CFRM 421/521, Spring 2022

[Insert your name here]

Homework 4

- Due: Tuesday, May 31, 2022, 11:59 PM
- Total marks: 47
- Late submissions are allowed, but a 20% penalty per day applies. Your last submission is considered for calculating the penalty.
- Use this Jupyter notebook as a template for your solutions. Your solution must be submitted as one Jupyter notebook on Canvas and one PDF file on Gradescope. The notebook must be already run, that is, make sure that you have run all your code, save the notebook, and then when you reopen the notebook, checked that all output appears as expected. You are allowed to use code from the textbook, textbook website, or lecture notes.

1. A regression MLP [10 marks]

Consider the California housing data from Homework 1 using the same training and test set there. Here, we split off 20% of the training set as a validation set, and keep the remaining 80% as the actual training set. The following code replicates the preprocessing of the dataset from Homework 1, creating the training set X_train , y_train , the validation set X_valid , y_valid and the test set X_test , y_test . The target variable has been divided by 100,000.

```
In [1]: pip install tensorflow
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-whe
els/public/simple/
Requirement already satisfied: tensorflow in /usr/local/lib/python3.7/dist-packa
ges (2.8.0+zzzcolab20220506162203)
Requirement already satisfied: h5py>=2.9.0 in /usr/local/lib/python3.7/dist-pack
ages (from tensorflow) (3.1.0)
Collecting tf-estimator-nightly==2.8.0.dev2021122109
  Downloading tf estimator nightly-2.8.0.dev2021122109-py2.py3-none-any.whl (462
kB)
                                      462 kB 5.2 MB/s
Requirement already satisfied: six>=1.12.0 in /usr/local/lib/python3.7/dist-pack
ages (from tensorflow) (1.15.0)
Requirement already satisfied: wrapt>=1.11.0 in /usr/local/lib/python3.7/dist-pa
ckages (from tensorflow) (1.14.1)
Requirement already satisfied: keras<2.9,>=2.8.0rc0 in /usr/local/lib/python3.7/
dist-packages (from tensorflow) (2.8.0)
```

```
Requirement already satisfied: google-pasta>=0.1.1 in /usr/local/lib/python3.7/d
ist-packages (from tensorflow) (0.2.0)
Requirement already satisfied: absl-py>=0.4.0 in /usr/local/lib/python3.7/dist-p
ackages (from tensorflow) (1.0.0)
Requirement already satisfied: protobuf>=3.9.2 in /usr/local/lib/python3.7/dist-
packages (from tensorflow) (3.17.3)
Requirement already satisfied: gast>=0.2.1 in /usr/local/lib/python3.7/dist-pack
ages (from tensorflow) (0.5.3)
Requirement already satisfied: tensorboard<2.9,>=2.8 in /usr/local/lib/python3.
7/dist-packages (from tensorflow) (2.8.0)
Requirement already satisfied: typing-extensions>=3.6.6 in /usr/local/lib/python
3.7/dist-packages (from tensorflow) (4.2.0)
Requirement already satisfied: flatbuffers>=1.12 in /usr/local/lib/python3.7/dis
t-packages (from tensorflow) (2.0)
Requirement already satisfied: termcolor>=1.1.0 in /usr/local/lib/python3.7/dist
-packages (from tensorflow) (1.1.0)
Requirement already satisfied: grpcio<2.0,>=1.24.3 in /usr/local/lib/python3.7/d
ist-packages (from tensorflow) (1.46.1)
Requirement already satisfied: tensorflow-io-gcs-filesystem>=0.23.1 in /usr/loca
1/lib/python3.7/dist-packages (from tensorflow) (0.26.0)
Requirement already satisfied: numpy>=1.20 in /usr/local/lib/python3.7/dist-pack
ages (from tensorflow) (1.21.6)
Requirement already satisfied: setuptools in /usr/local/lib/python3.7/dist-packa
ges (from tensorflow) (57.4.0)
Requirement already satisfied: libclang>=9.0.1 in /usr/local/lib/python3.7/dist-
packages (from tensorflow) (14.0.1)
Requirement already satisfied: astunparse>=1.6.0 in /usr/local/lib/python3.7/dis
t-packages (from tensorflow) (1.6.3)
Requirement already satisfied: opt-einsum>=2.3.2 in /usr/local/lib/python3.7/dis
t-packages (from tensorflow) (3.3.0)
Requirement already satisfied: keras-preprocessing>=1.1.1 in /usr/local/lib/pyth
on3.7/dist-packages (from tensorflow) (1.1.2)
Requirement already satisfied: wheel<1.0,>=0.23.0 in /usr/local/lib/python3.7/di
st-packages (from astunparse>=1.6.0->tensorflow) (0.37.1)
Requirement already satisfied: cached-property in /usr/local/lib/python3.7/dist-
packages (from h5py>=2.9.0->tensorflow) (1.5.2)
Requirement already satisfied: requests<3,>=2.21.0 in /usr/local/lib/python3.7/d
ist-packages (from tensorboard<2.9,>=2.8->tensorflow) (2.23.0)
Requirement already satisfied: google-auth-oauthlib<0.5,>=0.4.1 in /usr/local/li
b/python3.7/dist-packages (from tensorboard<2.9,>=2.8->tensorflow) (0.4.6)
Requirement already satisfied: tensorboard-data-server<0.7.0,>=0.6.0 in /usr/loc
al/lib/python3.7/dist-packages (from tensorboard<2.9,>=2.8->tensorflow) (0.6.1)
Requirement already satisfied: werkzeug>=0.11.15 in /usr/local/lib/python3.7/dis
t-packages (from tensorboard<2.9,>=2.8->tensorflow) (1.0.1)
Requirement already satisfied: google-auth<3,>=1.6.3 in /usr/local/lib/python3.
7/dist-packages (from tensorboard<2.9,>=2.8->tensorflow) (1.35.0)
Requirement already satisfied: tensorboard-plugin-wit>=1.6.0 in /usr/local/lib/p
ython3.7/dist-packages (from tensorboard<2.9,>=2.8->tensorflow) (1.8.1)
Requirement already satisfied: markdown>=2.6.8 in /usr/local/lib/python3.7/dist-
packages (from tensorboard<2.9,>=2.8->tensorflow) (3.3.7)
Requirement already satisfied: cachetools<5.0,>=2.0.0 in /usr/local/lib/python3.
7/dist-packages (from google-auth<3,>=1.6.3->tensorboard<2.9,>=2.8->tensorflow)
(4.2.4)
Requirement already satisfied: pyasn1-modules>=0.2.1 in /usr/local/lib/python3.
7/dist-packages (from google-auth<3,>=1.6.3->tensorboard<2.9,>=2.8->tensorflow)
(0.2.8)
Requirement already satisfied: rsa<5,>=3.1.4 in /usr/local/lib/python3.7/dist-pa
ckages (from google-auth<3,>=1.6.3->tensorboard<2.9,>=2.8->tensorflow) (4.8)
Requirement already satisfied: requests-oauthlib>=0.7.0 in /usr/local/lib/python
3.7/dist-packages (from google-auth-oauthlib<0.5,>=0.4.1->tensorboard<2.9,>=2.8-
>tensorflow) (1.3.1)
Requirement already satisfied: importlib-metadata>=4.4 in /usr/local/lib/python
3.7/dist-packages (from markdown>=2.6.8->tensorboard<2.9,>=2.8->tensorflow) (4.1
1.3)
Requirement already satisfied: zipp>=0.5 in /usr/local/lib/python3.7/dist-packag
```

```
es (from importlib-metadata>=4.4->markdown>=2.6.8->tensorboard<2.9,>=2.8->tensor
        flow) (3.8.0)
        Requirement already satisfied: pyasn1<0.5.0,>=0.4.6 in /usr/local/lib/python3.7/
        dist-packages (from pyasn1-modules>=0.2.1->google-auth<3,>=1.6.3->tensorboard<2.
        9, >= 2.8 - \text{tensorflow}) (0.4.8)
        Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.7/di
        st-packages (from requests<3,>=2.21.0->tensorboard<2.9,>=2.8->tensorflow) (2022.
        5.18.1)
        Requirement already satisfied: urllib3!=1.25.0,!=1.25.1,<1.26,>=1.21.1 in /usr/l
        ocal/lib/python3.7/dist-packages (from requests<3,>=2.21.0->tensorboard<2.9,>=2.
        8->tensorflow) (1.24.3)
        Requirement already satisfied: chardet<4,>=3.0.2 in /usr/local/lib/python3.7/dis
        t-packages (from requests<3,>=2.21.0->tensorboard<2.9,>=2.8->tensorflow) (3.0.4)
        Requirement already satisfied: idna<3,>=2.5 in /usr/local/lib/python3.7/dist-pac
        kages (from requests<3,>=2.21.0->tensorboard<2.9,>=2.8->tensorflow) (2.10)
        Requirement already satisfied: oauthlib>=3.0.0 in /usr/local/lib/python3.7/dist-
        packages (from requests-oauthlib>=0.7.0->google-auth-oauthlib<0.5,>=0.4.1->tenso
        rboard<2.9,>=2.8->tensorflow) (3.2.0)
        Installing collected packages: tf-estimator-nightly
        Successfully installed tf-estimator-nightly-2.8.0.dev2021122109
         import numpy as np
In [1]:
         import pandas as pd
         import tensorflow as tf
         import tensorflow.keras as keras
         from sklearn.pipeline import Pipeline
In [2]:
         from sklearn.impute import SimpleImputer
         from sklearn.compose import ColumnTransformer
         from sklearn.preprocessing import StandardScaler, OneHotEncoder
         from sklearn.model selection import StratifiedShuffleSplit
         import os
         import tarfile
         from six.moves import urllib
         HOUSING PATH = os.path.join("datasets", "housing")
         def fetch_housing_data(housing_url, housing_path=HOUSING_PATH):
             if not os.path.isdir(housing path):
                 os.makedirs(housing path)
             tgz_path = os.path.join(housing_path, "housing.tgz")
             urllib.request.urlretrieve(housing url, tgz path)
             housing tgz = tarfile.open(tgz path)
             housing tgz.extractall(path=housing path)
             housing tgz.close()
         def load housing data(housing path=HOUSING PATH):
             csv path = os.path.join(housing path, "housing.csv")
             return pd.read csv(csv path)
         HOUSING URL = ("https://raw.githubusercontent.com/ageron/"+
                        "handson-ml2/master/datasets/housing/housing.tgz")
         fetch housing data(HOUSING URL)
         data = load housing data()
         data["income cat"] = np.ceil(data["median income"] / 1.5)
         data["income cat"].where(data["income cat"] < 5, 5.0, inplace=True)</pre>
         split = StratifiedShuffleSplit(n splits=1, test size=0.2, random state=42)
         for train index, test index in split.split(data, data["income cat"]):
             strat train set = data.loc[train index]
```

```
strat test set = data.loc[test index]
# Split the traning set into training and validation
split2 = StratifiedShuffleSplit(n splits=1, test size=0.2, random state=42)
for train_index2, valid_index in split2.split(strat_train_set, strat_train_set["
    strat_train2_set = strat_train_set.iloc[train_index2]
    strat valid set = strat train set.iloc[valid index]
strat_train_set = strat_train2_set.copy().drop("income_cat", axis=1)
strat_valid_set = strat_valid_set.copy().drop("income_cat", axis=1)
strat_test_set = strat_test_set.copy().drop("income_cat", axis=1)
X_raw = strat_train_set.drop("median_house_value", axis=1)
y_train = strat_train_set["median_house_value"].copy()/100000
num_pipeline = Pipeline([
        ('imputer', SimpleImputer(strategy="median")),
        ('std_scaler', StandardScaler()),
    1)
num features = X raw.drop("ocean proximity", axis=1)
num_attribs = list(num_features)
cat_attribs = ["ocean_proximity"]
full_pipeline = ColumnTransformer([
        ("num", num pipeline, num attribs),
        ("cat", OneHotEncoder(), cat attribs),
    ])
# Apply the pipeline to the training set
X train = full pipeline.fit transform(X raw)
# Apply the pipeline to the validation set
X_valid_raw = strat_valid_set.drop("median_house_value", axis=1)
y valid = strat valid set["median house value"].copy()/100000
X valid = full pipeline.transform(X valid raw)
# Apply the pipeline to the validation set
X_test_raw = strat_test_set.drop("median_house_value", axis=1)
y test = strat test set["median house value"].copy()/100000
X test = full pipeline.transform(X test raw)
```

(a) [4 marks]

Use tensorflow.keras to train a regression MLP with one hidden layer of 50 ReLU neurons. For the output layer, try both a ReLU activation function and no activation function (which is equivalent to the identity function). Explain which choice is better. Use the appropriate weight initialization. Use the Nadam optimizer. Train for 30 epochs, and report the mean squared error on the validation set.

