb 03-cloud-training.ipynb 02-model-NYC_311.ip

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- 02-model.ipynb 12 hours ago
- 03-cloud-training.i... 3 hours ago
- CTA_Ridership_... an hour ago
- cta_ridership.csv 13 hours ago
- NYC_311_file.csv an hour ago

```
[23]: # 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 ==
R^2: -0.578
MAPE: 0.324
MAE: 59756.94
```

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)

```
[24]: 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]),
```

Untitled.ipynb jupyter@tensorflow-2: ~ 01-explore.ipynb 01-explore-NYC-311.ip 02-model.ipynb 03-cloud-training.ipynb 02-model-NYC_311.ip

Do you want to restart to install these updates now or try tonight?

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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)

```
[24]: 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
3/3 [=====] - 0s 99ms/step - loss: 0.9515 - val_loss: 1.8508
Epoch 2/1000
3/3 [=====] - 0s 31ms/step - loss: 0.8268 - val_loss: 1.8233
Epoch 3/1000
3/3 [=====] - 0s 27ms/step - loss: 0.7660 - val_loss: 1.8182
Epoch 4/1000
3/3 [=====] - 0s 27ms/step - loss: 0.5988 - val_loss: 1.8426
Epoch 5/1000
3/3 [=====] - 0s 29ms/step - loss: 0.5055 - val_loss: 1.8882
Epoch 6/1000
3/3 [=====] - 0s 26ms/step - loss: 0.4348 - val_loss: 1.9874
Epoch 7/1000
3/3 [=====] - 0s 26ms/step - loss: 0.3882 - val_loss: 2.0666
Epoch 8/1000
3/3 [=====] - 0s 26ms/step - loss: 0.3911 - val_loss: 2.1186

```
[25]: model.save('./cnn_export/')

INFO:tensorflow:Assets written to: ./cnn_export/assets
```

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

Do you want to restart to install these updates now or try tonight?

Untitled.ipynb x jupyter@tensorflow-2: x 01-explore.ipynb x 01-explore-NYC-311.ip x 02-model.ipynb x 03-cloud-training.ipynb x 02-model-NYC_311.ip

Python 3

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- 02-model.ipynb 12 hours ago
- 03-cloud-training.i... 3 hours ago
- CTA_-_Ridership_... an hour ago
- cta_ridership.csv 14 hours ago
- NYC_311_file.csv an hour ago

Epoch 8/1000
3/3 [=====] - 0s 26ms/step - loss: 0.3911 - val_loss: 2.1186
[25]: model.save('./cnn_export/')

INFO:tensorflow:Assets written to: ./cnn_export/assets

[26]: preds = model.predict(X_test)
y_pred_cnn = inverse_scale(preds)
evaluate(y_pred_cnn)

==== t=1 ====
R^2: -0.468
MAPE: 0.312
MAE: 58163.97

Conclusion

Great job! You've now completed the modeling portion of this workshop. You've covered:

- Removing outliers from the data
- Multi-step forecasting
- Neural network architectures for time-series forecasting: LSTM and CNN

Time Series Forecasting with the Cloud AI Platform and BQML

1 min remaining English R

1 Overview

2 Introduction to Time-Series Forecasting

3 Setup your Notebook environment

4 Explore and Visualize Data

5 Create a Model with BigQuery Time Series Forecasting

6 Build a Custom Forecasting Model

7 Train and Predict in the Cloud

8 Challenge

9 Cleanup

9. Cleanup

If you'd like to continue using this notebook, it is recommended that you turn it off when not in use. From the Notebooks UI in your Cloud Console, select the notebook and then select Stop.

Instance name	Region	Environment	Machine type	GPUs	Permission	Labels
OPEN JUPYTERLAB tensorflow-20191026-092711	us-west-1b	TensorFlow1.15	4 vCPUs, 15 GB RAM	None	Service account	No labels

If you'd like to delete all the resources you've created in this lab, simply Delete the notebook instance instead of stopping it.

Using the Navigation menu in your Cloud Console, browse to Storage and delete both buckets you created to store your model assets.

Back Report a mistake

console.cloud.google.com/ai-platform/notebooks/list/instances?project=legalpa-sandbox-4c9d

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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](#)

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Instance name	Zone	Environment	Machine type	GPUs	Permission	Labels
tensorflow-2-3-20210305-233812	us-west1-b	OPEN JUPYTERLAB	TensorFlow:2.3	4 vCPUs, 15 GB RAM	None	Service account
tensorflow-20200206-164348	us-east1-b	OPEN JUPYTERLAB	TensorFlow:1.15	2 vCPUs, 7.5 GB RAM	None	Service account

Info panel

DOCUMENTATION LABELS

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

