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        "#The IMDB dataset\n",
        "#Loading the IMDB dataset\n",
        "\n",
        "from tensorflow.keras.datasets import imdb\n",
        "(train_data, train_labels), (test_data, test_labels) =
imdb.load_data(\n",
        "    num_words=10000)\n",
        "\n",
        "train_data[0]\n",
        "train_labels[0]\n",
        "max([max(sequence) for sequence in train_data])\n",
        "\n"
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        "#Decoding reviews back to text\n",
```

```
        "\n",
        "word_index = imdb.get_word_index()\n",
        "reverse_word_index = dict(\n",
        "    [(value, key) for (key, value) in word_index.items()])\n",
        "decoded_review = \" \".join(\n",
        "    [reverse_word_index.get(i - 3, \"?\") for i in
train_data[0]])\n",
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        "import numpy as np\n",
        "def vectorize_sequences(sequences, dimension=10000):\n",
        "    results = np.zeros((len(sequences), dimension))\n",
        "    for i, sequence in enumerate(sequences):\n",
        "        for j in sequence:\n",
        "            results[i, j] = 1.\n",
        "    return results\n",
        "x_train = vectorize_sequences(train_data)\n",
        "x_test = vectorize_sequences(test_data)\n",
        "x_train[0]\n",
        "y_train = np.asarray(train_labels).astype(\"float32\")\n",
        "y_test = np.asarray(test_labels).astype(\"float32\")\n",
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        "from tensorflow import keras\n",
        "from tensorflow.keras import layers\n",
        "\n",
        "model = keras.Sequential([\n",
        "    layers.Dense(16, activation=\"relu\"),\n",
        "    layers.Dense(16, activation=\"relu\"),\n",
        "    layers.Dense(1, activation=\"sigmoid\")\n",
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      "              metrics=[\"accuracy\"])"
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      "y_val = y_train[:10000]\n",
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      "                    epochs=20,\n",
      "                    batch_size=512,\n",
      "                    validation_data=(x_val, y_val))\n",
      "history_dict = history.history\n",
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    "30/30 [==============================] - 3s 101ms/step - loss: 0.3452 - accuracy: 0.8911 - val_loss: 0.3242 - val_accuracy: 0.8833\n",
    "Epoch 3/20\n",
    "30/30 [==============================] - 5s 160ms/step - loss: 0.2553 - accuracy: 0.9157 - val_loss: 0.2892 - val_accuracy: 0.8879\n",
    "Epoch 4/20\n",
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    "Epoch 6/20\n",
    "30/30 [==============================] - 1s 48ms/step - loss: 0.1490 - accuracy: 0.9534 - val_loss: 0.2819 - val_accuracy: 0.8848\n",
    "Epoch 7/20\n",
    "30/30 [==============================] - 1s 40ms/step - loss: 0.1304 - accuracy: 0.9595 - val_loss: 0.2898 - val_accuracy: 0.8857\n",
    "Epoch 8/20\n",
    "30/30 [==============================] - 1s 41ms/step - loss: 0.1123 - accuracy: 0.9662 - val_loss: 0.3076 - val_accuracy: 0.8794\n",