Hint: In the .compile() method, use loss="mse" .

[Add your solution here]

```
Epoch 1/30
s: 0.5694
Epoch 2/30
s: 0.4686
Epoch 3/30
s: 0.4397
Epoch 4/30
s: 0.4175
Epoch 5/30
s: 0.4044
Epoch 6/30
s: 0.3949
Epoch 7/30
s: 0.3879
Epoch 8/30
s: 0.3795
Epoch 9/30
s: 0.3738
Epoch 10/30
s: 0.3694
Epoch 11/30
s: 0.3767
Epoch 12/30
s: 0.3660
Epoch 13/30
s: 0.3599
Epoch 14/30
s: 0.3553
Epoch 15/30
s: 0.3590
Epoch 16/30
s: 0.3537
Epoch 17/30
s: 0.3597
Epoch 18/30
s: 0.3531
Epoch 19/30
s: 0.3519
Epoch 20/30
```

```
s: 0.3544
   Epoch 21/30
   s: 0.3524
   Epoch 22/30
   s: 0.3486
   Epoch 23/30
   s: 0.3454
   Epoch 24/30
   s: 0.3451
   Epoch 25/30
   s: 0.3421
   Epoch 26/30
   s: 0.3417
   Epoch 27/30
   s: 0.3422
   Epoch 28/30
   s: 0.3454
   Epoch 29/30
   s: 0.3429
   Epoch 30/30
   s: 0.3379
Out[14]: <keras.callbacks.History at 0x7f99c125f390>
In [16]: | mse_act = mlp.evaluate(X_valid, y_valid)
    print(mse act)
   0.3379059135913849
   As using ReLU activation function, the MSE is 0.3379059135913849.
   from tensorflow.keras import Sequential, layers
In [17]:
    mlp2 = Sequential([
     layers.Dense(50, activation="relu",
           kernel initializer="he normal"),
     layers.Dense(1, activation= None )
    ])
    mlp2.compile(optimizer='Nadam',
In [18]:
         loss='mse')
    mlp2.fit(X_train, y_train,
         epochs=30, validation data=(X valid, y valid))
   Epoch 1/30
   s: 0.5339
   Epoch 2/30
   s: 0.4407
   Epoch 3/30
   s: 0.4178
```

```
Epoch 4/30
s: 0.3980
Epoch 5/30
s: 0.3849
Epoch 6/30
s: 0.3803
Epoch 7/30
s: 0.3705
Epoch 8/30
s: 0.3662
Epoch 9/30
s: 0.3648
Epoch 10/30
s: 0.3605
Epoch 11/30
s: 0.3618
Epoch 12/30
s: 0.3560
Epoch 13/30
s: 0.3539
Epoch 14/30
s: 0.3578
Epoch 15/30
s: 0.3483
Epoch 16/30
s: 0.3482
Epoch 17/30
s: 0.3463
Epoch 18/30
s: 0.3468
Epoch 19/30
s: 0.3445
Epoch 20/30
s: 0.3430
Epoch 21/30
s: 0.3459
Epoch 22/30
s: 0.3452
Epoch 23/30
s: 0.3402
Epoch 24/30
s: 0.3424
Epoch 25/30
```

```
s: 0.3385
     Epoch 26/30
                    ======== | - 1s 2ms/step - loss: 0.3210 - val los
     413/413 [======
     s: 0.3363
     Epoch 27/30
     s: 0.3393
     Epoch 28/30
     s: 0.3373
     Epoch 29/30
     413/413 [======
                  s: 0.3350
     Epoch 30/30
     s: 0.3360
Out[18]: <keras.callbacks.History at 0x7f99be5c4110>
In [19]: | mse_non_act = mlp2.evaluate(X_valid, y_valid)
     print(mse non act)
     104/104 [==============] - 0s 1ms/step - loss: 0.3360
```

As using ReLU non-activation function, the MSE of test set is 0.3359699845314026.

Conclusion: The MSE of outlayer with no activation function and with activation function are very close. The outlayer with no activation function has smaller MSE.

(b) [5 marks]

0.3359699845314026

Read the section "Fine-Tuning Neural Network Hyperparameters" in the textbook and the corresponding section in the Jupyter notebook on the textbook website. Then use a randomized search to search for the best number of hidden layers, neurons per hidden layer, and learning rate. For the randomized search use 3-fold CV, with 10 iterations, with the number of hidden layers uniformly sampled from $\{0,1,2,3\}$, the number of neurons per layer uniformly from $\{1,2,\ldots,100\}$, and the learning rate from the distribution $\mbox{reciprocal}(3e-4, 3e-2)$. Use early stopping with $\mbox{patience=10}$.

[Add your solution here]

```
In [20]: def build_model(n_hidden, n_neurons, learning_rate, input_shape=[13]):
    model = keras.models.Sequential()
    model.add(keras.layers.InputLayer(input_shape=input_shape))
    for layer in range(n_hidden):
        model.add(keras.layers.Dense(n_neurons, activation="relu"))
    model.add(keras.layers.Dense(1))
    optimizer = keras.optimizers.SGD(learning_rate=learning_rate)
    model.compile(loss="mse", optimizer=optimizer)
    return model

In [21]: keras_reg = keras.wrappers.scikit_learn.KerasRegressor(build_model)
```

/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:1: DeprecationWarni ng: KerasRegressor is deprecated, use Sci-Keras (https://github.com/adriangb/scikeras) instead. See https://www.adriangb.com/scikeras/stable/migration.html for

