time-series-gru-bike-and-rf

June 3, 2025

[1]:
```python
import numpy as np
import pandas as pd
from sklearn.preprocessing import MinMaxScaler
from tensorflow.keras.models import Sequential
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
from tensorflow.keras.layers import GRU, Bidirectional, Dense, Dropout
from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras.regularizers import l2

# Load your dataset
train_df = pd.read_csv("/kaggle/input/bike-sharing-demand/train.csv")
test_df_raw = pd.read_csv("/kaggle/input/bike-sharing-demand/test.csv")
```

A Gated Recurrent Unit (GRU) is a type of Recurrent Neural Network (RNN) designed to capture dependencies in sequential data. It introduces gating mechanisms—specifically, the update and reset gates—that regulate the flow of information, allowing the model to retain or discard information as needed. This architecture addresses challenges like the vanishing gradient problem, enabling GRUs to model long-term dependencies more effectively than traditional RNNs.

Key Characteristics of GRUs

Update Gate: Determines how much of the past information needs to be passed along to the future.

Reset Gate: Decides how much of the past information to forget.

Simplified Architecture: Compared to Long Short-Term Memory (LSTM) networks, GRUs have a more streamlined structure, often leading to faster training times while maintaining performance.

Source: https://aws.amazon.com/what-is/recurrent-neural-network/

[2]:
```python
train_df.head()
```

[2]:
```
              datetime  season  holiday  workingday  weather  temp   atemp  \
0  2011-01-01 00:00:00       1        0           0        1  9.84  14.395
1  2011-01-01 01:00:00       1        0           0        1  9.02  13.635
2  2011-01-01 02:00:00       1        0           0        1  9.02  13.635
3  2011-01-01 03:00:00       1        0           0        1  9.84  14.395
4  2011-01-01 04:00:00       1        0           0        1  9.84  14.395

   humidity  windspeed  casual  registered  count
```

```
0         81         0.0         3           13       16
1         80         0.0         8           32       40
2         80         0.0         5           27       32
3         75         0.0         3           10       13
4         75         0.0         0            1        1
```

[3]:
```
train_df.dtypes
```

[3]:
```
datetime       object
season          int64
holiday         int64
workingday      int64
weather         int64
temp          float64
atemp         float64
humidity        int64
windspeed     float64
casual          int64
registered      int64
count           int64
dtype: object
```

[4]:
```
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10886 entries, 0 to 10885
Data columns (total 12 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   datetime    10886 non-null  object
 1   season      10886 non-null  int64
 2   holiday     10886 non-null  int64
 3   workingday  10886 non-null  int64
 4   weather     10886 non-null  int64
 5   temp        10886 non-null  float64
 6   atemp       10886 non-null  float64
 7   humidity    10886 non-null  int64
 8   windspeed   10886 non-null  float64
 9   casual      10886 non-null  int64
 10  registered  10886 non-null  int64
 11  count       10886 non-null  int64
dtypes: float64(3), int64(8), object(1)
memory usage: 1020.7+ KB
```

[5]:
```
test_df_raw.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6493 entries, 0 to 6492
```

```
Data columns (total 9 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   datetime    6493 non-null   object
 1   season      6493 non-null   int64
 2   holiday     6493 non-null   int64
 3   workingday  6493 non-null   int64
 4   weather     6493 non-null   int64
 5   temp        6493 non-null   float64
 6   atemp       6493 non-null   float64
 7   humidity    6493 non-null   int64
 8   windspeed   6493 non-null   float64
dtypes: float64(3), int64(5), object(1)
memory usage: 456.7+ KB
```

[6]:

```python
# === 2. Feature Engineering: Extract datetime info ===
def add_time_features(df):
    df['datetime'] = pd.to_datetime(df['datetime'])  # Convert datetime string␣
 ↪to timestamp
    df['hour'] = df['datetime'].dt.hour              # Hour of the day (0-23)
    df['day'] = df['datetime'].dt.dayofweek          # Day of the week␣
 ↪(0=Monday)
    df['month'] = df['datetime'].dt.month            # Month (1-12)
    df['year'] = df['datetime'].dt.year              # Year (2011 or 2012)
    return df

# Apply time feature extraction
train_df = add_time_features(train_df)
test_df = add_time_features(test_df_raw)
```