    "Epoch 9/20\n",
    "30/30 [==============================] - 1s 37ms/step - loss: 0.0972 - accuracy: 0.9722 - val_loss: 0.3477 - val_accuracy: 0.8752\n",
    "Epoch 10/20\n",
    "30/30 [==============================] - 1s 37ms/step - loss: 0.0842 - accuracy: 0.9775 - val_loss: 0.3269 - val_accuracy: 0.8811\n",
    "Epoch 11/20\n",
    "30/30 [==============================] - 1s 45ms/step - loss: 0.0727 - accuracy: 0.9803 - val_loss: 0.3434 - val_accuracy: 0.8806\n",
    "Epoch 12/20\n",
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    "30/30 [==============================] - 1s 35ms/step - loss: 0.0555 - accuracy: 0.9871 - val_loss: 0.3874 - val_accuracy: 0.8759\n",
    "Epoch 14/20\n",

```
            "30/30 [==============================] - 1s 37ms/step -
loss: 0.0444 - accuracy: 0.9915 - val_loss: 0.4056 - val_accuracy:
0.8766\n",
            "Epoch 15/20\n",
            "30/30 [==============================] - 1s 36ms/step -
loss: 0.0410 - accuracy: 0.9913 - val_loss: 0.4340 - val_accuracy:
0.8720\n",
            "Epoch 16/20\n",
            "30/30 [==============================] - 1s 48ms/step -
loss: 0.0370 - accuracy: 0.9923 - val_loss: 0.4477 - val_accuracy:
0.8740\n",
            "Epoch 17/20\n",
            "30/30 [==============================] - 1s 37ms/step -
loss: 0.0280 - accuracy: 0.9951 - val_loss: 0.4677 - val_accuracy:
0.8721\n",
            "Epoch 18/20\n",
            "30/30 [==============================] - 1s 49ms/step -
loss: 0.0234 - accuracy: 0.9974 - val_loss: 0.4883 - val_accuracy:
0.8723\n",
            "Epoch 19/20\n",
            "30/30 [==============================] - 1s 44ms/step -
loss: 0.0219 - accuracy: 0.9968 - val_loss: 0.5377 - val_accuracy:
0.8633\n",
            "Epoch 20/20\n",
            "30/30 [==============================] - 1s 36ms/step -
loss: 0.0205 - accuracy: 0.9969 - val_loss: 0.5339 - val_accuracy:
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        "history_dict = history.history\n",
        "loss_values = history_dict[\"loss\"]\n",
        "val_loss_values = history_dict[\"val_loss\"]\n",
        "epochs = range(1, len(loss_values) + 1)\n",
        "plt.plot(epochs, loss_values, \"bo\", label=\"Training
loss\")\n",
        "plt.plot(epochs, val_loss_values, \"b\", label=\"Validation
loss\")\n",
        "plt.title(\"Training and validation loss\")\n",
        "plt.xlabel(\"Epochs\")\n",
```

```
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      "plt.legend()\n",
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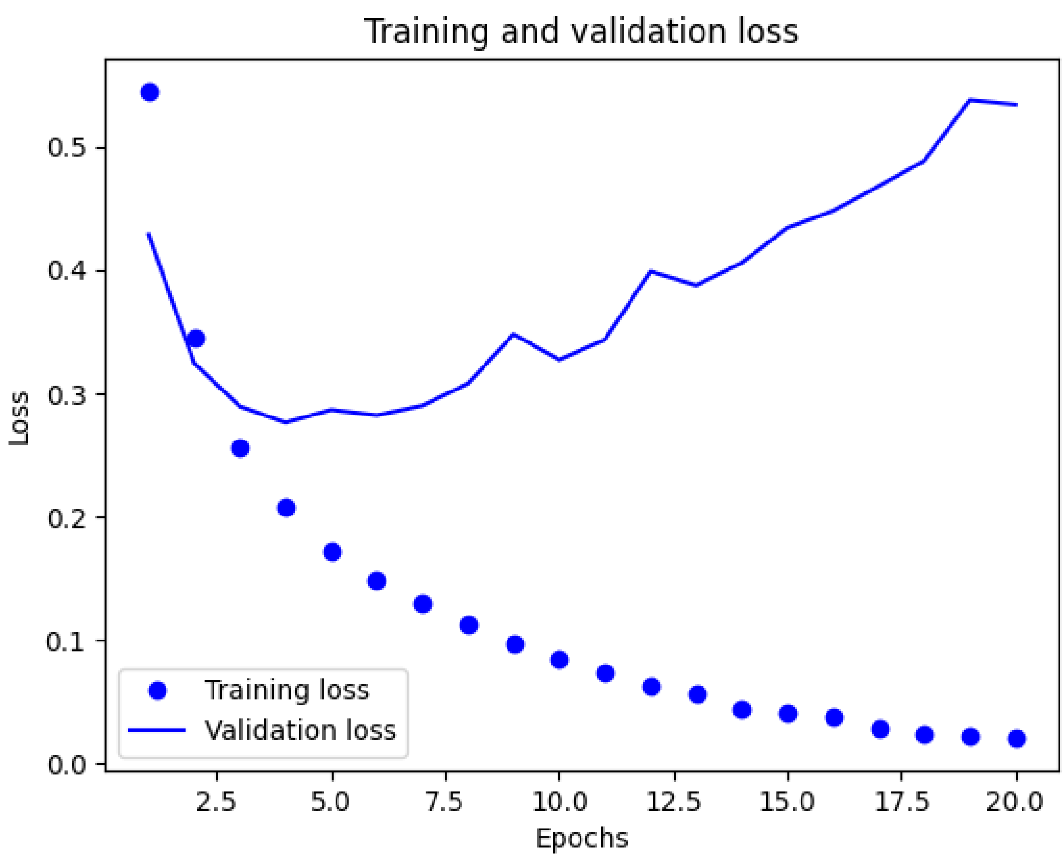


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      "#Plotting the training and validation accuracy\n",
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    "\n",
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    "acc = history_dict[\"accuracy\"]\n",
    "val_acc = history_dict[\"val_accuracy\"]\n",
    "plt.plot(epochs, acc, \"bo\", label=\"Training acc\")\n",
    "plt.plot(epochs, val_acc, \"b\", label=\"Validation acc\")\n",
    "plt.title(\"Training and validation accuracy\")\n",