help migrating.
"""Entry point for launching an IPython kernel.

```
from scipy.stats import reciprocal
In [22]:
    from sklearn.model_selection import RandomizedSearchCV
    param distribs = {
      "n_hidden": [0, 1, 2, 3],
      "n neurons": np.arange(1, 101).tolist(),
      "learning rate": reciprocal(3e-4, 3e-2).rvs(1000).tolist(),
    }
    rnd_search_cv = RandomizedSearchCV(keras_reg, param_distribs, n_iter=10, cv=3, v
    rnd_search_cv.fit(X_train, y_train, epochs=30,
           validation data=(X valid, y valid),
           callbacks=[keras.callbacks.EarlyStopping(patience=10)])
   Fitting 3 folds for each of 10 candidates, totalling 30 fits
    Epoch 1/30
    s: 0.4759
   Epoch 2/30
    s: 0.4373
   Epoch 3/30
    s: 0.4161
   Epoch 4/30
    s: 0.4018
   Epoch 5/30
    s: 0.3908
   Epoch 6/30
    s: 0.3834
   Epoch 7/30
    s: 0.3818
   Epoch 8/30
   s: 0.4039
   Epoch 9/30
    s: 0.3704
   Epoch 10/30
    s: 0.3737
   Epoch 11/30
   s: 0.3621
   Epoch 12/30
   s: 0.3622
   Epoch 13/30
   s: 0.3687
   Epoch 14/30
    s: 0.3854
   Epoch 15/30
    s: 0.3597
   Epoch 16/30
```

```
s: 0.3719
Epoch 17/30
s: 0.3713
Epoch 18/30
s: 0.3500
Epoch 19/30
276/276 [=============] - 1s 2ms/step - loss: 0.3438 - val_los
s: 0.3748
Epoch 20/30
s: 0.3476
Epoch 21/30
s: 0.3473
Epoch 22/30
s: 0.3799
Epoch 23/30
s: 0.3577
Epoch 24/30
s: 0.3676
Epoch 25/30
s: 0.3394
Epoch 26/30
s: 0.3548
Epoch 27/30
s: 0.3406
Epoch 28/30
s: 0.3500
Epoch 29/30
s: 0.3451
Epoch 30/30
s: 0.3373
[CV] END learning rate=0.01454409005200296, n hidden=1, n neurons=94; total time
= 17.5s
Epoch 1/30
s: 0.4796
Epoch 2/30
s: 0.4353
Epoch 3/30
s: 0.4242
Epoch 4/30
s: 0.4074
Epoch 5/30
s: 0.3932
Epoch 6/30
s: 0.3865
```

```
Epoch 7/30
s: 0.3865
Epoch 8/30
s: 0.3853
Epoch 9/30
s: 0.3873
Epoch 10/30
s: 0.3846
Epoch 11/30
s: 0.3705
Epoch 12/30
s: 0.3624
Epoch 13/30
s: 0.3952
Epoch 14/30
s: 0.4016
Epoch 15/30
s: 0.3619
Epoch 16/30
s: 0.3851
Epoch 17/30
s: 0.3971
Epoch 18/30
s: 0.3550
Epoch 19/30
s: 0.3817
Epoch 20/30
s: 0.3493
Epoch 21/30
276/276 [=============] - 1s 2ms/step - loss: 0.3310 - val_los
s: 0.3679
Epoch 22/30
s: 0.3529
Epoch 23/30
s: 0.3578
Epoch 24/30
s: 0.3482
Epoch 25/30
s: 0.3601
Epoch 26/30
s: 0.3697
Epoch 27/30
s: 0.3465
Epoch 28/30
```

```
s: 0.4361
Epoch 29/30
s: 0.3622
Epoch 30/30
s: 0.3409
[CV] END learning rate=0.01454409005200296, n hidden=1, n neurons=94; total time
= 17.5s
Epoch 1/30
s: 0.5000
Epoch 2/30
s: 0.4467
Epoch 3/30
s: 0.4240
Epoch 4/30
s: 0.4132
Epoch 5/30
s: 0.4000
Epoch 6/30
s: 0.4063
Epoch 7/30
s: 0.3886
Epoch 8/30
s: 0.3873
Epoch 9/30
s: 0.3803
Epoch 10/30
s: 0.3728
Epoch 11/30
s: 0.3819
Epoch 12/30
s: 0.3681
Epoch 13/30
s: 0.3720
Epoch 14/30
s: 0.3707
Epoch 15/30
s: 0.3748
Epoch 16/30
s: 0.3703
Epoch 17/30
s: 0.3647
Epoch 18/30
276/276 [=============] - 1s 2ms/step - loss: 0.3504 - val_los
s: 0.3565
Epoch 19/30
```

```
s: 0.3809
Epoch 20/30
s: 0.3853
Epoch 21/30
s: 0.3496
Epoch 22/30
276/276 [=============] - 1s 2ms/step - loss: 0.3427 - val_los
s: 0.3763
Epoch 23/30
s: 0.3754
Epoch 24/30
s: 0.3571
Epoch 25/30
s: 0.3580
Epoch 26/30
s: 0.3640
Epoch 27/30
s: 0.3468
Epoch 28/30
s: 0.3508
Epoch 29/30
s: 0.3609
Epoch 30/30
s: 0.3464
138/138 [============] - 0s 1ms/step - loss: 0.3365
[CV] END learning rate=0.01454409005200296, n hidden=1, n neurons=94; total time
= 17.8s
Epoch 1/30
s: 3.9815
Epoch 2/30
s: 2.6000
Epoch 3/30
s: 1.8039
Epoch 4/30
s: 1.3295
Epoch 5/30
s: 1.0417
Epoch 6/30
s: 0.8653
Epoch 7/30
s: 0.7567
Epoch 8/30
s: 0.6885
Epoch 9/30
s: 0.6458
```

```
Epoch 10/30
s: 0.6183
Epoch 11/30
s: 0.6004
Epoch 12/30
s: 0.5884
Epoch 13/30
s: 0.5799
Epoch 14/30
s: 0.5737
Epoch 15/30
s: 0.5690
Epoch 16/30
s: 0.5651
Epoch 17/30
s: 0.5619
Epoch 18/30
s: 0.5592
Epoch 19/30
s: 0.5568
Epoch 20/30
s: 0.5545
Epoch 21/30
s: 0.5524
Epoch 22/30
s: 0.5506
Epoch 23/30
s: 0.5488
Epoch 24/30
s: 0.5471
Epoch 25/30
s: 0.5454
Epoch 26/30
s: 0.5439
Epoch 27/30
s: 0.5424
Epoch 28/30
s: 0.5410
Epoch 29/30
s: 0.5397
Epoch 30/30
s: 0.5384
[CV] END learning rate=0.000366880691774657, n hidden=0, n neurons=59; total tim
```

```
e = 15.7s
Epoch 1/30
s: 3.4604
Epoch 2/30
s: 2.4102
Epoch 3/30
s: 1.7827
Epoch 4/30
s: 1.3961
Epoch 5/30
s: 1.1525
Epoch 6/30
s: 0.9964
Epoch 7/30
s: 0.8934
Epoch 8/30
s: 0.8235
Epoch 9/30
s: 0.7749
Epoch 10/30
s: 0.7398
Epoch 11/30
s: 0.7134
Epoch 12/30
s: 0.6927
Epoch 13/30
s: 0.6761
Epoch 14/30
s: 0.6623
Epoch 15/30
s: 0.6506
Epoch 16/30
s: 0.6402
Epoch 17/30
s: 0.6310
Epoch 18/30
s: 0.6228
Epoch 19/30
s: 0.6153
Epoch 20/30
s: 0.6083
Epoch 21/30
276/276 [=============] - 0s 2ms/step - loss: 0.5658 - val_los
s: 0.6020
Epoch 22/30
```

```
s: 0.5960
Epoch 23/30
s: 0.5905
Epoch 24/30
s: 0.5853
Epoch 25/30
s: 0.5803
Epoch 26/30
s: 0.5758
Epoch 27/30
s: 0.5716
Epoch 28/30
s: 0.5675
Epoch 29/30
s: 0.5637
Epoch 30/30
s: 0.5601
[CV] END learning_rate=0.000366880691774657, n_hidden=0, n_neurons=59; total tim
e=16.1s
Epoch 1/30
s: 4.9611
Epoch 2/30
s: 3.1427
Epoch 3/30
s: 2.1091
Epoch 4/30
s: 1.5092
Epoch 5/30
s: 1.1550
Epoch 6/30
s: 0.9429
Epoch 7/30
s: 0.8152
Epoch 8/30
s: 0.7363
Epoch 9/30
s: 0.6863
Epoch 10/30
s: 0.6539
Epoch 11/30
s: 0.6317
Epoch 12/30
s: 0.6161
```

```
Epoch 13/30
s: 0.6043
Epoch 14/30
s: 0.5949
Epoch 15/30
s: 0.5871
Epoch 16/30
s: 0.5806
Epoch 17/30
s: 0.5748
Epoch 18/30
s: 0.5696
Epoch 19/30
s: 0.5649
Epoch 20/30
s: 0.5605
Epoch 21/30
s: 0.5565
Epoch 22/30
s: 0.5529
Epoch 23/30
s: 0.5494
Epoch 24/30
s: 0.5464
Epoch 25/30
s: 0.5434
Epoch 26/30
s: 0.5406
Epoch 27/30
276/276 [=============] - 1s 2ms/step - loss: 0.5174 - val_los
s: 0.5381
Epoch 28/30
s: 0.5356
Epoch 29/30
s: 0.5333
Epoch 30/30
[CV] END learning_rate=0.000366880691774657, n_hidden=0, n_neurons=59; total tim
e=16.0s
Epoch 1/30
s: 1.3437
Epoch 2/30
s: 0.9073
Epoch 3/30
```

```
s: 0.7867
Epoch 4/30
s: 0.7142
Epoch 5/30
s: 0.6632
Epoch 6/30
s: 0.6262
Epoch 7/30
s: 0.6000
Epoch 8/30
s: 0.5787
Epoch 9/30
s: 0.5626
Epoch 10/30
s: 0.5502
Epoch 11/30
s: 0.5385
Epoch 12/30
s: 0.5292
Epoch 13/30
s: 0.5217
Epoch 14/30
s: 0.5149
Epoch 15/30
s: 0.5078
Epoch 16/30
s: 0.5026
Epoch 17/30
s: 0.4968
Epoch 18/30
s: 0.4922
Epoch 19/30
s: 0.4884
Epoch 20/30
s: 0.4843
Epoch 21/30
s: 0.4815
Epoch 22/30
s: 0.4778
Epoch 23/30
s: 0.4747
Epoch 24/30
s: 0.4719
Epoch 25/30
```

```
s: 0.4683
Epoch 26/30
s: 0.4653
Epoch 27/30
s: 0.4628
Epoch 28/30
276/276 [=============] - 1s 2ms/step - loss: 0.4487 - val_los
s: 0.4605
Epoch 29/30
s: 0.4580
Epoch 30/30
s: 0.4559
138/138 [=============] - 0s 1ms/step - loss: 0.4283
[CV] END learning_rate=0.0006169423117905509, n_hidden=3, n_neurons=22; total ti
me=18.5s
Epoch 1/30
s: 1.6579
Epoch 2/30
s: 0.9539
Epoch 3/30
s: 0.7910
Epoch 4/30
s: 0.7087
Epoch 5/30
s: 0.6612
Epoch 6/30
s: 0.6289
Epoch 7/30
s: 0.6033
Epoch 8/30
s: 0.5825
Epoch 9/30
s: 0.5649
Epoch 10/30
s: 0.5498
Epoch 11/30
s: 0.5371
Epoch 12/30
s: 0.5265
Epoch 13/30
s: 0.5162
Epoch 14/30
s: 0.5074
Epoch 15/30
s: 0.4999
```

```
Epoch 16/30
s: 0.4929
Epoch 17/30
s: 0.4869
Epoch 18/30
s: 0.4816
Epoch 19/30
s: 0.4762
Epoch 20/30
s: 0.4713
Epoch 21/30
s: 0.4671
Epoch 22/30
s: 0.4636
Epoch 23/30
s: 0.4600
Epoch 24/30
s: 0.4568
Epoch 25/30
s: 0.4539
Epoch 26/30
s: 0.4517
Epoch 27/30
s: 0.4492
Epoch 28/30
s: 0.4465
Epoch 29/30
s: 0.4443
Epoch 30/30
s: 0.4424
[CV] END learning rate=0.0006169423117905509, n hidden=3, n neurons=22; total ti
me=18.7s
Epoch 1/30
s: 1.2355
Epoch 2/30
s: 0.8953
Epoch 3/30
s: 0.7409
Epoch 4/30
s: 0.6669
Epoch 5/30
s: 0.6243
Epoch 6/30
```

```
s: 0.5965
Epoch 7/30
s: 0.5745
Epoch 8/30
s: 0.5587
Epoch 9/30
s: 0.5443
Epoch 10/30
s: 0.5331
Epoch 11/30
s: 0.5232
Epoch 12/30
s: 0.5164
Epoch 13/30
s: 0.5080
Epoch 14/30
s: 0.5028
Epoch 15/30
s: 0.4977
Epoch 16/30
s: 0.4924
Epoch 17/30
s: 0.4876
Epoch 18/30
s: 0.4840
Epoch 19/30
s: 0.4804
Epoch 20/30
s: 0.4773
Epoch 21/30
s: 0.4741
Epoch 22/30
s: 0.4731
Epoch 23/30
s: 0.4698
Epoch 24/30
s: 0.4698
Epoch 25/30
s: 0.4651
Epoch 26/30
s: 0.4620
Epoch 27/30
s: 0.4610
Epoch 28/30
```

```
s: 0.4577
Epoch 29/30
s: 0.4557
Epoch 30/30
s: 0.4542
[CV] END learning_rate=0.0006169423117905509, n_hidden=3, n_neurons=22; total ti
me=21.2s
Epoch 1/30
s: 1.7168
Epoch 2/30
s: 1.1910
Epoch 3/30
s: 1.0042
Epoch 4/30
s: 0.8797
Epoch 5/30
s: 0.8015
Epoch 6/30
s: 0.7494
Epoch 7/30
s: 0.7107
Epoch 8/30
s: 0.6794
Epoch 9/30
s: 0.6529
Epoch 10/30
s: 0.6301
Epoch 11/30
s: 0.6091
Epoch 12/30
s: 0.5909
Epoch 13/30
s: 0.5749
Epoch 14/30
s: 0.5597
Epoch 15/30
s: 0.5471
Epoch 16/30
s: 0.5358
Epoch 17/30
s: 0.5266
Epoch 18/30
s: 0.5170
```

```
Epoch 19/30
s: 0.5088
Epoch 20/30
s: 0.5018
Epoch 21/30
s: 0.4954
Epoch 22/30
s: 0.4902
Epoch 23/30
s: 0.4850
Epoch 24/30
s: 0.4807
Epoch 25/30
s: 0.4769
Epoch 26/30
s: 0.4727
Epoch 27/30
s: 0.4694
Epoch 28/30
s: 0.4667
Epoch 29/30
s: 0.4634
Epoch 30/30
s: 0.4608
138/138 [============== ] - 0s 1ms/step - loss: 0.4288
[CV] END learning rate=0.0005862763480424351, n hidden=3, n neurons=15; total ti
me=21.3s
Epoch 1/30
s: 1.3674
Epoch 2/30
276/276 [=============] - 1s 2ms/step - loss: 1.0469 - val_los
s: 0.9304
Epoch 3/30
s: 0.7740
Epoch 4/30
s: 0.7083
Epoch 5/30
s: 0.6706
Epoch 6/30
s: 0.6434
Epoch 7/30
s: 0.6228
Epoch 8/30
s: 0.6058
Epoch 9/30
```

```
