Regression: predict fuel efficiency

Run in Google Colab (https://colab.research.google.com/github/tensorflow/docs/blob/master/site/er

In a *regression* problem, we aim to predict the output of a continuous value, like a price or a probability. Contrast this with a *classification* problem, where we aim to select a class from a list of classes (for example, where a picture contains an apple or an orange, recognizing which fruit is in the picture).

This notebook uses the classic Auto MPG (https://archive.ics.uci.edu/ml/datasets/auto+mpg) Dataset and builds a model to predict the fuel efficiency of late-1970s and early 1980s automobiles. To do this, we'll provide the model with a description of many automobiles from that time period. This description includes attributes like: cylinders, displacement, horsepower, and weight.

This example uses the `tf.keras` (https://www.tensorflow.org/api_docs/python/tf/keras) API, see this guide (https://www.tensorflow.org/guide/keras) for details.

```
# Use seaborn for pairplot
!pip install -q seaborn
```

```
from __future__ import absolute_import, division, print_function

import pathlib
```

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

import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers

print(tf.__version__)
```

```
1.13.0-rc2
```

The Auto MPG dataset

The dataset is available from the UCI Machine Learning Repository (https://archive.ics.uci.edu/ml/).

Get the data

First download the dataset.

```
dataset_path = keras.utils.get_file("auto-mpg.data", "https://archive.ics.uci.ed
dataset_path
```

```
Downloading data from https://archive.ics.uci.edu/ml/machine-learning-databases/
32768/30286 [================================] - 0s 1us/step

'/root/.keras/datasets/auto-mpg.data'
```

Import it using pandas

```
column_names = ['MPG','Cylinders','Displacement','Horsepower','Weight',
                'Acceleration', 'Model Year', 'Origin']
raw_dataset = pd.read_csv(dataset_path, names=column_names,
                      na_values = "?", comment='\t',
                      sep=" ", skipinitialspace=True)

dataset = raw_dataset.copy()
dataset.tail()
```

	MPG	Cylinders	Displacement	Horsepower	Weight	Acceleration	Model Year	Origin
393	27.0	4	140.0	86.0	2790.0	15.6	82	1
394	44.0	4	97.0	52.0	2130.0	24.6	82	2
395	32.0	4	135.0	84.0	2295.0	11.6	82	1
396	28.0	4	120.0	79.0	2625.0	18.6	82	1
397	31.0	4	119.0	82.0	2720.0	19.4	82	1

Clean the data

The dataset contains a few unknown values.

```
dataset.isna().sum()
```

```
MPG             0
Cylinders       0
Displacement    0
Horsepower      6
Weight          0
Acceleration    0
Model Year      0
```

```
Origin          0
dtype: int64
```

To keep this initial tutorial simple drop those rows.

```
dataset = dataset.dropna()
```

The "**`Origin`**" column is really categorical, not numeric. So convert that to a one-hot:

```
origin = dataset.pop('Origin')
```

```
dataset['USA'] = (origin == 1)*1.0
dataset['Europe'] = (origin == 2)*1.0
dataset['Japan'] = (origin == 3)*1.0
dataset.tail()
```

	MPG	Cylinders	Displacement	Horsepower	Weight	Acceleration	Model Year	USA	Europe	Japan
393	27.0	4	140.0	86.0	2790.0	15.6	82	1.0	0.0	0.0
394	44.0	4	97.0	52.0	2130.0	24.6	82	0.0	1.0	0.0
395	32.0	4	135.0	84.0	2295.0	11.6	82	1.0	0.0	0.0
396	28.0	4	120.0	79.0	2625.0	18.6	82	1.0	0.0	0.0
397	31.0	4	119.0	82.0	2720.0	19.4	82	1.0	0.0	0.0

Split the data into train and test

Now split the dataset into a training set and a test set.

We will use the test set in the final evaluation of our model.

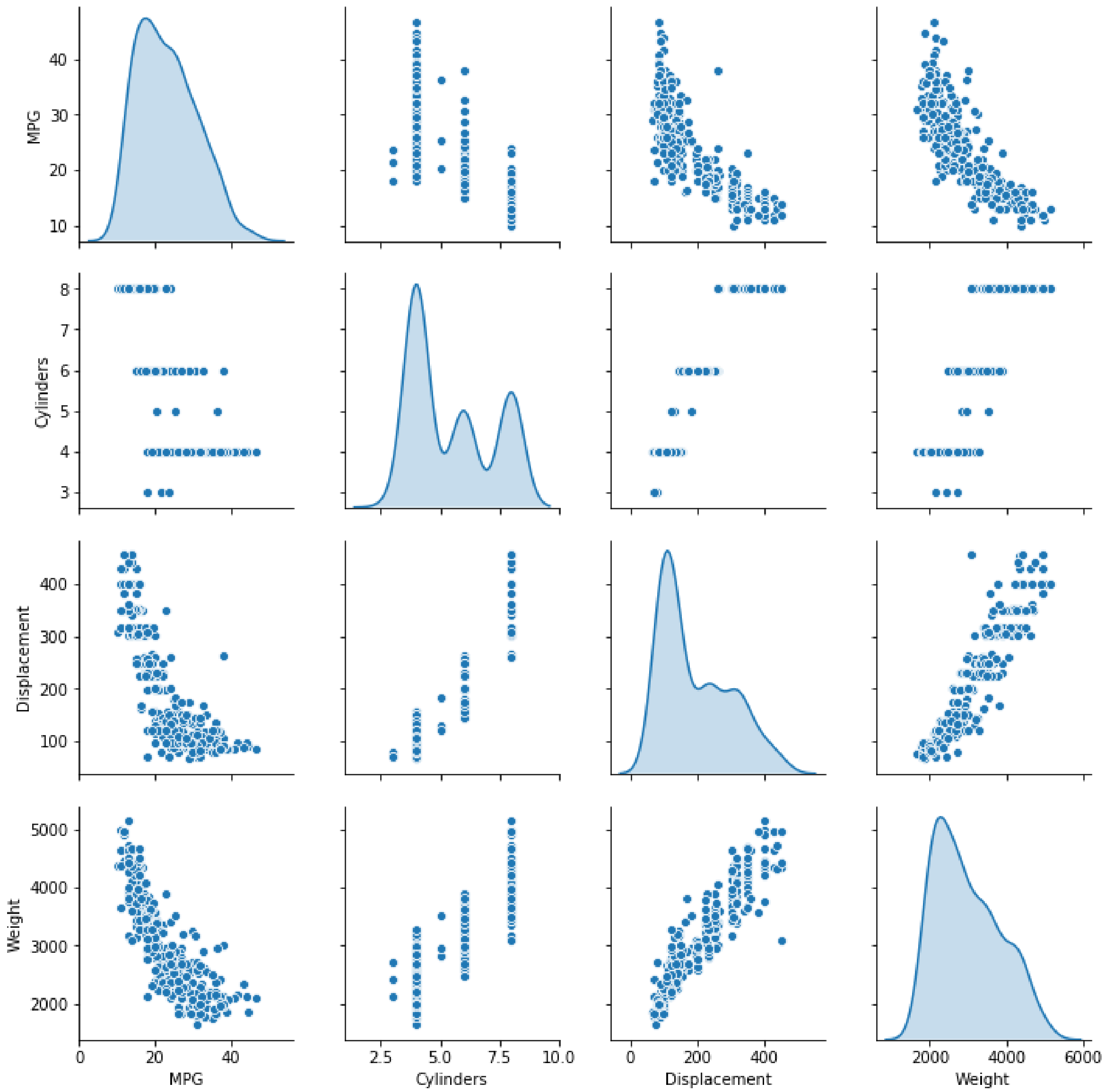
```
train_dataset = dataset.sample(frac=0.8,random_state=0)
test_dataset = dataset.drop(train_dataset.index)
```

Inspect the data

Have a quick look at the joint distribution of a few pairs of columns from the training set.