    "plt.xlabel(\"Epochs\")\n",
    "plt.ylabel(\"Accuracy\")\n",
    "plt.legend()\n",
    "plt.show()"
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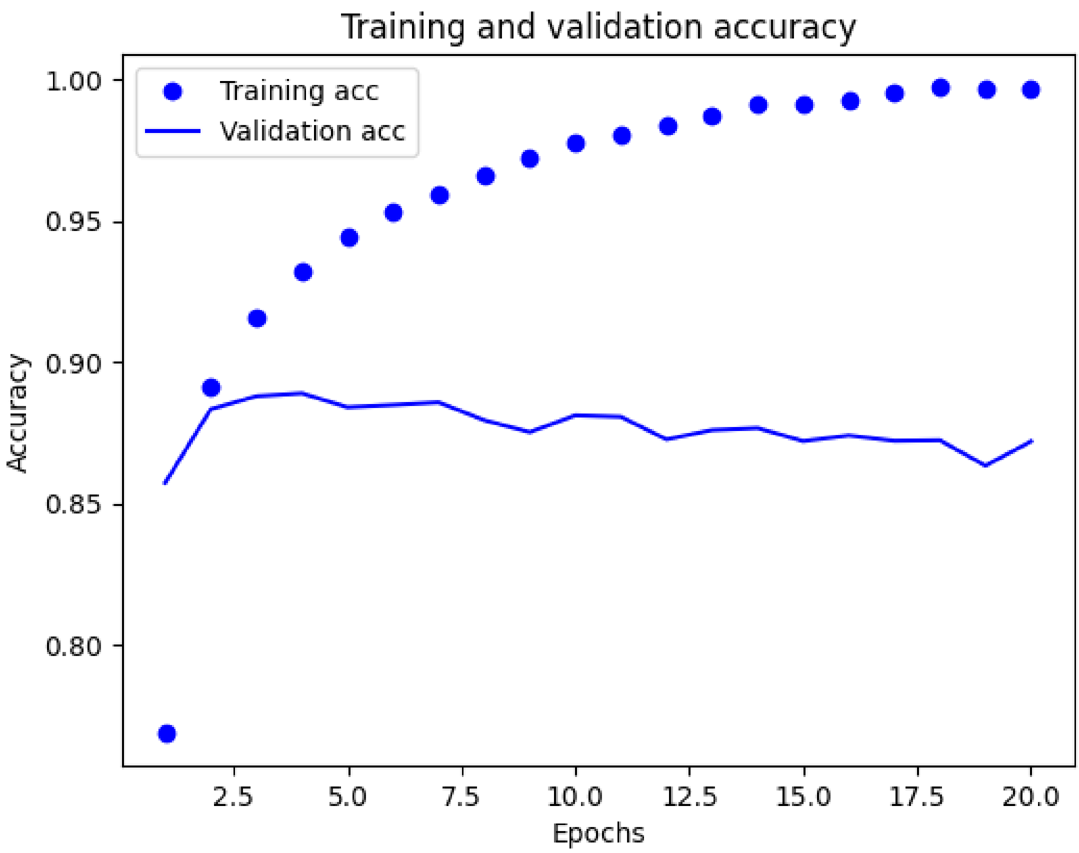


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        "    layers.Dense(16, activation=\"relu\"),\n",
        "    layers.Dense(1, activation=\"sigmoid\")\n",
        "])\n",
        "model.compile(optimizer=\"rmsprop\",\n",
        "              loss=\"binary_crossentropy\",\n",
        "              metrics=[\"accuracy\"])\n",
        "model.fit(x_train, y_train, epochs=4, batch_size=512)\n",
        "results = model.evaluate(x_test, y_test)\n",
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loss: 0.4970 - accuracy: 0.8015\n",
            "Epoch 2/4\n",
            "49/49 [==============================] - 2s 31ms/step -
loss: 0.2880 - accuracy: 0.8977\n",
            "Epoch 3/4\n",
            "49/49 [==============================] - 2s 39ms/step -
loss: 0.2231 - accuracy: 0.9191\n",
            "Epoch 4/4\n",
            "49/49 [==============================] - 1s 29ms/step -
loss: 0.1879 - accuracy: 0.9328\n",
            "782/782 [==============================] - 2s 3ms/step -
loss: 0.2890 - accuracy: 0.8852\n"
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              "       [0.11608151],\n",
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        "#Loading the Reuters dataset\n",
        "\n",
        "from tensorflow.keras.datasets import reuters\n",
        "(train_data, train_labels), (test_data, test_labels) =
reuters.load_data(\n",
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```

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      "reverse_word_index = dict([(value, key) for (key, value) in
word_index.items()])\n",
      "decoded_newswire = \" \".join([reverse_word_index.get(i - 3,
\"?\") for i in\n",
      "    train_data[0]])\n",
      "train_labels[10]"
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```
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    "    results = np.zeros((len(labels), dimension))\n",
    "    for i, label in enumerate(labels):\n",
    "        results[i, label] = 1.\n",
    "    return results\n",
    "y_train = to_one_hot(train_labels)\n",
    "y_test = to_one_hot(test_labels)\n",
    "from tensorflow.keras.utils import to_categorical\n",
    "y_train = to_categorical(train_labels)\n",
    "y_test = to_categorical(test_labels)"
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    "#Model definition\n",
    "\n",
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    "    layers.Dense(64, activation=\"relu\"),\n",
    "    layers.Dense(64, activation=\"relu\"),\n",
    "    layers.Dense(46, activation=\"softmax\")\n",
    "])\n",
    "\n",
    "#Compiling the model\n",
    "\n",
    "model.compile(optimizer=\"rmsprop\",\n",
    "              loss=\"categorical_crossentropy\",\n",
    "              metrics=[\"accuracy\"])"
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        "#Setting aside a validation set\n",
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        "x_val = x_train[:1000]\n",