s: 0.5914
Epoch 10/30
s: 0.5799
Epoch 11/30
s: 0.5692
Epoch 12/30
s: 0.5602
Epoch 13/30
s: 0.5515
Epoch 14/30
s: 0.5434
Epoch 15/30
s: 0.5365
Epoch 16/30
s: 0.5302
Epoch 17/30
s: 0.5243
Epoch 18/30
s: 0.5183
Epoch 19/30
s: 0.5132
Epoch 20/30
s: 0.5083
Epoch 21/30
s: 0.5037
Epoch 22/30
s: 0.4992
Epoch 23/30
s: 0.4951
Epoch 24/30
s: 0.4914
Epoch 25/30
s: 0.4879
Epoch 26/30
s: 0.4842
Epoch 27/30
s: 0.4809
Epoch 28/30
s: 0.4777
Epoch 29/30
s: 0.4747
Epoch 30/30
s: 0.4718
```

```
[CV] END learning rate=0.0005862763480424351, n hidden=3, n neurons=15; total ti
me=18.6s
Epoch 1/30
s: 2.2019
Epoch 2/30
s: 1.1573
Epoch 3/30
276/276 [============] - 1s 2ms/step - loss: 0.9717 - val_los
s: 0.8670
Epoch 4/30
s: 0.7213
Epoch 5/30
s: 0.6540
Epoch 6/30
s: 0.6210
Epoch 7/30
s: 0.6003
Epoch 8/30
s: 0.5851
Epoch 9/30
s: 0.5716
Epoch 10/30
s: 0.5623
Epoch 11/30
s: 0.5526
Epoch 12/30
s: 0.5447
Epoch 13/30
s: 0.5378
Epoch 14/30
s: 0.5326
Epoch 15/30
s: 0.5271
Epoch 16/30
s: 0.5221
Epoch 17/30
s: 0.5173
Epoch 18/30
s: 0.5135
Epoch 19/30
s: 0.5093
Epoch 20/30
s: 0.5047
Epoch 21/30
s: 0.5022
```

```
Epoch 22/30
s: 0.4986
Epoch 23/30
s: 0.4956
Epoch 24/30
s: 0.4929
Epoch 25/30
s: 0.4909
Epoch 26/30
s: 0.4879
Epoch 27/30
s: 0.4864
Epoch 28/30
s: 0.4843
Epoch 29/30
s: 0.4823
Epoch 30/30
s: 0.4789
[CV] END learning_rate=0.0005862763480424351, n_hidden=3, n_neurons=15; total ti
me=18.8s
Epoch 1/30
s: 1.3361
Epoch 2/30
s: 0.7660
Epoch 3/30
s: 0.6738
Epoch 4/30
s: 0.6327
Epoch 5/30
276/276 [=============] - 1s 2ms/step - loss: 0.5903 - val_los
s: 0.6047
Epoch 6/30
s: 0.5848
Epoch 7/30
s: 0.5695
Epoch 8/30
s: 0.5573
Epoch 9/30
s: 0.5480
Epoch 10/30
s: 0.5412
Epoch 11/30
s: 0.5345
Epoch 12/30
```

```
s: 0.5306
Epoch 13/30
s: 0.5260
Epoch 14/30
s: 0.5230
Epoch 15/30
s: 0.5210
Epoch 16/30
s: 0.5179
Epoch 17/30
s: 0.5162
Epoch 18/30
s: 0.5149
Epoch 19/30
s: 0.5127
Epoch 20/30
s: 0.5111
Epoch 21/30
s: 0.5106
Epoch 22/30
s: 0.5090
Epoch 23/30
s: 0.5079
Epoch 24/30
s: 0.5066
Epoch 25/30
s: 0.5057
Epoch 26/30
s: 0.5051
Epoch 27/30
s: 0.5046
Epoch 28/30
s: 0.5037
Epoch 29/30
s: 0.5039
Epoch 30/30
s: 0.5023
[CV] END learning rate=0.0017492192506017832, n hidden=0, n neurons=89; total ti
me=16.9s
Epoch 1/30
s: 1.2149
Epoch 2/30
276/276 [=============] - 1s 2ms/step - loss: 0.8316 - val_los
s: 0.6881
Epoch 3/30
```

```
s: 0.6045
Epoch 4/30
s: 0.5768
Epoch 5/30
s: 0.5610
Epoch 6/30
276/276 [=============] - 1s 2ms/step - loss: 0.5205 - val_los
s: 0.5493
Epoch 7/30
s: 0.5405
Epoch 8/30
s: 0.5341
Epoch 9/30
s: 0.5269
Epoch 10/30
s: 0.5222
Epoch 11/30
s: 0.5186
Epoch 12/30
s: 0.5147
Epoch 13/30
s: 0.5119
Epoch 14/30
s: 0.5091
Epoch 15/30
s: 0.5072
Epoch 16/30
s: 0.5065
Epoch 17/30
s: 0.5038
Epoch 18/30
s: 0.5029
Epoch 19/30
s: 0.5013
Epoch 20/30
s: 0.5001
Epoch 21/30
s: 0.4991
Epoch 22/30
s: 0.4984
Epoch 23/30
s: 0.4979
Epoch 24/30
s: 0.4971
```

```
Epoch 25/30
s: 0.4966
Epoch 26/30
s: 0.4972
Epoch 27/30
s: 0.4958
Epoch 28/30
s: 0.4952
Epoch 29/30
s: 0.4953
Epoch 30/30
s: 0.4944
138/138 [=============== ] - 0s 1ms/step - loss: 0.4929
[CV] END learning_rate=0.0017492192506017832, n_hidden=0, n_neurons=89; total ti
me=17.6s
Epoch 1/30
s: 1.2724
Epoch 2/30
s: 0.6811
Epoch 3/30
s: 0.5982
Epoch 4/30
s: 0.5708
Epoch 5/30
s: 0.5540
Epoch 6/30
s: 0.5418
Epoch 7/30
s: 0.5320
Epoch 8/30
276/276 [=============] - 1s 2ms/step - loss: 0.5082 - val_los
s: 0.5244
Epoch 9/30
s: 0.5182
Epoch 10/30
s: 0.5133
Epoch 11/30
s: 0.5095
Epoch 12/30
s: 0.5065
Epoch 13/30
s: 0.5041
Epoch 14/30
s: 0.5016
Epoch 15/30
```

```
s: 0.4999
Epoch 16/30
s: 0.4986
Epoch 17/30
s: 0.4976
Epoch 18/30
s: 0.4961
Epoch 19/30
s: 0.4952
Epoch 20/30
s: 0.4945
Epoch 21/30
s: 0.4938
Epoch 22/30
s: 0.4928
Epoch 23/30
s: 0.4926
Epoch 24/30
s: 0.4925
Epoch 25/30
s: 0.4917
Epoch 26/30
s: 0.4915
Epoch 27/30
s: 0.4911
Epoch 28/30
s: 0.4909
Epoch 29/30
s: 0.4906
Epoch 30/30
s: 0.4907
[CV] END learning rate=0.0017492192506017832, n hidden=0, n neurons=89; total ti
me=21.5s
Epoch 1/30
s: 1.7579
Epoch 2/30
s: 0.9995
Epoch 3/30
s: 0.7656
Epoch 4/30
s: 0.6797
Epoch 5/30
s: 0.6346
Epoch 6/30
```

```
s: 0.6052
Epoch 7/30
s: 0.5836
Epoch 8/30
s: 0.5662
Epoch 9/30
276/276 [=============] - 1s 2ms/step - loss: 0.5410 - val_los
s: 0.5522
Epoch 10/30
s: 0.5394
Epoch 11/30
s: 0.5291
Epoch 12/30
s: 0.5201
Epoch 13/30
s: 0.5124
Epoch 14/30
s: 0.5060
Epoch 15/30
s: 0.5001
Epoch 16/30
s: 0.4950
Epoch 17/30
s: 0.4909
Epoch 18/30
s: 0.4869
Epoch 19/30
s: 0.4830
Epoch 20/30
s: 0.4804
Epoch 21/30
s: 0.4774
Epoch 22/30
s: 0.4751
Epoch 23/30
s: 0.4734
Epoch 24/30
s: 0.4707
Epoch 25/30
s: 0.4687
Epoch 26/30
s: 0.4672
Epoch 27/30
s: 0.4654
```

```
Epoch 28/30
s: 0.4638
Epoch 29/30
s: 0.4620
Epoch 30/30
s: 0.4605
[CV] END learning_rate=0.0006243610734880342, n_hidden=1, n_neurons=27; total ti
me=18.7s
Epoch 1/30
s: 1.7235
Epoch 2/30
s: 1.1304
Epoch 3/30
s: 0.9301
Epoch 4/30
s: 0.8309
Epoch 5/30
s: 0.7723
Epoch 6/30
s: 0.7319
Epoch 7/30
s: 0.7018
Epoch 8/30
s: 0.6762
Epoch 9/30
s: 0.6550
Epoch 10/30
s: 0.6369
Epoch 11/30
276/276 [==============] - 1s 2ms/step - loss: 0.5781 - val_los
s: 0.6214
Epoch 12/30
s: 0.6077
Epoch 13/30
s: 0.5954
Epoch 14/30
s: 0.5843
Epoch 15/30
s: 0.5741
Epoch 16/30
s: 0.5645
Epoch 17/30
s: 0.5563
Epoch 18/30
```

```
s: 0.5487
Epoch 19/30
s: 0.5411
Epoch 20/30
s: 0.5342
Epoch 21/30
s: 0.5280
Epoch 22/30
s: 0.5222
Epoch 23/30
s: 0.5167
Epoch 24/30
s: 0.5116
Epoch 25/30
s: 0.5069
Epoch 26/30
s: 0.5024
Epoch 27/30
s: 0.4982
Epoch 28/30
s: 0.4943
Epoch 29/30
s: 0.4908
Epoch 30/30
s: 0.4873
138/138 [=============== ] - 0s 2ms/step - loss: 0.4839
[CV] END learning rate=0.0006243610734880342, n hidden=1, n neurons=27; total ti
me= 21.1s
Epoch 1/30
s: 1.2698
Epoch 2/30
s: 0.8815
Epoch 3/30
s: 0.7917
Epoch 4/30
s: 0.7405
Epoch 5/30
s: 0.7018
Epoch 6/30
s: 0.6706
Epoch 7/30
s: 0.6449
Epoch 8/30
s: 0.6230
Epoch 9/30
```

```
s: 0.6047
Epoch 10/30
s: 0.5889
Epoch 11/30
s: 0.5750
Epoch 12/30
276/276 [=============] - 1s 2ms/step - loss: 0.5357 - val_los
s: 0.5632
Epoch 13/30
s: 0.5528
Epoch 14/30
s: 0.5438
Epoch 15/30
s: 0.5359
Epoch 16/30
s: 0.5289
Epoch 17/30
s: 0.5229
Epoch 18/30
s: 0.5173
Epoch 19/30
s: 0.5123
Epoch 20/30
s: 0.5078
Epoch 21/30
s: 0.5036
Epoch 22/30
s: 0.4996
Epoch 23/30
s: 0.4963
Epoch 24/30
s: 0.4932
Epoch 25/30
s: 0.4901
Epoch 26/30
s: 0.4876
Epoch 27/30
s: 0.4849
Epoch 28/30
s: 0.4826
Epoch 29/30
s: 0.4805
Epoch 30/30
s: 0.4778
```

```
[CV] END learning rate=0.0006243610734880342, n hidden=1, n neurons=27; total ti
me= 18.8s
Epoch 1/30
s: 0.6821
Epoch 2/30
s: 0.5870
Epoch 3/30
s: 0.5466
Epoch 4/30
s: 0.5123
Epoch 5/30
s: 0.4984
Epoch 6/30
s: 0.4794
Epoch 7/30
s: 0.4696
Epoch 8/30
s: 0.4617
Epoch 9/30
s: 0.4595
Epoch 10/30
s: 0.4551
Epoch 11/30
s: 0.4479
Epoch 12/30
s: 0.4451
Epoch 13/30
s: 0.4395
Epoch 14/30
s: 0.4416
Epoch 15/30
s: 0.4376
Epoch 16/30
s: 0.4325
Epoch 17/30
s: 0.4300
Epoch 18/30
s: 0.4304
Epoch 19/30
s: 0.4267
Epoch 20/30
s: 0.4273
Epoch 21/30
```

```
s: 0.4229
Epoch 22/30
s: 0.4218
Epoch 23/30
s: 0.4229
Epoch 24/30
s: 0.4291
Epoch 25/30
s: 0.4180
Epoch 26/30
s: 0.4200
Epoch 27/30
s: 0.4146
Epoch 28/30
s: 0.4206
Epoch 29/30
s: 0.4242
Epoch 30/30
s: 0.4122
[CV] END learning rate=0.003652084074475273, n hidden=3, n neurons=4; total time
= 19.5s
Epoch 1/30
s: 0.7913
Epoch 2/30
s: 0.6529
Epoch 3/30
s: 0.5946
Epoch 4/30
s: 0.5537
Epoch 5/30
s: 0.5347
Epoch 6/30
s: 0.5126
Epoch 7/30
s: 0.5010
Epoch 8/30
s: 0.4905
Epoch 9/30
s: 0.4838
Epoch 10/30
s: 0.4783
Epoch 11/30
s: 0.4726
Epoch 12/30
```

```
s: 0.4693
Epoch 13/30
s: 0.4635
Epoch 14/30
s: 0.4590
Epoch 15/30
276/276 [=============] - 1s 2ms/step - loss: 0.4340 - val_los
s: 0.4550
Epoch 16/30
s: 0.4518
Epoch 17/30
s: 0.4480
Epoch 18/30
s: 0.4480
Epoch 19/30
s: 0.4427
Epoch 20/30
s: 0.4429
Epoch 21/30
s: 0.4400
Epoch 22/30
s: 0.4360
Epoch 23/30
s: 0.4438
Epoch 24/30
s: 0.4348
Epoch 25/30
s: 0.4413
Epoch 26/30
s: 0.4298
Epoch 27/30
s: 0.4281
Epoch 28/30
s: 0.4265
Epoch 29/30
s: 0.4266
Epoch 30/30
s: 0.4261
[CV] END learning rate=0.003652084074475273, n hidden=3, n neurons=4; total time
= 19.4s
Epoch 1/30
s: 0.6799
Epoch 2/30
s: 0.5584
```

```
Epoch 3/30
s: 0.5231
Epoch 4/30
s: 0.5104
Epoch 5/30
s: 0.4974
Epoch 6/30
s: 0.4938
Epoch 7/30
s: 0.4864
Epoch 8/30
s: 0.4836
Epoch 9/30
s: 0.4797
Epoch 10/30
s: 0.4805
Epoch 11/30
s: 0.4788
Epoch 12/30
s: 0.4722
Epoch 13/30
s: 0.4736
Epoch 14/30
s: 0.4666
Epoch 15/30
s: 0.4672
Epoch 16/30
s: 0.4659
Epoch 17/30
s: 0.4674
Epoch 18/30
s: 0.4634
Epoch 19/30
s: 0.4817
Epoch 20/30
s: 0.4618
Epoch 21/30
s: 0.4564
Epoch 22/30
s: 0.4563
Epoch 23/30
s: 0.4578
Epoch 24/30
```

```
s: 0.4554
Epoch 25/30
s: 0.4550
Epoch 26/30
s: 0.4534
Epoch 27/30
s: 0.4530
Epoch 28/30
s: 0.4497
Epoch 29/30
s: 0.4492
Epoch 30/30
s: 0.4478
[CV] END learning_rate=0.003652084074475273, n_hidden=3, n_neurons=4; total time
= 19.9s
Epoch 1/30
s: 0.4224
Epoch 2/30
s: 0.3906
Epoch 3/30
s: 0.3741
Epoch 4/30
s: 0.4230
Epoch 5/30
s: 0.3781
Epoch 6/30
s: 0.6053
Epoch 7/30
s: 0.3667
Epoch 8/30
s: 0.3764
Epoch 9/30
s: 0.3781
Epoch 10/30
s: 0.3371
Epoch 11/30
s: 0.3392
Epoch 12/30
s: 0.3703
Epoch 13/30
s: 0.6352
Epoch 14/30
s: 0.3452
Epoch 15/30
```

```
s: 0.3470
Epoch 16/30
s: 0.3438