```
sns.pairplot(train_dataset[["MPG", "Cylinders", "Displacement", "Weight"]], diag
```

```
<seaborn.axisgrid.PairGrid at 0x7f4b8be6a160>
```



Also look at the overall statistics:

```
train_stats = train_dataset.describe()
train_stats.pop("MPG")
train_stats = train_stats.transpose()
train_stats
```

	count	mean	std	min	25%	50%	75%	max
Cylinders	314.0	5.477707	1.699788	3.0	4.00	4.0	8.00	8.0

	count	mean	std	min	25%	50%	75%	max
Displacement	314.0	195.318471	104.331589	68.0	105.50	151.0	265.75	455.0
Horsepower	314.0	104.869427	38.096214	46.0	76.25	94.5	128.00	225.0
Weight	314.0	2990.251592	843.898596	1649.0	2256.50	2822.5	3608.00	5140.0
Acceleration	314.0	15.559236	2.789230	8.0	13.80	15.5	17.20	24.8
Model Year	314.0	75.898089	3.675642	70.0	73.00	76.0	79.00	82.0
USA	314.0	0.624204	0.485101	0.0	0.00	1.0	1.00	1.0
Europe	314.0	0.178344	0.383413	0.0	0.00	0.0	0.00	1.0
Japan	314.0	0.197452	0.398712	0.0	0.00	0.0	0.00	1.0

Split features from labels

Separate the target value, or "label", from the features. This label is the value that you will train the model to predict.

```
train_labels = train_dataset.pop('MPG')
test_labels = test_dataset.pop('MPG')
```

Normalize the data

Look again at the `train_stats` block above and note how different the ranges of each feature are.

It is good practice to normalize features that use different scales and ranges. Although the model *might* converge without feature normalization, it makes training more difficult, and it makes the resulting model dependent on the choice of units used in the input.

Note: Although we intentionally generate these statistics from only the training dataset, these statistics will also be used to normalize the test dataset. We need to do that to project the test dataset into the same distribution that the model has been trained on.

```
def norm(x):
  return (x - train_stats['mean']) / train_stats['std']
normed_train_data = norm(train_dataset)
normed_test_data = norm(test_dataset)
```

This normalized data is what we will use to train the model.

Caution: The statistics used to normalize the inputs here (mean and standard deviation) need to be applied to any other data that is fed to the model, along with the one-hot encoding that we did earlier. That includes the test set as well as live data when the model is used in production.

The model

Build the model

Let's build our model. Here, we'll use a **`Sequential`** model with two densely connected hidden layers, and an output layer that returns a single, continuous value. The model building steps are wrapped in a function, **`build_model`**, since we'll create a second model, later on.

```
def build_model():
  model = keras.Sequential([
    layers.Dense(64, activation=tf.nn.relu, input_shape=[len(train_dataset.keys(
    layers.Dense(64, activation=tf.nn.relu),
    layers.Dense(1)
  ])

  optimizer = tf.keras.optimizers.RMSprop(0.001)

  model.compile(loss='mean_squared_error',
```

```
                optimizer=optimizer,
                metrics=['mean_absolute_error', 'mean_squared_error'])
  return model
```

```
model = build_model()
```

```
WARNING:tensorflow:From /usr/local/lib/python3.5/dist-packages/tensorflow/python
Instructions for updating:
Colocations handled automatically by placer.
WARNING:tensorflow:From /usr/local/lib/python3.5/dist-packages/tensorflow/python
Instructions for updating:
Use tf.cast instead.
```

Inspect the model

Use the `.summary` method to print a simple description of the model

```
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense (Dense)                (None, 64)                640
_________________________________________________________________
dense_1 (Dense)              (None, 64)                4160
_________________________________________________________________
dense_2 (Dense)              (None, 1)                 65
=================================================================
Total params: 4,865
Trainable params: 4,865
Non-trainable params: 0
_________________________________________________________________
```

Now try out the model. Take a batch of `10` examples from the training data and call `model.predict` on it.

```
example_batch = normed_train_data[:10]
example_result = model.predict(example_batch)
example_result
```

```
array([[ 0.3102367 ],
       [-0.03239854],
       [ 0.03091731],
       [-0.06153622],
       [-0.30039132],
       [-0.04769488],
       [-0.35117304],
       [ 0.13059786],
       [ 0.23485906],
       [-0.3152904 ]], dtype=float32)
```

It seems to be working, and it produces a result of the expected shape and type.

Train the model

Train the model for 1000 epochs, and record the training and validation accuracy in the `history` object.