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        "y_val = y_train[:1000]\n",
        "partial_y_train = y_train[1000:]"
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        "                    batch_size=512,\n",
        "                    validation_data=(x_val, y_val))"
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0.6220\n",
            "Epoch 2/20\n",
            "16/16 [==============================] - 1s 54ms/step -
loss: 1.5123 - accuracy: 0.6855 - val_loss: 1.4070 - val_accuracy:
0.6740\n",
            "Epoch 3/20\n",
            "16/16 [==============================] - 1s 53ms/step -
loss: 1.1652 - accuracy: 0.7451 - val_loss: 1.1919 - val_accuracy:
0.7350\n",
            "Epoch 4/20\n",
            "16/16 [==============================] - 1s 52ms/step -
loss: 0.9570 - accuracy: 0.7907 - val_loss: 1.0894 - val_accuracy:
0.7610\n",
            "Epoch 5/20\n",
```

"16/16 [==============================] - 1s 57ms/step - loss: 0.8010 - accuracy: 0.8249 - val_loss: 1.0376 - val_accuracy: 0.7650\n",
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"Epoch 8/20\n",
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"Epoch 10/20\n",
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"Epoch 11/20\n",
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"Epoch 17/20\n",
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        "val_loss = history.history[\"val_loss\"]\n",
        "epochs = range(1, len(loss) + 1)\n",
        "plt.plot(epochs, loss, \"bo\", label=\"Training loss\")\n",
        "plt.plot(epochs, val_loss, \"b\", label=\"Validation loss\")\n",
        "plt.title(\"Training and validation loss\")\n",
        "plt.xlabel(\"Epochs\")\n",
        "plt.ylabel(\"Loss\")\n",
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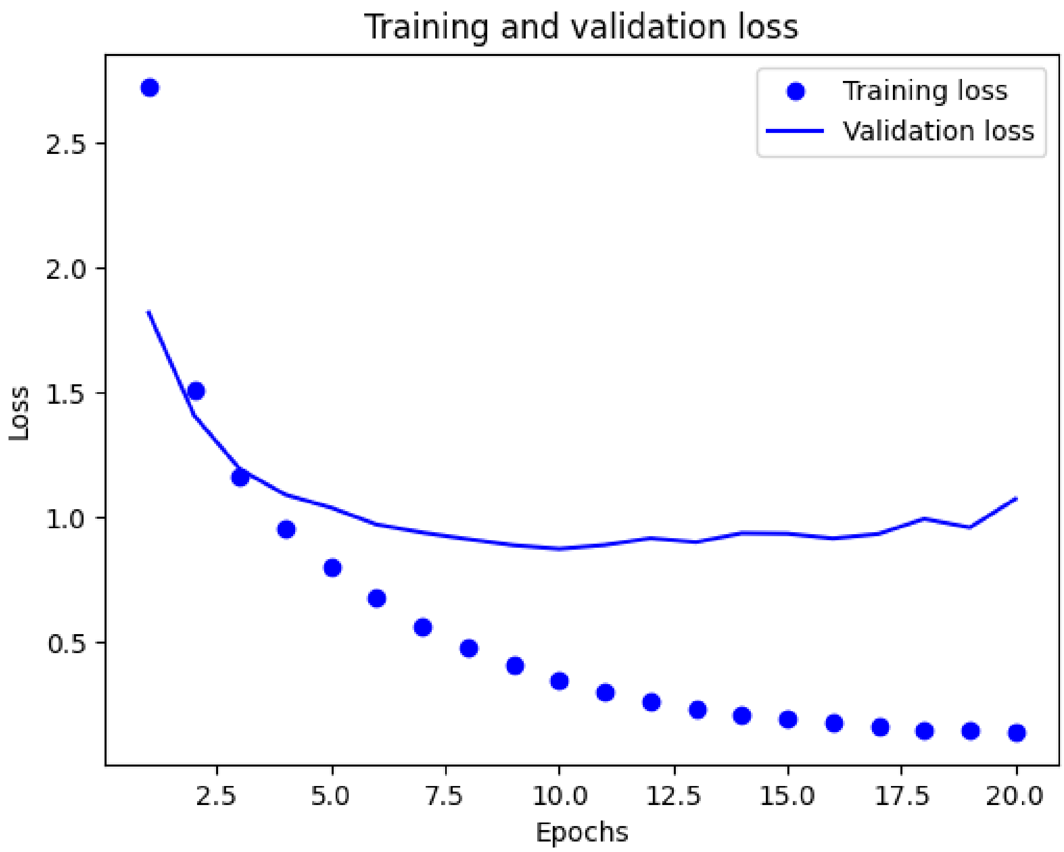


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        "plt.plot(epochs, val_acc, \"b\", label=\"Validation
accuracy\")\n",
        "plt.title(\"Training and validation accuracy\")\n",
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        "plt.ylabel(\"Accuracy\")\n",
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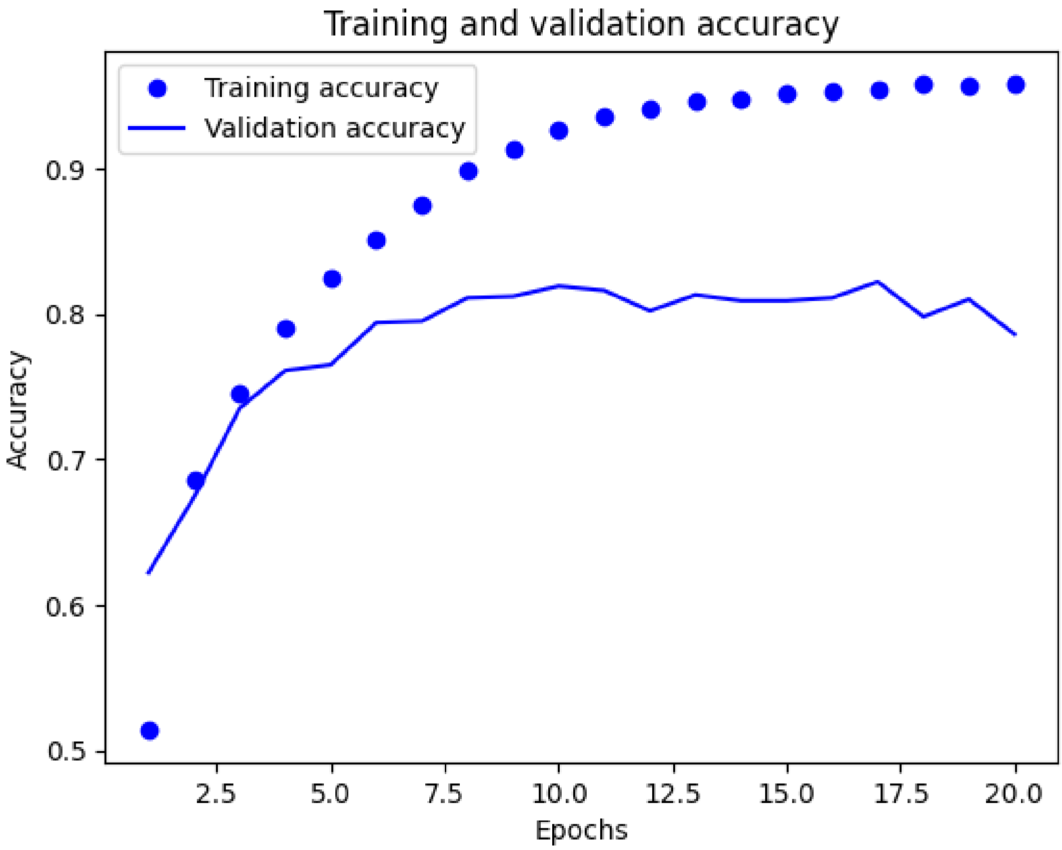


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    "   layers.Dense(64, activation=\"relu\"),\n",
    "   layers.Dense(46, activation=\"softmax\")\n",
    "])\n",
    "model.compile(optimizer=\"rmsprop\",\n",
    "              loss=\"categorical_crossentropy\",\n",
    "              metrics=[\"accuracy\"])\n",
    "model.fit(x_train,\n",
    "          y_train,\n",
```

```
        "          epochs=9,\n",
        "          batch_size=512)\n",
        "results = model.evaluate(x_test, y_test)\n",
        "results\n",
        "\n",
        "import copy\n",
        "test_labels_copy = copy.copy(test_labels)\n",
        "np.random.shuffle(test_labels_copy)\n",
        "hits_array = np.array(test_labels) ==
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        "hits_array.mean()"
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loss: 2.6564 - accuracy: 0.5148\n",
            "Epoch 2/9\n",