Epoch 17/30
s: 0.3355
Epoch 18/30
276/276 [=============] - 1s 2ms/step - loss: 0.3153 - val_los
s: 0.4272
Epoch 19/30
s: 0.4802
Epoch 20/30
s: 0.3628
Epoch 21/30
s: 0.3113
Epoch 22/30
s: 0.3409
Epoch 23/30
s: 0.3879
Epoch 24/30
s: 0.3409
Epoch 25/30
s: 0.3966
Epoch 26/30
s: 0.3214
Epoch 27/30
s: 0.3211
Epoch 28/30
s: 0.3877
Epoch 29/30
s: 0.3077
Epoch 30/30
s: 0.3146
[CV] END learning rate=0.026493843442839206, n hidden=2, n neurons=42; total tim
e = 19.9s
Epoch 1/30
s: 0.5203
Epoch 2/30
s: 0.4940
Epoch 3/30
s: 0.4404
Epoch 4/30
s: 0.4514
Epoch 5/30
s: 0.3747
```

```
Epoch 6/30
s: 0.3522
Epoch 7/30
s: 0.3755
Epoch 8/30
s: 0.3583
Epoch 9/30
s: 0.3846
Epoch 10/30
s: 0.3477
Epoch 11/30
s: 0.3451
Epoch 12/30
s: 0.3362
Epoch 13/30
s: 0.3355
Epoch 14/30
s: 0.4134
Epoch 15/30
s: 0.3406
Epoch 16/30
s: 0.3569
Epoch 17/30
s: 0.3304
Epoch 18/30
s: 0.3393
Epoch 19/30
s: 0.3433
Epoch 20/30
276/276 [=============] - 1s 2ms/step - loss: 0.3028 - val_los
s: 0.3301
Epoch 21/30
s: 0.3276
Epoch 22/30
s: 0.3493
Epoch 23/30
s: 0.3353
Epoch 24/30
s: 0.3203
Epoch 25/30
s: 0.3538
Epoch 26/30
s: 0.3120
Epoch 27/30
```

```
s: 0.3165
Epoch 28/30
s: 0.3440
Epoch 29/30
s: 0.4070
Epoch 30/30
s: 0.3445
138/138 [============== ] - 0s 2ms/step - loss: 0.3590
[CV] END learning rate=0.026493843442839206, n hidden=2, n neurons=42; total tim
e = 20.2s
Epoch 1/30
s: 0.4435
Epoch 2/30
s: 0.9387
Epoch 3/30
s: 0.4654
Epoch 4/30
s: 0.4030
Epoch 5/30
s: 0.3610
Epoch 6/30
s: 0.4274
Epoch 7/30
s: 0.3467
Epoch 8/30
s: 0.3905
Epoch 9/30
s: 0.3487
Epoch 10/30
s: 0.3518
Epoch 11/30
s: 0.4041
Epoch 12/30
s: 0.3496
Epoch 13/30
s: 0.3292
Epoch 14/30
s: 0.3321
Epoch 15/30
s: 0.3466
Epoch 16/30
s: 0.3291
Epoch 17/30
276/276 [=============] - 1s 2ms/step - loss: 0.3103 - val_los
s: 0.3294
Epoch 18/30
```

```
s: 0.3199
Epoch 19/30
s: 0.3481
Epoch 20/30
s: 0.3207
Epoch 21/30
276/276 [=============] - 1s 2ms/step - loss: 0.2987 - val_los
s: 0.4965
Epoch 22/30
s: 0.3438
Epoch 23/30
s: 0.3805
Epoch 24/30
s: 0.3539
Epoch 25/30
s: 0.3264
Epoch 26/30
s: 0.3977
Epoch 27/30
s: 0.3188
Epoch 28/30
s: 0.3598
Epoch 29/30
s: 0.3889
Epoch 30/30
s: 0.3134
[CV] END learning rate=0.026493843442839206, n hidden=2, n neurons=42; total tim
e = 19.8s
Epoch 1/30
s: 0.6121
Epoch 2/30
s: 0.5205
Epoch 3/30
s: 0.4767
Epoch 4/30
s: 0.4515
Epoch 5/30
s: 0.4376
Epoch 6/30
s: 0.4215
Epoch 7/30
s: 0.4117
Epoch 8/30
s: 0.4008
```

```
Epoch 9/30
s: 0.3994
Epoch 10/30
s: 0.3928
Epoch 11/30
s: 0.3853
Epoch 12/30
s: 0.3801
Epoch 13/30
s: 0.3868
Epoch 14/30
s: 0.3720
Epoch 15/30
s: 0.3666
Epoch 16/30
s: 0.3653
Epoch 17/30
s: 0.3643
Epoch 18/30
s: 0.3584
Epoch 19/30
s: 0.3583
Epoch 20/30
s: 0.3539
Epoch 21/30
s: 0.3528
Epoch 22/30
s: 0.3549
Epoch 23/30
276/276 [=============] - 1s 2ms/step - loss: 0.3437 - val_los
s: 0.3513
Epoch 24/30
s: 0.3491
Epoch 25/30
s: 0.3518
Epoch 26/30
s: 0.3464
Epoch 27/30
s: 0.3487
Epoch 28/30
s: 0.3468
Epoch 29/30
s: 0.3491
Epoch 30/30
```

```
s: 0.3411
138/138 [============== ] - 0s 2ms/step - loss: 0.3395
[CV] END learning rate=0.003866289668516478, n hidden=2, n neurons=50; total tim
e = 20.2s
Epoch 1/30
s: 0.6714
Epoch 2/30
s: 0.5622
Epoch 3/30
s: 0.4984
Epoch 4/30
s: 0.4636
Epoch 5/30
s: 0.4450
Epoch 6/30
s: 0.4288
Epoch 7/30
s: 0.4217
Epoch 8/30
s: 0.4125
Epoch 9/30
s: 0.4068
Epoch 10/30
s: 0.3997
Epoch 11/30
s: 0.4025
Epoch 12/30
s: 0.3883
Epoch 13/30
s: 0.3839
Epoch 14/30
s: 0.3821
Epoch 15/30
s: 0.3815
Epoch 16/30
s: 0.3752
Epoch 17/30
s: 0.3743
Epoch 18/30
s: 0.3694
Epoch 19/30
s: 0.3714
Epoch 20/30
276/276 [=============] - 1s 2ms/step - loss: 0.3459 - val_los
s: 0.3657
Epoch 21/30
```

```
s: 0.3660
Epoch 22/30
s: 0.3633
Epoch 23/30
s: 0.3797
Epoch 24/30
276/276 [=============] - 1s 2ms/step - loss: 0.3388 - val_los
s: 0.3599
Epoch 25/30
s: 0.3628
Epoch 26/30
s: 0.3563
Epoch 27/30
s: 0.3635
Epoch 28/30
s: 0.3541
Epoch 29/30
s: 0.3536
Epoch 30/30
s: 0.3538
[CV] END learning rate=0.003866289668516478, n hidden=2, n neurons=50; total tim
e= 21.2s
Epoch 1/30
s: 0.5869
Epoch 2/30
s: 0.5033
Epoch 3/30
s: 0.4744
Epoch 4/30
s: 0.4470
Epoch 5/30
s: 0.4322
Epoch 6/30
s: 0.4266
Epoch 7/30
s: 0.4138
Epoch 8/30
s: 0.4127
Epoch 9/30
s: 0.3993
Epoch 10/30
s: 0.3963
Epoch 11/30
s: 0.3951
```

```
Epoch 12/30
s: 0.3888
Epoch 13/30
s: 0.3860
Epoch 14/30
s: 0.3818
Epoch 15/30
s: 0.3783
Epoch 16/30
s: 0.3818
Epoch 17/30
s: 0.3734
Epoch 18/30
s: 0.3756
Epoch 19/30
s: 0.3717
Epoch 20/30
s: 0.3679
Epoch 21/30
s: 0.3713
Epoch 22/30
s: 0.3665
Epoch 23/30
s: 0.3691
Epoch 24/30
s: 0.3613
Epoch 25/30
s: 0.3604
Epoch 26/30
276/276 [=============] - 1s 2ms/step - loss: 0.3476 - val_los
s: 0.3594
Epoch 27/30
s: 0.3707
Epoch 28/30
s: 0.3624
Epoch 29/30
s: 0.3545
Epoch 30/30
s: 0.3548
[CV] END learning rate=0.003866289668516478, n hidden=2, n neurons=50; total tim
e= 20.9s
Epoch 1/30
s: 0.5676
Epoch 2/30
```

```
s: 0.4841
Epoch 3/30
s: 0.4305
Epoch 4/30
s: 0.4133
Epoch 5/30
s: 0.3966
Epoch 6/30
s: 0.3912
Epoch 7/30
s: 0.3832
Epoch 8/30
s: 0.3819
Epoch 9/30
s: 0.3711
Epoch 10/30
s: 0.3687
Epoch 11/30
s: 0.3695
Epoch 12/30
s: 0.3709
Epoch 13/30
s: 0.3531
Epoch 14/30
s: 0.3686
Epoch 15/30
s: 0.3591
Epoch 16/30
s: 0.3562
Epoch 17/30
s: 0.3467
Epoch 18/30
s: 0.3452
Epoch 19/30
s: 0.3409
Epoch 20/30
s: 0.3402
Epoch 21/30
s: 0.3424
Epoch 22/30
s: 0.3406
Epoch 23/30
s: 0.3516
Epoch 24/30
```

```
s: 0.3383
Epoch 25/30
s: 0.3440
Epoch 26/30
s: 0.3344
Epoch 27/30
s: 0.3373
Epoch 28/30
s: 0.3293
Epoch 29/30
s: 0.3339
Epoch 30/30
s: 0.3554
138/138 [============== ] - 0s 2ms/step - loss: 0.3564
[CV] END learning rate=0.005265222470937165, n hidden=3, n neurons=73; total tim
e = 21.8s
Epoch 1/30
s: 0.5337
Epoch 2/30
s: 0.4653
Epoch 3/30
s: 0.4407
Epoch 4/30
s: 0.4118
Epoch 5/30
s: 0.4056
Epoch 6/30
s: 0.3983
Epoch 7/30
s: 0.3877
Epoch 8/30
s: 0.3778
Epoch 9/30
s: 0.3708
Epoch 10/30
s: 0.3747
Epoch 11/30
s: 0.3686
Epoch 12/30
s: 0.3554
Epoch 13/30
s: 0.3507
Epoch 14/30
s: 0.3494
```

```
Epoch 15/30
s: 0.3478
Epoch 16/30
s: 0.3469
Epoch 17/30
s: 0.3606
Epoch 18/30
s: 0.3451
Epoch 19/30
s: 0.3438
Epoch 20/30
s: 0.3379
Epoch 21/30
s: 0.3404
Epoch 22/30
s: 0.3390
Epoch 23/30
s: 0.3597
Epoch 24/30
s: 0.3726
Epoch 25/30
s: 0.3528
Epoch 26/30
s: 0.3362
Epoch 27/30
s: 0.3359
Epoch 28/30
s: 0.4076
Epoch 29/30
s: 0.3353
Epoch 30/30
s: 0.3414
[CV] END learning rate=0.005265222470937165, n hidden=3, n neurons=73; total tim
e = 21.8s
Epoch 1/30
s: 0.5337
Epoch 2/30
s: 0.4617
Epoch 3/30
s: 0.4276
Epoch 4/30
s: 0.4149
Epoch 5/30
```

```
s: 0.3984
Epoch 6/30
s: 0.3907
Epoch 7/30
s: 0.3857
Epoch 8/30
s: 0.3816
Epoch 9/30
s: 0.3769
Epoch 10/30
s: 0.3691
Epoch 11/30
s: 0.3623
Epoch 12/30
s: 0.3661
Epoch 13/30
s: 0.3621
Epoch 14/30
s: 0.3616
Epoch 15/30
s: 0.3531
Epoch 16/30
s: 0.3568
Epoch 17/30
s: 0.3494
Epoch 18/30
s: 0.3634
Epoch 19/30
s: 0.4087
Epoch 20/30
s: 0.3648
Epoch 21/30
s: 0.3614
Epoch 22/30
s: 0.3432
Epoch 23/30
s: 0.3465
Epoch 24/30
s: 0.3433
Epoch 25/30
s: 0.3422
Epoch 26/30
s: 0.3378
Epoch 27/30
```

```
s: 0.3357
Epoch 28/30
s: 0.3435
Epoch 29/30
s: 0.3507
Epoch 30/30
s: 0.3365
[CV] END learning_rate=0.005265222470937165, n_hidden=3, n_neurons=73; total tim
e= 22.6s
Epoch 1/30
s: 0.4356
Epoch 2/30
s: 0.6350
Epoch 3/30
s: 0.3917
Epoch 4/30
s: 0.3568
Epoch 5/30
s: 0.3593
Epoch 6/30
s: 0.3753
Epoch 7/30
s: 0.3975
Epoch 8/30
s: 0.3595
Epoch 9/30
s: 0.3362
Epoch 10/30
s: 0.3277
Epoch 11/30
s: 0.3195
Epoch 12/30
s: 0.3200
Epoch 13/30
s: 0.3250
Epoch 14/30
s: 0.3400
Epoch 15/30
s: 0.3377
Epoch 16/30
s: 0.3099
Epoch 17/30
s: 0.3355
```

```
Epoch 18/30
    s: 0.3120
    Epoch 19/30
    s: 0.3070
    Epoch 20/30
    s: 0.3123
    Epoch 21/30
    s: 0.3048
    Epoch 22/30
    s: 0.3263
    Epoch 23/30
    s: 0.3040
    Epoch 24/30
    s: 0.3368
    Epoch 25/30
    s: 0.3141
    Epoch 26/30
    s: 0.3283
    Epoch 27/30
    s: 0.3036
    Epoch 28/30
    s: 0.3189
    Epoch 29/30
    s: 0.2927
    Epoch 30/30
    s: 0.3079
Out[22]: RandomizedSearchCV(cv=3,
             estimator=<keras.wrappers.scikit learn.KerasRegressor object
    at 0x7f99c0ed9ed0>,
             param distributions={'learning rate': [0.018660324072369908,
                               0.007644504723105013,
                               0.0006520854051037825,
                               0.018195520549468946,
                               0.007759773905501517,
                               0.002416434498857632,
                               0.028154254335988504,
                               0.01236727955030516,
                               0.001430026349082893,
                               0.004085515660209816,
                               0...
                               0.0031246507390906143,
                               0.0017485292281239227,
                               0.002098148407433953,
                               0.0019359456955505697,
                               0.0008873943214929799,
                               0.0013761511693017496,
                               0.004668993857464526,
                               0.0009542231770992221,
                               0.009483872212692068,
                               0.016898283698526653,
    ...],
```