```
# Display training progress by printing a single dot for each completed epoch
class PrintDot(keras.callbacks.Callback):
  def on_epoch_end(self, epoch, logs):
    if epoch % 100 == 0: print('')
    print('.', end='')

EPOCHS = 1000

history = model.fit(
  normed_train_data, train_labels,
  epochs=EPOCHS, validation_split = 0.2, verbose=0,
  callbacks=[PrintDot()])
```

```
WARNING:tensorflow:From /usr/local/lib/python3.5/dist-packages/tensorflow/pytho
Instructions for updating:
Use tf.cast instead.

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```

Visualize the model's training progress using the stats stored in the `history` object.

```
hist = pd.DataFrame(history.history)
hist['epoch'] = history.epoch
hist.tail()
```

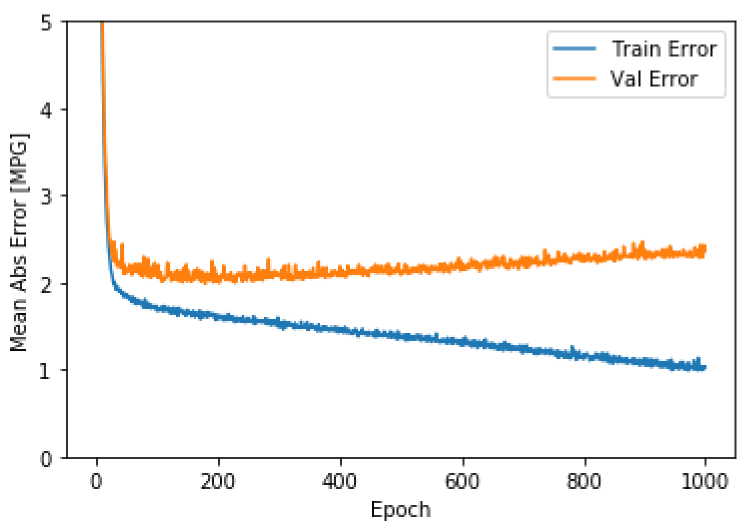
	loss	mean_absolute_error	mean_squared_error	val_loss	val_mean_absolute_error	val_
995	2.617521	0.997720	2.617521	9.083421	2.291849	9.08
996	2.553326	1.013858	2.553326	8.938567	2.285523	8.93
997	2.389780	1.034613	2.389781	9.429494	2.358692	9.42
998	2.590127	1.008238	2.590127	10.137694	2.428234	10.1
999	2.590747	1.035228	2.590747	9.496686	2.356818	9.49

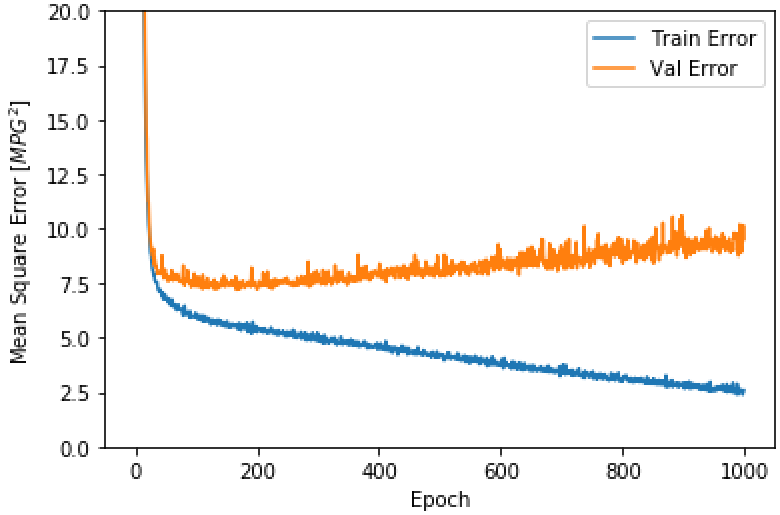
```
def plot_history(history):
  hist = pd.DataFrame(history.history)
  hist['epoch'] = history.epoch
```

```
  plt.figure()
  plt.xlabel('Epoch')
  plt.ylabel('Mean Abs Error [MPG]')
  plt.plot(hist['epoch'], hist['mean_absolute_error'],
           label='Train Error')
  plt.plot(hist['epoch'], hist['val_mean_absolute_error'],
           label = 'Val Error')
  plt.ylim([0,5])
  plt.legend()

  plt.figure()
  plt.xlabel('Epoch')
  plt.ylabel('Mean Square Error [$MPG^2$]')
  plt.plot(hist['epoch'], hist['mean_squared_error'],
           label='Train Error')
  plt.plot(hist['epoch'], hist['val_mean_squared_error'],
           label = 'Val Error')
  plt.ylim([0,20])
  plt.legend()
  plt.show()


plot_history(history)
```