            "18/18 [==============================] - 1s 49ms/step -
loss: 1.4806 - accuracy: 0.6819\n",
            "Epoch 3/9\n",
            "18/18 [==============================] - 1s 51ms/step -
loss: 1.1260 - accuracy: 0.7503\n",
            "Epoch 4/9\n",
            "18/18 [==============================] - 1s 60ms/step -
loss: 0.9199 - accuracy: 0.8012\n",
            "Epoch 5/9\n",
            "18/18 [==============================] - 1s 48ms/step -
loss: 0.7598 - accuracy: 0.8342\n",
            "Epoch 6/9\n",
            "18/18 [==============================] - 1s 50ms/step -
loss: 0.6312 - accuracy: 0.8642\n",
            "Epoch 7/9\n",
            "18/18 [==============================] - 1s 46ms/step -
loss: 0.5254 - accuracy: 0.8868\n",
            "Epoch 8/9\n",
            "18/18 [==============================] - 1s 62ms/step -
loss: 0.4435 - accuracy: 0.9063\n",
            "Epoch 9/9\n",
            "18/18 [==============================] - 1s 75ms/step -
loss: 0.3725 - accuracy: 0.9194\n",
            "71/71 [==============================] - 1s 5ms/step - loss:
0.9168 - accuracy: 0.7890\n"
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        "np.argmax(predictions[0])"
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        "y_test = np.array(test_labels)\n",
        "model.compile(optimizer=\"rmsprop\",\n",
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        "              metrics=[\"accuracy\"])"
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        "    layers.Dense(46, activation=\"softmax\")\n",
        "])\n",
        "model.compile(optimizer=\"rmsprop\",\n",
        "              loss=\"categorical_crossentropy\",\n",
        "              metrics=[\"accuracy\"])\n",
        "model.fit(partial_x_train,\n",
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0.5140\n",
            "Epoch 2/20\n",
            "63/63 [==============================] - 1s 19ms/step -
loss: 1.7775 - accuracy: 0.5678 - val_loss: 1.6408 - val_accuracy:
0.5790\n",
            "Epoch 3/20\n",
            "63/63 [==============================] - 1s 19ms/step -
loss: 1.4859 - accuracy: 0.5986 - val_loss: 1.5342 - val_accuracy:
0.5890\n",
            "Epoch 4/20\n",
            "63/63 [==============================] - 1s 18ms/step -
loss: 1.3407 - accuracy: 0.6250 - val_loss: 1.4276 - val_accuracy:
0.6150\n",
            "Epoch 5/20\n",
```

```
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loss: 1.2326 - accuracy: 0.6555 - val_loss: 1.3840 - val_accuracy: 
0.6370\n",
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loss: 1.1496 - accuracy: 0.6788 - val_loss: 1.3693 - val_accuracy: 
0.6650\n",
            "Epoch 7/20\n",
            "63/63 [==============================] - 2s 27ms/step - 
loss: 1.0819 - accuracy: 0.6956 - val_loss: 1.3408 - val_accuracy: 
0.6520\n",
            "Epoch 8/20\n",
            "63/63 [==============================] - 1s 19ms/step - 
loss: 1.0185 - accuracy: 0.7209 - val_loss: 1.3346 - val_accuracy: 
0.6840\n",
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            "63/63 [==============================] - 1s 19ms/step - 