'n_hidden': [0, 1, 2, 3],

```
'n_neurons': [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, ...]},
```

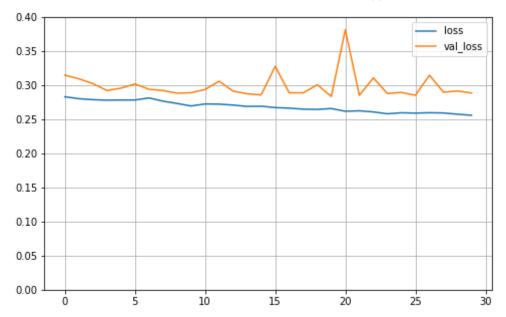
verbose=2)

(c) [1 mark]

Plot the learning curves for the best model in (c). Does it look like the model is overfitting?

```
best model = rnd search cv.best estimator .model
In [24]:
   res = best_model.fit(X_train, y_train, epochs=30,
In [25]:
       validation_data=(X_valid, y_valid))
  Epoch 1/30
  s: 0.3147
  Epoch 2/30
  s: 0.3094
  Epoch 3/30
  s: 0.3023
  Epoch 4/30
  s: 0.2922
  Epoch 5/30
  s: 0.2957
  Epoch 6/30
  s: 0.3018
  Epoch 7/30
  s: 0.2940
  Epoch 8/30
  s: 0.2922
  Epoch 9/30
  s: 0.2882
  Epoch 10/30
  s: 0.2890
  Epoch 11/30
  s: 0.2937
  Epoch 12/30
  s: 0.3058
  Epoch 13/30
  s: 0.2913
  Epoch 14/30
```

```
s: 0.2874
  Epoch 15/30
  s: 0.2857
  Epoch 16/30
  s: 0.3277
  Epoch 17/30
  s: 0.2889
  Epoch 18/30
  s: 0.2888
  Epoch 19/30
  s: 0.3006
  Epoch 20/30
  s: 0.2835
  Epoch 21/30
  s: 0.3814
  Epoch 22/30
  s: 0.2851
  Epoch 23/30
  s: 0.3107
  Epoch 24/30
  s: 0.2878
  Epoch 25/30
  s: 0.2894
  Epoch 26/30
  s: 0.2852
  Epoch 27/30
  s: 0.3147
  Epoch 28/30
  s: 0.2897
  Epoch 29/30
  s: 0.2915
  Epoch 30/30
  s: 0.2885
  import pandas as pd
In [26]:
  import matplotlib.pyplot as plt
  pd.DataFrame(res.history).plot(figsize=(8, 5))
  plt.grid(True)
  plt.gca().set ylim(0, 0.4)
  plt.show()
```



Yes, the model looks like overfitting.

2. Binary classification DNN [23 marks]

Consider the Caravan insurance data. The data gives sociodemographic and product ownership data from customers of an insurance company, some of which purchased caravan insurance. You can read ther data description from that website. Download the data as a csv file from Canvas.

The target variable is $\mbox{Purchase}$, which is binary and you should convert it to 1 for \mbox{Yes} and 0 for \mbox{No} .

(a) [3 marks]

Load, split and preprocess the data. In particular, for the splitting, you will need to create a test set (20% of the full data), a validation set (20% of the remaining data after creating the test set), and a training set, and stratify using the target variable because this is an imbalanced dataset. For both splits, use random_state=42. The features MOSTYPE and MOSHOOFD are categorical so one hot encoding needs to be applied to them. All other features are numerical so a standard scaler needs to be applied to them. Print the training set X_train, y_train using print().

```
In [84]: X_raw = pd.read_csv("caravan.csv")
    from sklearn.model_selection import StratifiedShuffleSplit

# split raw data set into 20% test set
    split = StratifiedShuffleSplit(n_splits=1, test_size=0.2, random_state=42)
    for train_index, test_index in split.split(X_raw, X_raw["Purchase"]):
        strat_train_set = X_raw.loc[train_index]
        strat_test_set_1 = X_raw.loc[test_index]
```

```
# split the remaining 20% data after creating the test set into validation set
          # and the training set
          for valid_index, train_index in split.split(strat_test_set_1,
                                                        strat_test_set_1["Purchase"]):
               strat_test_set = strat_test_set_1.iloc[valid_index]
               strat valid set = strat test set 1.iloc[train index]
          X_train_new = strat_train_set.drop("Purchase", axis=1)
In [85]:
          y_train = (strat_train_set["Purchase"] == "Yes") + 0
          from sklearn.pipeline import Pipeline
In [86]:
          from sklearn.preprocessing import StandardScaler
          from sklearn.compose import ColumnTransformer
          from sklearn.preprocessing import OneHotEncoder
          num pipeline = Pipeline([
                   ('std_scaler', StandardScaler()),
          X_train_new_num = X_train_new.drop(["MOSTYPE", "MOSHOOFD"], axis=1)
          num_attribs = list(X_train_new_num)
          cat attribs = ["MOSTYPE", "MOSHOOFD"]
          full_pipeline = ColumnTransformer([
                   ("num", num_pipeline, num_attribs),
                   ("cat", OneHotEncoder(), cat_attribs),
               1)
In [87]: | X train = full pipeline.fit transform(X train new)
          X test new = strat test set.drop("Purchase", axis=1)
          y test = (strat test set["Purchase"] == "Yes") + 0
          X test = full pipeline.transform(X test new)
          X valid new = strat valid set.drop("Purchase", axis=1)
          y_valid = (strat_valid_set["Purchase"] == "Yes") + 0
          X valid = full pipeline.transform(X valid new)
In [88]: | print(X_train)
          [[-0.27440493 -0.85901763 0.0055585 ... 1.
                                                                   0.
           [-0.27440493 \quad 0.40694601 \quad 0.0055585 \quad \dots \quad 1.
                                                                   0.
           [-0.27440493 \quad 0.40694601 \quad 0.0055585
                                                                   0.
            0.
           [-0.27440493 -0.85901763 0.0055585 ... 0.
                                                                   1.
           [-0.27440493 -0.85901763 2.4708858 ... 1.
                                                                   0.
           [-0.27440493 \quad 0.40694601 \quad 1.23822215 \quad ... \quad 1.
                                                                   0.
                       ]]
In [89]:
         print(y train)
         198
                  0
         676
         330
                  0
         1231
                  0
         5545
                  0
```

```
5341 0
1486 0
5077 0
1170 0
5819 1
Name: Purchase, Length: 4657, dtype: int64
```

(b) [3 marks]

In the next part (c), you will build and fit a DNN with 5 hidden layers of 200, 200, 100, 100, 50 neurons, respectively. Use the following specifications:

- (i) He initialization and the ELU activation function.
- (ii) The output layer has 1 neuron with sigmoid activation.
- (iii) Compile with loss="binary_crossentropy" and metrics=["AUC"] (which is ROC AUC).

In this question, explain why the choices (i), (ii), and (iii) are justified.

[Add your solution here]

Since the ELU has negative values, which allows ELU not only has lower computational complecity but also with close zero mean unit activation, like batch nomalization does. The He initialization takes into account the non-linearity of activation functions. So it is suitable for using both ELU and He initialization. Since there is only one target variable, the output layer has one neuron with sigmoid activation. Hence, we should compile with command "loss="binary_crossentropy" and metrics=["AUC"].

(c) [3 marks]

Train the model in (b) for 30 epochs and use exponential scheduling and the NAG optimizer with momentum=0.9. Use a learning curve to comment on whether it is overfitting.