[7]:

```python
train_df.describe()
```

[7]:

```
                            datetime        season       holiday  \
count                          10886  10886.000000  10886.000000
mean   2011-12-27 05:56:22.399411968      2.506614      0.028569
min              2011-01-01 00:00:00      1.000000      0.000000
25%              2011-07-02 07:15:00      2.000000      0.000000
50%              2012-01-01 20:30:00      3.000000      0.000000
75%              2012-07-01 12:45:00      4.000000      0.000000
max              2012-12-19 23:00:00      4.000000      1.000000
std                              NaN      1.116174      0.166599

         workingday       weather         temp         atemp      humidity  \
count  10886.000000  10886.000000  10886.00000  10886.000000  10886.000000
mean       0.680875      1.418427     20.23086     23.655084     61.886460
min        0.000000      1.000000      0.82000      0.760000      0.000000
25%        0.000000      1.000000     13.94000     16.665000     47.000000
```

```
50%        1.000000      1.000000     20.50000     24.240000     62.000000
75%        1.000000      2.000000     26.24000     31.060000     77.000000
max        1.000000      4.000000     41.00000     45.455000    100.000000
std        0.466159      0.633839      7.79159      8.474601     19.245033

          windspeed        casual    registered         count          hour  \
count  10886.000000  10886.000000  10886.000000  10886.000000  10886.000000
mean      12.799395     36.021955    155.552177    191.574132     11.541613
min        0.000000      0.000000      0.000000      1.000000      0.000000
25%        7.001500      4.000000     36.000000     42.000000      6.000000
50%       12.998000     17.000000    118.000000    145.000000     12.000000
75%       16.997900     49.000000    222.000000    284.000000     18.000000
max       56.996900    367.000000    886.000000    977.000000     23.000000
std        8.164537     49.960477    151.039033    181.144454      6.915838

                day         month          year
count  10886.000000  10886.000000  10886.000000
mean       3.013963      6.521495   2011.501929
min        0.000000      1.000000   2011.000000
25%        1.000000      4.000000   2011.000000
50%        3.000000      7.000000   2012.000000
75%        5.000000     10.000000   2012.000000
max        6.000000     12.000000   2012.000000
std        2.004585      3.444373      0.500019
```

[8]:
```
print(train_df.dtypes)
```

```
datetime      datetime64[ns]
season                 int64
holiday                int64
workingday             int64
weather                int64
temp                 float64
atemp                float64
humidity               int64
windspeed            float64
casual                 int64
registered             int64
count                  int64
hour                   int32
day                    int32
month                  int32
year                   int32
dtype: object
```

[9]:
```
print(test_df.dtypes)
```

```
datetime      datetime64[ns]
```

```
season                  int64
holiday                 int64
workingday              int64
weather                 int64
temp                  float64
atemp                 float64
humidity                int64
windspeed             float64
hour                    int32
day                     int32
month                   int32
year                    int32
dtype: object
```

[10]:
```
# === 3. Define input features and target ===
features = ['hour', 'day', 'month', 'year', 'temp', 'humidity', 'windspeed']
target = 'count'  # This is what we want to predict


#===3.5 Dropping unncecessary features
dropFeatures = ["datetime"]
train_df = train_df.drop('casual', axis=1)
train_df = train_df.drop('registered', axis=1)
train_df = train_df.drop(dropFeatures,axis=1)
test_df = test_df.drop(dropFeatures,axis=1)

# === 4. Normalize features using MinMaxScaler ===
scaler = MinMaxScaler()
X_train_all = scaler.fit_transform(train_df[features])  # Fit only on train data
X_test_all = scaler.transform(test_df[features])        # Transform test data␣
↪using same scaler

# Save target variable separately
y_train_all = np.log1p(train_df['count'].values)
#The following is for ensemble and tree methods
```