loss: 0.9660 - accuracy: 0.7453 - val_loss: 1.3311 - val_accuracy: 
0.6870\n",
            "Epoch 10/20\n",
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loss: 0.9163 - accuracy: 0.7615 - val_loss: 1.3240 - val_accuracy: 
0.6880\n",
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loss: 0.8759 - accuracy: 0.7667 - val_loss: 1.3629 - val_accuracy: 
0.6850\n",
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loss: 0.8401 - accuracy: 0.7762 - val_loss: 1.3709 - val_accuracy: 
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loss: 0.8076 - accuracy: 0.7849 - val_loss: 1.3758 - val_accuracy: 
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loss: 0.7292 - accuracy: 0.7977 - val_loss: 1.5199 - val_accuracy: 
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loss: 0.7077 - accuracy: 0.7993 - val_loss: 1.4769 - val_accuracy: 
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loss: 0.6892 - accuracy: 0.8013 - val_loss: 1.5256 - val_accuracy: 
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```

```
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loss: 0.6699 - accuracy: 0.8028 - val_loss: 1.5625 - val_accuracy:
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        "#The Boston Housing Price dataset\n",
        "#Loading the Boston housing dataset\n",
        "\n",
        "from tensorflow.keras.datasets import boston_housing\n",
        "(train_data, train_targets), (test_data, test_targets) =
boston_housing.load_data()\n",
        "train_data.shape\n",
        "test_data.shape\n",
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        "std = train_data.std(axis=0)\n",
        "train_data /= std\n",
        "test_data -= mean\n",
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        "#Model definition\n",
        "\n",
        "def build_model():\n",
        "    model = keras.Sequential([\n",
        "        layers.Dense(64, activation=\"relu\"),\n",
        "        layers.Dense(64, activation=\"relu\"),\n",
        "        layers.Dense(1)\n",
        "    ])\n",
```

```
        "    model.compile(optimizer=\"rmsprop\", loss=\"mse\",
metrics=[\"mae\"])\n",
        "    return model"
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        "#Validating your approach using K-fold validation\n",
        "#K-fold validation\n",
        "!pip install numpy\n",
        "import numpy as np\n",
        "\n",
        "\n",
        "k = 4\n",
        "num_val_samples = len(train_data) // k\n",
        "num_epochs = 100\n",
        "all_scores = []\n",
        "\n",
        "for i in range(k):\n",
        "    print(f\"Processing fold #{i}\")\n",
        "\n",
        "    val_data = train_data[i * num_val_samples: (i + 1) *
num_val_samples]\n",
        "    val_targets = train_targets[i * num_val_samples: (i + 1) *
num_val_samples]\n",
        "\n",
        "    partial_train_data = np.concatenate(\n",
        "        [train_data[:i * num_val_samples],\n",
        "         train_data[(i + 1) * num_val_samples:]],\n",
        "        axis=0)\n",
        "\n",
        "    partial_train_targets = np.concatenate(\n",