This graph shows little improvement, or even degradation in the validation error after about 100 epochs. Let's update the **`model.fit`** call to automatically stop training when the validation score doesn't improve. We'll use an *EarlyStopping callback* that tests a training condition for every epoch. If a set amount of epochs elapses without showing improvement, then automatically stop the training.

You can learn more about this callback here (https://www.tensorflow.org/versions/master/api_docs/python/tf/keras/callbacks/EarlyStopping)
.

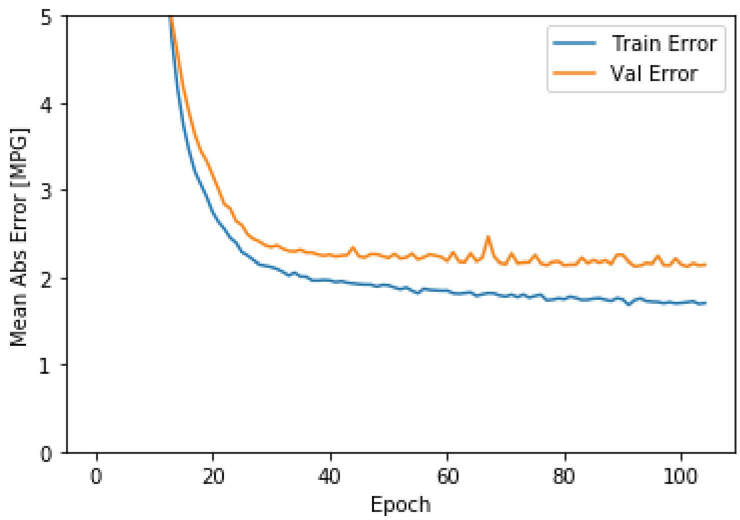
```
model = build_model()

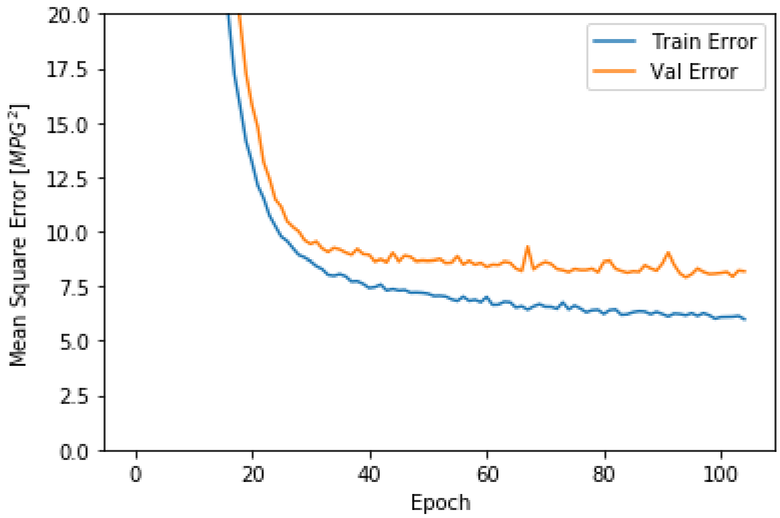
# The patience parameter is the amount of epochs to check for improvement
early_stop = keras.callbacks.EarlyStopping(monitor='val_loss', patience=10)

history = model.fit(normed_train_data, train_labels, epochs=EPOCHS,
                    validation_split = 0.2, verbose=0, callbacks=[early_stop, Pr

plot_history(history)
```

```
.........................................................................................
.....
```





The graph shows that on the validation set, the average error is usually around +/- 2 MPG. Is this good? We'll leave that decision up to you.