[11]:
```
# === 6. Create time-series sequences for GRU ===
def create_sequences(X, y=None, look_back=24):
    Xs, ys = [], []
    for i in range(len(X) - look_back):
        Xs.append(X[i:i + look_back])
        if y is not None:
            ys.append(y[i + look_back])
    return np.array(Xs), np.array(ys) if y is not None else np.array(Xs)

look_back = 6  # Using past 6 time value
```

```
X_train_seq, y_train_seq = create_sequences(X_train_all, y_train_all, look_back)

#y_train_seq = np.log1p(y_train_seq)
```

[12]:
```
# === 7. Split training data into train/validation ===
X_train_final, X_val, y_train_final, y_val = train_test_split(
    X_train_seq, y_train_seq, test_size=0.2, random_state=42, shuffle=False
)
# Note: shuffle=False preserves time order, which is critical for time series

# === 8. Build deeper GRU model ===
model = Sequential()
model.add(Bidirectional(GRU(512, return_sequences=True),␣
 ↪input_shape=(look_back, len(features))))
#model.add(Dropout(0.05))
model.add(Bidirectional(GRU(128)))
model.add(Dense(1))  # Output: predicted log(count)
model.compile(optimizer='adam', loss='mean_squared_error')


# === 10. Add early stopping ===
early_stop = EarlyStopping(monitor='val_loss', patience=10,␣
 ↪restore_best_weights=True)

# === 11. Train model with validation data ===
history = model.fit(
    X_train_final, y_train_final,
    validation_data=(X_val, y_val),
    epochs=1000,
    batch_size=32,
    callbacks=[early_stop],
    verbose=1
)
```

```
/usr/local/lib/python3.10/dist-
packages/keras/src/layers/rnn/bidirectional.py:107: UserWarning: Do not pass an
`input_shape`/`input_dim` argument to a layer. When using Sequential models,
prefer using an `Input(shape)` object as the first layer in the model instead.
  super().__init__(**kwargs)

Epoch 1/1000
272/272             7s 12ms/step -
loss: 2.1393 - val_loss: 0.4221
Epoch 2/1000
272/272             2s 8ms/step -
loss: 0.3986 - val_loss: 0.3224
Epoch 3/1000
272/272             2s 8ms/step -
```