        "        [train_targets[:i * num_val_samples],\n",
        "         train_targets[(i + 1) * num_val_samples:]],\n",
        "        axis=0)\n",
        "\n",
        "import numpy as np\n",
        "from tensorflow import keras\n",
        "from tensorflow.keras import layers\n",
        "\n",
        "# Rest of your code...\n",
        "\n",
        "def build_model():\n",
        "    model = keras.Sequential([\n",
        "        layers.Dense(64, activation=\"relu\"),\n",
        "        layers.Dense(64, activation=\"relu\"),\n",
        "        layers.Dense(1)  # Adjust the number of units according
to your problem\n",
        "    ])\n",
        "\n",
        "    model.compile(optimizer='adam', loss='mse',
metrics=['mae'])\n",
```

```
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        "    return model\n"
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        "#Saving the validation logs at each fold\n",
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        "num_epochs = 500\n",
        "all_mae_histories = []\n",
        "for i in range(k):\n",
        "    print(f\"Processing fold #{i}\")\n",
        "    val_data = train_data[i * num_val_samples: (i + 1) *
num_val_samples]\n",
        "    val_targets = train_targets[i * num_val_samples: (i + 1) *
num_val_samples]\n",
        "    partial_train_data = np.concatenate(\n",
        "        [train_data[:i * num_val_samples],\n",
        "         train_data[(i + 1) * num_val_samples:]],\n",
        "        axis=0)\n",
        "    partial_train_targets = np.concatenate(\n",
        "        [train_targets[:i * num_val_samples],\n",
        "         train_targets[(i + 1) * num_val_samples:]],\n",
        "        axis=0)\n",
        "    model = build_model()\n",
        "    history = model.fit(partial_train_data,
partial_train_targets,\n",
        "                        validation_data=(val_data,
val_targets),\n",
        "                        epochs=num_epochs, batch_size=16,
verbose=0)\n",
        "    mae_history = history.history[\"val_mae\"]\n",
        "    all_mae_histories.append(mae_history)"
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scores\n",
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        "average_mae_history = [\n",
        "    np.mean([x[i] for x in all_mae_histories]) for i in
range(num_epochs)]"
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        "import matplotlib.pyplot as plt\n",
        "\n",
        "# Assuming you have defined `average_mae_history` before this
point\n",
        "\n",
        "%matplotlib inline\n",
        "\n",
        "plt.plot(range(1, len(average_mae_history) + 1),
average_mae_history)\n",
        "plt.xlabel(\"Epochs\")\n",
        "plt.ylabel(\"Validation MAE\")\n",
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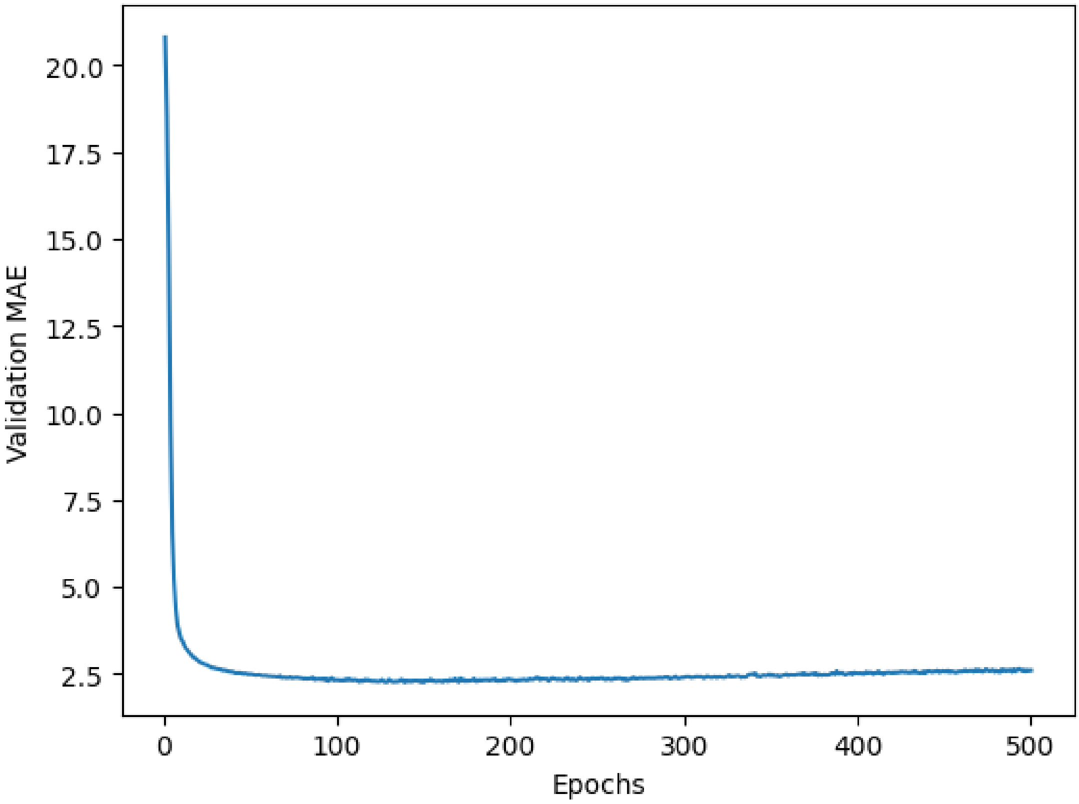

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"model.fit(train_data, train_targets,\n",
"   epochs=130, batch_size=16, verbose=0)\n",
"test_mse_score, test_mae_score = model.evaluate(test_data, test_targets)\n",
"test_mae_score"