Let's see how well the model generalizes by using the **test** set, which we did not use when training the model. This tells us how well we can expect the model to predict when we use it in the real world.

```
loss, mae, mse = model.evaluate(normed_test_data, test_labels, verbose=0)

print("Testing set Mean Abs Error: {:5.2f} MPG".format(mae))
```

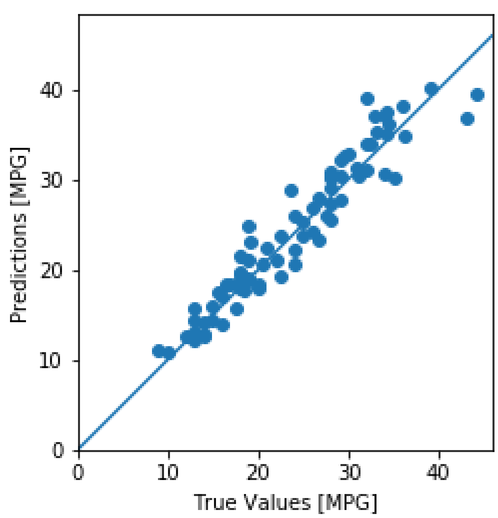
```
Testing set Mean Abs Error:  1.95 MPG
```

Make predictions

Finally, predict MPG values using data in the testing set:

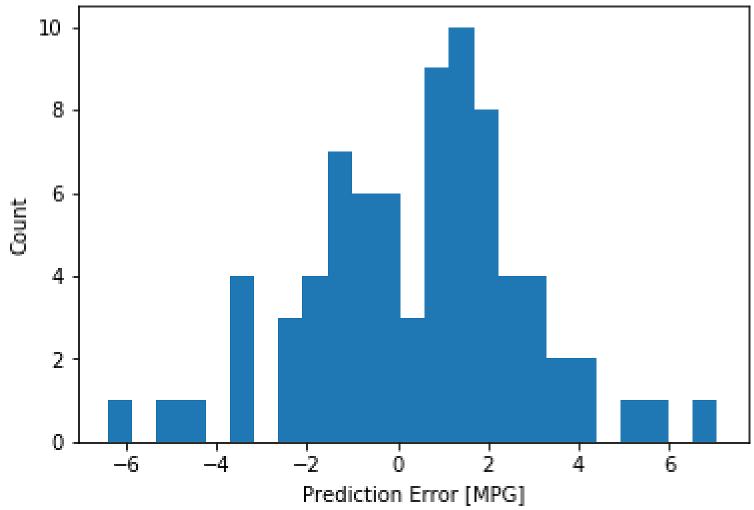
```
test_predictions = model.predict(normed_test_data).flatten()

plt.scatter(test_labels, test_predictions)
plt.xlabel('True Values [MPG]')
plt.ylabel('Predictions [MPG]')
plt.axis('equal')
plt.axis('square')
plt.xlim([0,plt.xlim()[1]])
plt.ylim([0,plt.ylim()[1]])
_ = plt.plot([-100, 100], [-100, 100])
```



It looks like our model predicts reasonably well. Let's take a look at the error distribution.

```
error = test_predictions - test_labels
plt.hist(error, bins = 25)
plt.xlabel("Prediction Error [MPG]")
_ = plt.ylabel("Count")
```



It's not quite gaussian, but we might expect that because the number of samples is very small.

Conclusion

This notebook introduced a few techniques to handle a regression problem.

- Mean Squared Error (MSE) is a common loss function used for regression problems (different loss functions are used for classification problems).
- Similarly, evaluation metrics used for regression differ from classification. A common regression metric is Mean Absolute Error (MAE).
- When numeric input data features have values with different ranges, each feature should be scaled independently to the same range.
- If there is not much training data, one technique is to prefer a small network with few hidden layers to avoid overfitting.
- Early stopping is a useful technique to prevent overfitting.

```
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```

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```