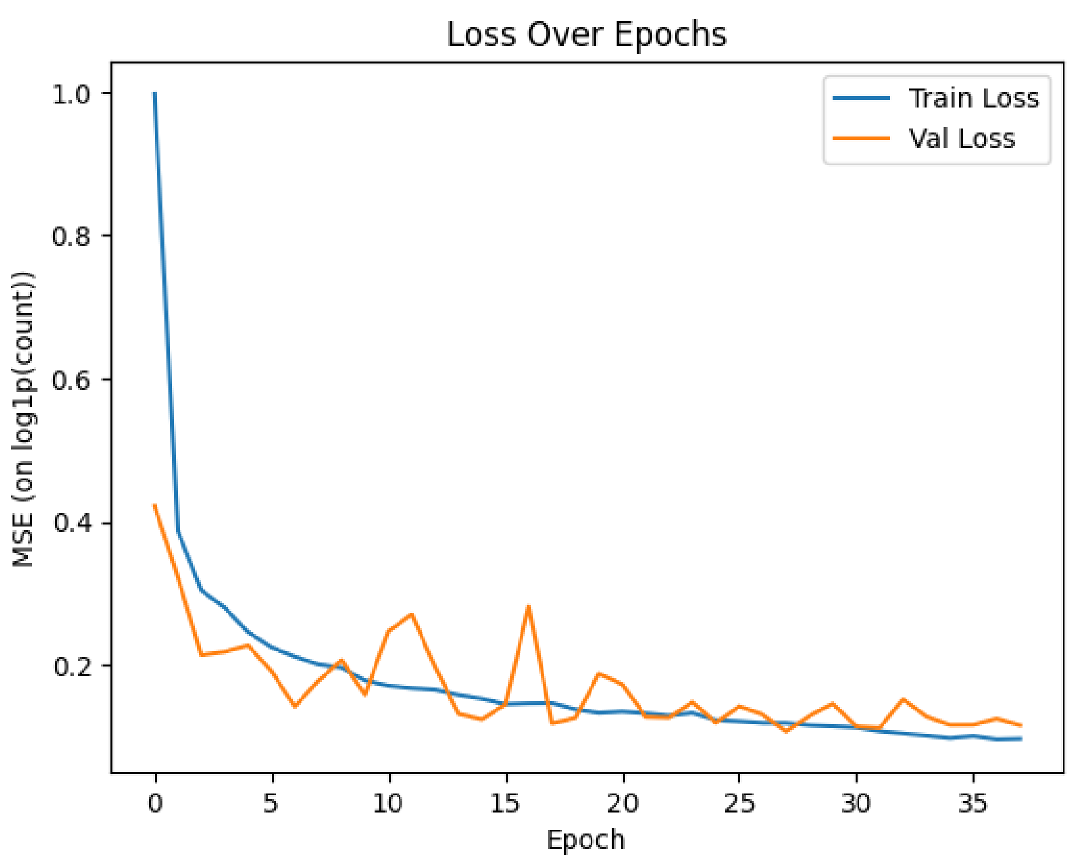
```
loss: 0.3169 - val_loss: 0.2133
Epoch 4/1000
272/272              2s 8ms/step -
loss: 0.2870 - val_loss: 0.2182
Epoch 5/1000
272/272              2s 8ms/step -
loss: 0.2639 - val_loss: 0.2270
Epoch 6/1000
272/272              2s 8ms/step -
loss: 0.2214 - val_loss: 0.1910
Epoch 7/1000
272/272              2s 8ms/step -
loss: 0.2117 - val_loss: 0.1415
Epoch 8/1000
272/272              2s 8ms/step -
loss: 0.2023 - val_loss: 0.1773
Epoch 9/1000
272/272              2s 8ms/step -
loss: 0.1893 - val_loss: 0.2063
Epoch 10/1000
272/272              2s 8ms/step -
loss: 0.1852 - val_loss: 0.1581
Epoch 11/1000
272/272              2s 8ms/step -
loss: 0.1641 - val_loss: 0.2467
Epoch 12/1000
272/272              2s 8ms/step -
loss: 0.1696 - val_loss: 0.2703
Epoch 13/1000
272/272              2s 8ms/step -
loss: 0.1669 - val_loss: 0.1968
Epoch 14/1000
272/272              2s 8ms/step -
loss: 0.1586 - val_loss: 0.1314
Epoch 15/1000
272/272              2s 8ms/step -
loss: 0.1494 - val_loss: 0.1238
Epoch 16/1000
272/272              2s 8ms/step -
loss: 0.1448 - val_loss: 0.1443
Epoch 17/1000
272/272              2s 8ms/step -
loss: 0.1433 - val_loss: 0.2815
Epoch 18/1000
272/272              2s 8ms/step -
loss: 0.1486 - val_loss: 0.1181
Epoch 19/1000
272/272              2s 8ms/step -
```

```
loss: 0.1351 - val_loss: 0.1258
Epoch 20/1000
272/272              2s 8ms/step -
loss: 0.1289 - val_loss: 0.1875
Epoch 21/1000
272/272              2s 8ms/step -
loss: 0.1409 - val_loss: 0.1726
Epoch 22/1000
272/272              2s 8ms/step -
loss: 0.1280 - val_loss: 0.1272
Epoch 23/1000
272/272              2s 8ms/step -
loss: 0.1249 - val_loss: 0.1261
Epoch 24/1000
272/272              2s 8ms/step -
loss: 0.1352 - val_loss: 0.1477
Epoch 25/1000
272/272              2s 8ms/step -
loss: 0.1274 - val_loss: 0.1189
Epoch 26/1000
272/272              2s 8ms/step -
loss: 0.1173 - val_loss: 0.1418
Epoch 27/1000
272/272              2s 8ms/step -
loss: 0.1155 - val_loss: 0.1304
Epoch 28/1000
272/272              2s 8ms/step -
loss: 0.1228 - val_loss: 0.1066
Epoch 29/1000
272/272              2s 8ms/step -
loss: 0.1151 - val_loss: 0.1285
Epoch 30/1000
272/272              2s 8ms/step -
loss: 0.1164 - val_loss: 0.1456
Epoch 31/1000
272/272              2s 8ms/step -
loss: 0.1089 - val_loss: 0.1137
Epoch 32/1000
272/272              2s 8ms/step -
loss: 0.1046 - val_loss: 0.1119
Epoch 33/1000
272/272              2s 8ms/step -
loss: 0.1023 - val_loss: 0.1518
Epoch 34/1000
272/272              2s 8ms/step -
loss: 0.1030 - val_loss: 0.1275
Epoch 35/1000
272/272              2s 8ms/step -
```

```
loss: 0.0944 - val_loss: 0.1161
Epoch 36/1000
272/272              2s 8ms/step -
loss: 0.0918 - val_loss: 0.1162
Epoch 37/1000
272/272              2s 8ms/step -
loss: 0.0925 - val_loss: 0.1246
Epoch 38/1000
272/272              2s 8ms/step -
loss: 0.0930 - val_loss: 0.1156
```