At the start of fitting your model, run reset_session() given by the following code.

```
import random as python_random

def reset_session(seed=42):
    tf.random.set_seed(seed)
    python_random.seed(seed)
    np.random.seed(seed)
    tf.keras.backend.clear_session()
```

```
In [34]: def exponential_decay(lr0, s):
    return lambda epoch: lr0 * 0.1**(epoch / s)
    lr_scheduler = keras.callbacks.LearningRateScheduler(exponential_decay(lr0=0.01,
In [35]: reset_session()
```

```
model = keras.models.Sequential()
         model.add(keras.layers.Dense(200, activation="elu", kernel_initializer="he_norma")
         model.add(keras.layers.Dense(200, activation="elu", kernel_initializer="he_norma
         model.add(keras.layers.Dense(100, activation="elu", kernel_initializer="he_norma")
         model.add(keras.layers.Dense(100, activation="elu", kernel_initializer="he_norma
         model.add(keras.layers.Dense(50, activation="elu", kernel_initializer="he_normal
         model.add(keras.layers.Dense(1, activation="sigmoid"))
In [36]:
         optimizer= keras.optimizers.SGD(momentum=0.9, nesterov=True)
In [37]:
         model.compile(loss="binary_crossentropy",
                       optimizer=optimizer,
                       metrics=["AUC"])
         model.evaluate(X_train, y_train)
In [38]:
         Out[38]: [0.8543457388877869, 0.5158929824829102]
         model.evaluate(X_valid, y_valid)
In [39]:
         8/8 [========================== ] - 0s 3ms/step - loss: 0.8979 - auc: 0.5802
Out[39]: [0.8979277014732361, 0.5802348852157593]
         res = model.fit(X_train, y_train, epochs=30,
In [41]:
                         callbacks=[lr scheduler],
                         validation data=(X valid, y valid),
                         verbose=0)
         import matplotlib.pyplot as plt
In [42]:
         pd.DataFrame(res.history).plot(figsize=(8, 5))
         plt.grid(True)
         plt.gca().set ylim(0, 1.1)
         plt.show()
         1.0
         0.8
                 055
         0.6
                 val loss
                 val auc
         0.4
         0.2
         0.0
```

20

The learning curve shows it is overfitting.

(d) [12 marks]

Fit separate models using the same specification as in (c) but with the following regularization techniques:

- (i) batch normalization,
- (ii) early stopping based on validation AUC with patience=10 (look at the documentation and note the mode argument).
- (iv) dropout with probability 0.2,
- (v) ℓ_2 regularization and early stopping both as above,
- (vi) batch normalization and dropout both as above.

At the start of each one of the above models, run reset_session().

The performance measure is validation AUC. State this for the model in (c), and for each of the models here comment on whether it is better than the model in (c).

```
In [43]:
          reset session()
          # i
          model1 = keras.models.Sequential([
              keras.layers.BatchNormalization(),
              keras.layers.Dense(200, activation="elu", kernel initializer="he normal"),
              keras.layers.BatchNormalization(),
              keras.layers.Dense(200, activation="elu", kernel initializer="he normal"),
              keras.layers.BatchNormalization(),
              keras.layers.Dense(100, activation="elu", kernel initializer="he normal"),
              keras.layers.BatchNormalization(),
              keras.layers.Dense(100, activation="elu", kernel initializer="he normal"),
              keras.layers.BatchNormalization(),
              keras.layers.Dense(50, activation="elu", kernel initializer="he normal"),
              keras.layers.BatchNormalization(),
              keras.layers.Dense(1, activation="sigmoid")])
```

```
        Out[44]:
        loss
        auc
        val_loss
        val_auc

        19
        0.037061
        0.997744
        0.433728
        0.651500

        20
        0.036454
        0.997948
        0.435424
        0.648402

        21
        0.036612
        0.997720
        0.440464
        0.646771
```

```
val_loss
        loss
                                  val_auc
                  auc
22
   0.035727
             0.997982
                       0.444318
                                 0.648076
23
    0.036115
             0.997784
                       0.445730
                                0.647260
   0.035835
             0.997901
                       0.442805
                                0.648565
    0.035551 0.997922
                      0.443962
                                 0.644977
25
   0.035000 0.997952 0.444988
                                 0.654762
26
    0.034991 0.997942
                       0.455614 0.649543
   0.034601 0.997943
                       0.456901
                                 0.647913
28
29 0.034580 0.998054 0.454539 0.652316
```

```
In [45]:
          # ii
          reset session()
          model2 = keras.models.Sequential()
          for n_hidden in (200, 200, 100, 100, 50):
              model2.add(keras.layers.Dense(n_hidden, activation="elu",
                                           kernel_initializer="he_normal"))
          model2.add(keras.layers.Dense(1, activation="sigmoid"))
          optimizer = keras.optimizers.SGD(momentum=0.9, nesterov=True)
          model2.compile(loss="binary_crossentropy", optimizer=optimizer,
                        metrics=["AUC"])
          early stopping cb = keras.callbacks.EarlyStopping(monitor='auc',
                                                             mode='max', patience=10)
          run 2 = model2.fit(X train, y train, epochs=30,
                          validation data =(X valid, y valid),
                          callbacks=[early stopping cb],
                          verbose=0)
          pd.DataFrame(run_2.history).iloc[-11:]
```

```
val_loss
Out[45]:
                  loss
                            auc
                                           val_auc
          19 0.058405 0.990124
                                 0.387275 0.592629
          20 0.057483 0.989366
                                 0.375193
                                          0.615134
          21 0.053640 0.991564 0.405090 0.564579
          22 0.051944 0.990699 0.397597 0.532290
          23 0.053488 0.992204 0.406501 0.636986
          24
             0.051599 0.993019
                                 0.416124 0.609426
                                 0.369791 0.632583
          25 0.049535 0.991685
          26 0.046170 0.994740 0.423418 0.595727
             0.044461 0.993052 0.420730 0.562296
          28 0.041400 0.995591 0.455073
                                         0.570776
          29 0.043516 0.995098 0.475823 0.604371
```

```
In [91]: # iii
    from functools import partial
    RegularizedDense = partial(keras.layers.Dense,
```

```
activation="elu",
                     kernel initializer="he normal",
                     kernel_regularizer=keras.regularizers.12(0.001))
reset session()
model3 = keras.models.Sequential()
for n_hidden in (200, 200, 100, 100, 50):
    model3.add(RegularizedDense(n hidden))
model3.add(keras.layers.Dense(1, activation="sigmoid",
                               kernel regularizer=keras.regularizers.12(0.001)))
optimizer = keras.optimizers.SGD(momentum=0.9, nesterov=True)
model3.compile(loss="binary crossentropy",
              optimizer=optimizer,
              metrics=["AUC"])
res_3 = model3.fit(X_train, y_train, epochs=30,
                validation data=(X valid, y valid), verbose=0)
pd.DataFrame(res_3.history).iloc[-11:]
```

```
loss
                                  val_loss
Out[91]:
                            auc
                                            val_auc
              0.606591
                        0.931749
                                 0.727074 0.647260
          19
          20 0.580834 0.938801
                                 0.731760
                                          0.630137
          21 0.563246 0.934317
                                 0.723209 0.606490
          22 0.540377 0.939650 0.689933 0.663405
          23 0.527437 0.930050
                                0.678146
                                          0.568167
          24 0.504876 0.937013
                                 0.675902 0.609100
          25 0.490270 0.934447 0.624446 0.668460
          26 0.468684 0.945603 0.629763 0.632420
          27 0.460482 0.937413
                                  0.617241 0.593444
          28 0.440436 0.945255 0.646946 0.555284
```

29 0.429026 0.944608 0.634787

```
# iv
In [47]:
          ## (iv) dropout with probability 0.2
          reset session()
          model4 = keras.models.Sequential()
          model4.add(keras.layers.Dropout(rate=0.2))
          for n hidden in (200, 200, 100, 100, 50):
              model4.add(keras.layers.Dense(n hidden, activation="elu",
                                           kernel initializer="he normal"))
              keras.layers.BatchNormalization()
              model4.add(keras.layers.Dropout(rate=0.2))
          model4.add(keras.layers.Dense(1, activation="sigmoid"))
          optimizer = keras.optimizers.SGD(momentum=0.9, nesterov=True)
          model4.compile(loss="binary_crossentropy", optimizer=optimizer,
                        metrics=["AUC"])
          res 4 = model4.fit(X train, y train, epochs=30,
                          validation data=(X valid, y valid), verbose=0)
          pd.DataFrame(res 4.history).iloc[-11:]
```

0.614971

loss auc val_loss val_auc Out[47]: **19** 0.202673 0.758046 0.207132 0.763699

```
val_loss
                              val_auc
       loss
                auc
20 0.195413 0.778679
                     0.211865
                             0.729126
21 0.195602 0.779355
                    0.213022 0.728637
22 0.192624 0.790284 0.208898 0.753098
23
   0.198521 0.769023
                     0.211828 0.706458
24
   0.197901 0.768586 0.209718 0.730267
25
   0.197451 0.777869 0.204722 0.746575
26 0.190487 0.804407 0.206622 0.735323
27 0.193868 0.787001 0.209975 0.733040
   29 0.190029 0.803976 0.220603 0.710209
```

```
# v
In [48]:
          from functools import partial
          RegularizedDense = partial(keras.layers.Dense,
                               activation="elu",
                               kernel initializer="he normal",
                               kernel regularizer=keras.regularizers.12(0.001))
          reset_session()
          model5 = keras.models.Sequential()
          for n hidden in (200, 200, 100, 100, 50):
              model5.add(RegularizedDense(n hidden))
          model5.add(keras.layers.Dense(1, activation="sigmoid"))
          optimizer = keras.optimizers.SGD(momentum=0.9, nesterov=True)
          model5.compile(loss="binary_crossentropy", optimizer=optimizer,
                        metrics=["AUC"])
          early stopping cb = keras.callbacks.EarlyStopping(monitor='auc',
                                                             mode='max', patience=10)
          res 5 = model5.fit(X train, y train, epochs=30,
                          validation data =(X valid, y valid),
                          callbacks=early stopping cb, verbose=0)
          pd.DataFrame(res 5.history).iloc[-11:]
```

Out[48]:		loss	auc	val_loss	val_auc
	19	0.601281	0.933645	0.728743	0.651990
	20	0.574888	0.941391	0.739134	0.593607
	21	0.563113	0.933531	0.720304	0.609589
	22	0.535514	0.939799	0.709157	0.639759
	23	0.522086	0.931753	0.680604	0.582192
	24	0.500186	0.937534	0.686488	0.607958
	25	0.484851	0.936012	0.654018	0.641553
	26	0.464267	0.947101	0.633350	0.632420
	27	0.454924	0.939407	0.621614	0.603066
	28	0.435375	0.945061	0.650451	0.562785

 loss
 auc
 val_loss
 val_auc

 29
 0.423037
 0.946966
 0.639060
 0.617254

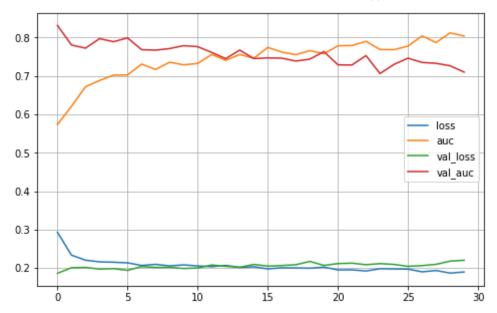
```
In [49]:
          # vi
          reset_session()
          model6 = keras.models.Sequential()
          keras.layers.BatchNormalization()
          model6.add(keras.layers.Dropout(rate=0.2))
          for n_hidden in (200, 200, 100, 100, 50):
              model6.add(keras.layers.Dense(n_hidden, activation="elu",
                                            kernel_initializer="he_normal"))
              model6.add
              model6.add(keras.layers.Dropout(rate=0.2))
          model6.add(keras.layers.Dense(1, activation="sigmoid"))
          optimizer = keras.optimizers.SGD(momentum=0.9, nesterov=True)
          model6.compile(loss="binary_crossentropy",
                        optimizer=optimizer,
                        metrics=["AUC"])
          res_6 = model6.fit(X_train, y_train, epochs=30,
                          validation_data=(X_valid, y_valid), verbose=0)
          pd.DataFrame(res_6.history).iloc[-11:]
```

Out[49]:		loss	auc	val_loss	val_auc
	19	0.202673	0.758046	0.207132	0.763699
	20	0.195413	0.778679	0.211865	0.729126
	21	0.195602	0.779355	0.213022	0.728637
	22	0.192624	0.790284	0.208898	0.753098
	23	0.198521	0.769023	0.211828	0.706458
	24	0.197901	0.768586	0.209718	0.730267
	25	0.197451	0.777869	0.204722	0.746575
	26	0.190487	0.804407	0.206622	0.735323
	27	0.193868	0.787001	0.209975	0.733040
	28	0.187155	0.812326	0.218294	0.726680
	29	0.190029	0.803976	0.220603	0.710209

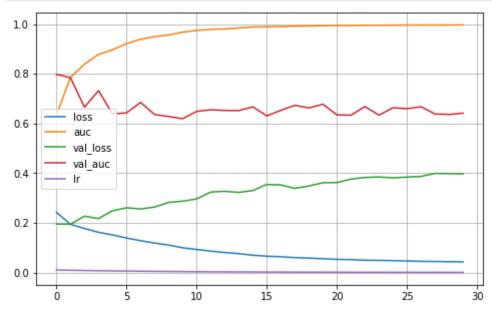
(e) [1 mark]

For the dropout model in (d)(iv) determine whether or not it is overfitting less than the model in (c).

```
In [50]: #d(iv)
    pd.DataFrame(res_4.history).plot(figsize=(8, 5))
    plt.grid(True)
    plt.show()
```



```
In [51]: #c
    pd.DataFrame(res.history).plot(figsize=(8, 5))
    plt.grid(True)
    plt.show()
```



The model in d(iv) is less overfitting than model in c.