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        "predictions = model.predict(test_data)\n",
        "predictions[0]"
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```

```
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        "#Summary"
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Summary

It is a binary classification model for movie reviews using the IMDB dataset. It loads and preprocesses the data, encoding reviews into multi-hot vectors. The neural network, built with **TensorFlow and Keras**, consists of two hidden layers with **ReLU activation** and a final layer with sigmoid activation. The model is compiled using binary **crossentropy** loss and RMSprop optimizer. Training and validation sets are prepared, and the model is trained over **20 epochs**. The code includes decoding functions for text representation. It offers a concise example of natural language processing, data preparation, model definition, and training for binary classification tasks.

The provided code compiles and trains a binary classification model for movie reviews using the IMDB dataset. It utilizes the RMSprop optimizer and binary crossentropy loss for compilation. The dataset is split into training and validation sets, and the model is trained over 20 epochs with batch **size 512.** Training history is stored, and the code generates plots for training and validation accuracy, as well as training and validation loss. The plots reveal the model's performance over epochs, showcasing potential overfitting. The code offers insights into model training and evaluation for natural language processing tasks, highlighting the importance of validation sets and performance visualization.

The code initiates a new neural network for multiclass classification using the Reuters dataset. It loads the data, consisting of newswires and their corresponding topics, encodes the sequences into vectors, and preprocesses the labels using one-hot encoding. The model architecture comprises two hidden layers with ReLU activation and a final layer with **softmax activation.** It compiles the model using categorical crossentropy loss and trains it on the training data. The code demonstrates essential steps in multiclass classification, including data loading, preprocessing, model building, and training. Further experiments and the potential for improvements are indicated, providing a foundation for exploring advanced techniques in natural language processing.

It explores the impact of intermediate layer size on a neural network's performance. It defines a model for multiclass classification with an information bottleneck, using smaller intermediate layers. The model is trained on the Reuters dataset, revealing limitations in learning complex patterns due to the constrained layer size. Further experimentation is encouraged. Additionally, the code introduces a regression example for predicting house prices using the Boston Housing dataset. The regression model is defined with two hidden layers and compiled with mean squared error loss. This code provides insights into the importance of layer size in neural networks for classification and regression tasks.