[13]:

```
# === 12. Plot training & validation loss ===
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Val Loss')
plt.title('Loss Over Epochs')
plt.xlabel('Epoch')
plt.ylabel('MSE (on log1p(count))')
plt.legend()
plt.show()
```



[14]:
```
#We can also check root mean square error if need be

def rmsle(y, y_,convertExp=True):
    log1 = np.nan_to_num(np.array([np.log(v + 1) for v in y]))
    log2 = np.nan_to_num(np.array([np.log(v + 1) for v in y_]))
    calc = (log1 - log2) ** 2
    return np.sqrt(np.mean(calc))
```

[15]:
```
# === 13. Prepare test sequences using last part of train ===
X_test_seq = []
seed_seq = X_train_all[-look_back:].tolist()
for row in X_test_all:
    seed_seq.append(row)
    seq = seed_seq[-look_back:]
    X_test_seq.append(seq)
X_test_seq = np.array(X_test_seq)

# === 14. Predict and inverse log1p ==
test_preds = model.predict(X_test_seq).flatten()
```

```
203/203              1s 3ms/step
```

[16]:
```
# === 13. Submission file ===
datetimecol = test_df_raw["datetime"]
submission = pd.DataFrame({
        "datetime": datetimecol,
        "count": [max(0, x) for x in np.exp(test_preds)]
    })
submission.to_csv('bike_predictions3.csv', index=False)
```

[18]:
```
from sklearn.ensemble import GradientBoostingRegressor
gbm = GradientBoostingRegressor(n_estimators=4000)
gbm.fit(X_train_all, y_train_all)
preds = gbm.predict(X=X_train_all)
print ("RMSLE Value For Gradient Boost: ", rmsle(np.exp(y_train_all), np.
 ↪exp(preds), False))
```

```
RMSLE Value For Gradient Boost:  0.2256738796033782
```

[19]:
```
test_preds2 = gbm.predict(X=X_test_all)
```

[20]:
```
submission2 = pd.read_csv('/kaggle/input/bike-sharing-demand/sampleSubmission.
 ↪csv')
datetimecol = test_df_raw["datetime"]
submission2 = pd.DataFrame({
        "datetime": datetimecol,
        "count": [max(0, x) for x in np.exp(test_preds2)]
    })
```

```python
submission2.to_csv('gbr_estt.csv', index=False)
```

[21]:
```python
from sklearn.ensemble import RandomForestRegressor
rfModel = RandomForestRegressor(n_estimators=100)
rfModel.fit(X_train_all, y_train_all)
preds = rfModel.predict(X=X_train_all)
print ("RMSLE Value For Random Forest: ",rmsle(np.exp(y_train_all), np.
 ↪exp(preds), False))
```

```
RMSLE Value For Random Forest:  0.11502367206001117
```

[22]:
```python
test_pred = rfModel.predict(X=X_test_all)
```

[23]:
```python
submission3 = pd.read_csv('/kaggle/input/bike-sharing-demand/sampleSubmission.
 ↪csv')
datetimecol = test_df_raw["datetime"]
submission3 = pd.DataFrame({
        "datetime": datetimecol,
        "count": [max(0, x) for x in np.exp(test_pred)]
    })
submission3.to_csv('bikeseparate_rf.csv', index=False)
```

Random forest gace the best result as a public socre 0.39. GRU wasn't the best. However I haven't utilized grid search for the best hyperparameters

[ ]:
```python

```