(f) [1 mark]

Of the models in (c) and (d), one would now choose the best model according to the performance metric (validation AUC) to evaluate on the test set. But instead, evaluate the model in (d)(v) on the test set in terms of the AUC and confusion matrix (regardless of whether it is the best model given your results).

```
In [53]: # in (d)(v)
test_mse = model5.evaluate(X_test, y_test)
```

3. Time series using machine learning [14 marks]

Obtain daily values of the Japan/U.S. Foreign Exchange Rate (DEXJPUS) starting from Jan 1, 1990, to Jan 1, 2022, from FRED. This can be obtained using the code below or you can download the data as a csv file from Canvas.

```
In [55]: import pandas as pd
   import pandas_datareader as pdr
   from datetime import datetime
   data = pdr.get_data_fred('DEXJPUS', datetime(1990,1,1),datetime(2022,1,1))
In [56]: data
```

Out[56]: DEXJPUS

DATE	
1990-01-01	NaN
1990-01-02	146.25
1990-01-03	145.70
1990-01-04	143.37
1990-01-05	143.82
•••	
2021-12-27	114.85
2021-12-28	114.75
2021-12-29	114.97

DEXJPUS

DATE	
2021-12-30	115.17
2021-12-31	NaN

8350 rows × 1 columns

(a) [2 marks]

Create a training set (before 2010), a validation set (Jan 2010 to Dec 2015), and a test set (the rest of the data). Turn the time series data into a supervised learning dataset where the features are the value of the exchange rate in the last 10 days inclusive of the current day, and the target is the value of the exchange rate in the next day.

[Add your solution here]

```
In [57]: data = data.dropna()
In [58]:
          train = data[data.index < datetime(2010,1,1)]</pre>
           test_raw = data[data.index > datetime(2010,1,1)]
           valid = test raw[test raw.index < datetime(2016,1,1)]</pre>
           test = test raw[test raw.index > datetime(2016,1,1)]
          def ts split(ts, feature steps=10, target steps=1):
In [59]:
               n obs = len(ts) - feature steps - target steps + 1
               X = np.array([ts[idx:idx + feature steps] for idx in range(n obs)])
               y = np.array([ts[idx + feature steps:idx + feature steps + target steps]
                              for idx in range(n obs)])
               return X, y
In [60]:
          X train, y train = ts split(train, feature steps=10, target steps=1)
           X valid, y valid = ts split(valid, feature steps=10, target steps=1)
           X test, y test = ts split(test, feature steps=10, target steps=1)
In [61]:
          X \text{ train} = X \text{ train}[:,:,-1]
           X \text{ valid} = X \text{ valid}[:,:,-1]
          X_{\text{test}} = X_{\text{test}}[:,:,-1]
          y train = y train[:,:,-1]
           y_valid = y_valid[:,:,-1]
           y_test = y_test[:,:,-1]
```

(b) [3 marks]

Fit a random forest regressor to predict the value of the exchange rate in the next day. Using the test set, report the mean squared error and the accuracy for the movement direction.

Hint: You can calculate the accuracy of the movement direction by determining what the actual movement direction is and comparing it to the movement direction corresponding to the

predicted value of the exchange rate. For instance, the movement direction of the test set X_test and y_test where a strictly up movement is True can be computed as follows.

```
In [62]: movement_test = X_test[:,-1] < y_test.ravel()</pre>
```

[Add your solution here]

```
In [63]: from sklearn.ensemble import RandomForestRegressor
    from sklearn.metrics import mean_squared_error
    regr = RandomForestRegressor(random_state=42)
    regr.fit(X_train, y_train)
    y_pred = regr.predict(X_test)
    mse = mean_squared_error(y_test, y_pred)
```

/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:4: DataConversionWa rning: A column-vector y was passed when a 1d array was expected. Please change the shape of y to (n_samples,), for example using ravel().

after removing the cwd from sys.path.

```
In [64]: mse
```

Out[64]: 0.3738088196839275

The mean squared error is 0.3738088196839275.

```
In [65]: movement_pred = X_test[:,-1] < y_pred.ravel()
In [66]: from sklearn.metrics import accuracy_score
    accuracy_score(movement_test, movement_pred)</pre>
```

Out[66]: 0.5137861466039004

The accuracy score is 0.5137861466039004.

(c) [4 marks]

Repeat (b), but now fit a deep RNN with 2 recurrent layers of 20 and 20 neurons, and an output layer which is 1 dense neuron. Use 100 epochs and the Nadam optimizer. Comment on the result and the learning curve (the validation set is used for the learning curve).

```
import numpy as np
import matplotlib as mpl
import matplotlib.pyplot as plt
import pandas as pd
%matplotlib inline

import tensorflow as tf
import tensorflow.keras as keras
```

5/31/22, 10:52 PM

```
Homework4 (2)
               keras.layers.Dense(1)
           ])
           model_rnn.compile(loss="mse", optimizer="nadam")
           run = model_rnn.fit(X_train[..., np.newaxis], y_train, epochs=100,
In [69]:
                            validation_data=(X_valid[..., np.newaxis], y_valid),
                            verbose=0)
           pd.DataFrame(run.history).iloc[-11:]
                  loss
                        val_loss
Out[69]:
          89
              3.591288
                        1.419493
             3.325146 2.030276
          90
          91 3.072608 1.041342
          92 2.879261 0.744411
             2.591041 0.558906
          93
          94 2.410072 1.589572
          95 2.260275 4.533248
             2.116478 0.650367
          97 2.050760 1.693222
              1.975142 1.852917
          98
          99 1.878468 1.274725
In [70]:
           pd.DataFrame(run.history).plot(figsize=(8, 5))
           plt.grid(True)
           plt.show()
                                                                       loss
          12000
                                                                       val loss
          10000
           8000
           6000
           4000
           2000
              0
                             20
                                        40
                                                    60
                                                                          100
```

```
y_pred = model_rnn.predict(X_test[..., np.newaxis])
In [71]:
          mse = mean_squared_error(y_test, y_pred)
          print(mse)
```

```
0.4559698234802101
```

The mean squared error is 0.4559698234802101.

```
In [73]: movement_pred = X_test[:,-1] < y_pred.ravel()
    accuracy_score(movement_test,movement_pred)

Out[73]: 0.4969737726967048</pre>
```

75].

The accuracy score is 0.4969737726967048.

(d) [5 marks]

Create a supervised learning dataset suitable for predicting 3 days ahead instead of 1 day ahead. Adjust the deep RNN in (c) so that it predicts 3 days ahead. Use 100 epochs and the Nadam optimizer. Using the test set, report the mean squared error and the accuracy for the movement direction for each of the 3 days ahead predictions. Comment on the result and the learning curve.

```
In [74]:
          X_train_3ahead, y_train_3ahead = ts_split(train, feature_steps=10, target_steps=
          X_valid_3ahead, y_valid_3ahead = ts_split(valid, feature_steps=10, target_steps=
          X test 3ahead, y test 3ahead = ts split(test, feature steps=10, target steps=3)
          X train 3ahead = X train 3ahead[:,:,-1]
In [75]:
          X valid 3ahead = X valid 3ahead[:,:,-1]
          X test 3ahead = X test 3ahead[:,:,-1]
          y train 3ahead = y train 3ahead[:,:,-1]
          y_valid_3ahead = y_valid_3ahead[:,:,-1]
          y_test_3ahead = y_test_3ahead[:,:,-1]
          reset_session()
In [76]:
          model = keras.models.Sequential([
              keras.layers.SimpleRNN(20, return_sequences=True, input_shape=[None,1]),
              keras.layers.SimpleRNN(20),
              keras.layers.Dense(3)
          model.compile(loss="mse", optimizer="nadam")
          run 3ahead = model.fit(X train 3ahead, y train 3ahead, epochs=100,
                           validation_data=(X_valid_3ahead, y_valid_3ahead),
                           verbose=0)
          pd.DataFrame(run 3ahead.history).iloc[-11:]
In [77]:
                       val_loss
                 loss
Out[77]:
         89
              4.023217 2.634159
          90 3.848800 2.776287
          91 3.478850 1.589141
          92
             3.422472 5.212845
          93 3.076504
                       1.621511
```

```
        loss
        val_loss

        94
        2.945980
        4.762773

        95
        2.803193
        2.063807

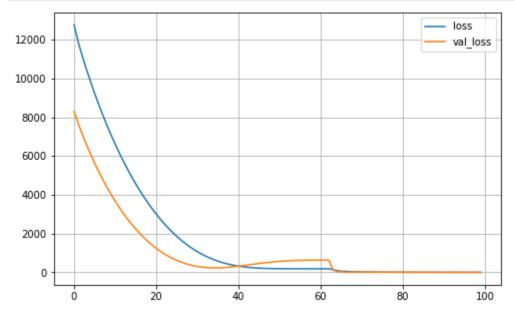
        96
        2.686125
        2.201125

        97
        2.503860
        2.098512

        98
        2.514158
        1.557434

        99
        2.344383
        1.996375
```

```
In [78]: pd.DataFrame(run_3ahead.history).plot(figsize=(8, 5))
plt.grid(True)
plt.show()
```



```
In [80]: y_pred_3ahead = model.predict(X_test_3ahead[..., np.newaxis])
    mse_3ahead = mean_squared_error(y_test_3ahead, y_pred_3ahead)
```

```
In [81]: mse_3ahead
```

Out[81]: 0.7284091227683439

The mean squared error is 0.7284091227683439.

```
In [82]: movement_test_1 = X_test_3ahead[:,-1] < y_test_3ahead[:,0].ravel()
    movement_test_2 = X_test_3ahead[:,-1] < y_test_3ahead[:,1].ravel()
    movement_test_3 = X_test_3ahead[:,-1] < y_test_3ahead[:,2].ravel()
    movement_test_d = np.concatenate((movement_test_1,movement_test_2,movement_test_)

    movement_pred_1 = X_test_3ahead[:,-1] < y_pred_3ahead[:,0].ravel()
    movement_pred_2 = X_test_3ahead[:,-1] < y_pred_3ahead[:,1].ravel()
    movement_pred_3 = X_test_3ahead[:,-1] < y_pred_3ahead[:,2].ravel()
    movement_pred_d = np.concatenate((movement_pred_1,movement_pred_2,movement_pred_)

In [83]: accuracy_score(movement_test_d,movement_pred_d)</pre>
```

Out[83]: 0.4920314253647587

Conclusion: mse of model in (d) is bigger than the model in (c). The accuracy in (d) is smaller than the accuracy in (c). Hence, model (c) has better performance than mdoel (d).

The accuracy now is 0.4920314253647587.