```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
```

Part A: Build a classification model using text data

```
text_data = pd.read_csv("text_training_data.csv")
text_data.head()
```

	headline	label
0	MyBook Disk Drive Handles Lots of Easy Backups	not clickbait
1	CIT Posts Eighth Loss in a Row	not clickbait
2	Candy Carson Singing The "National Anthem" Is ...	clickbait
3	Why You Need To Stop What You're Doing And Dat...	clickbait
4	27 Times Adele Proved She's Actually The Reale...	clickbait

```
#NOTE: THIS CODE IS FROM WEEK 10 CLASS CODE
# Helper function to plot top positive and negative coefficients

def visualize_coefficients(coefficients, feature_names, n_top_features=25):
    """Visualize coefficients of a linear model.
    Parameters
    ----------
    coefficients : nd-array, shape (n_features,)
        Model coefficients.
    feature_names : list or nd-array of strings, shape (n_features,)
        Feature names for labeling the coefficients.
    n_top_features : int, default=25
        How many features to show. The function will show the largest (most
        positive) and smallest (most negative)  n_top_features coefficients,
        for a total of 2 * n_top_features coefficients.
    """
    coefficients = coefficients.squeeze()
    if coefficients.ndim > 1:
        # this is not a row or column vector
        raise ValueError("coeffients must be 1d array or column vector, got"
                         " shape {}".format(coefficients.shape))
    coefficients = coefficients.ravel()

    if len(coefficients) != len(feature_names):
        raise ValueError("Number of coefficients {} doesn't match number of"
                         "feature names {}.".format(len(coefficients),
                                                    len(feature_names)))
    # get coefficients with large absolute values
    coef = coefficients.ravel()
    positive_coefficients = np.argsort(coef)[-n_top_features:]
    negative_coefficients = np.argsort(coef)[:n_top_features]
    interesting_coefficients = np.hstack([negative_coefficients,
                                          positive_coefficients])
    # plot them
    plt.figure(figsize=(15, 5))
    colors = ['#ff2020' if c < 0 else '#0000aa'
              for c in coef[interesting_coefficients]]
    plt.bar(np.arange(2 * n_top_features), coef[interesting_coefficients],
            color=colors)
    feature_names = np.array(feature_names)
    plt.subplots_adjust(bottom=0.3)
    plt.xticks(np.arange(1, 1 + 2 * n_top_features),
               feature_names[interesting_coefficients], rotation=60,
               ha="right")
    plt.ylabel("Coefficient magnitude")
    plt.xlabel("Feature")
```

CountVectorizer + GridSearchCV + LogisticRegression

```
from sklearn.feature_extraction.text import CountVectorizer
cv = CountVectorizer()
X_cv = pd.DataFrame(cv.fit_transform(text_data["headline"]).toarray())
y = text_data['label'].map({'clickbait': 1, 'not clickbait': 0})
```

```
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import f1_score, classification_report
```

```
X_train, X_test, y_train, y_test = train_test_split(X_cv, y, train_size=0.3, random_state=110)
X_train.shape
```

```
(7493, 20332)
```

```
param_grid = {
    'C': [0.1, 1, 10, 100],
}
lr = LogisticRegression()
grid = GridSearchCV(lr, param_grid, cv=5, scoring = 'f1')
```

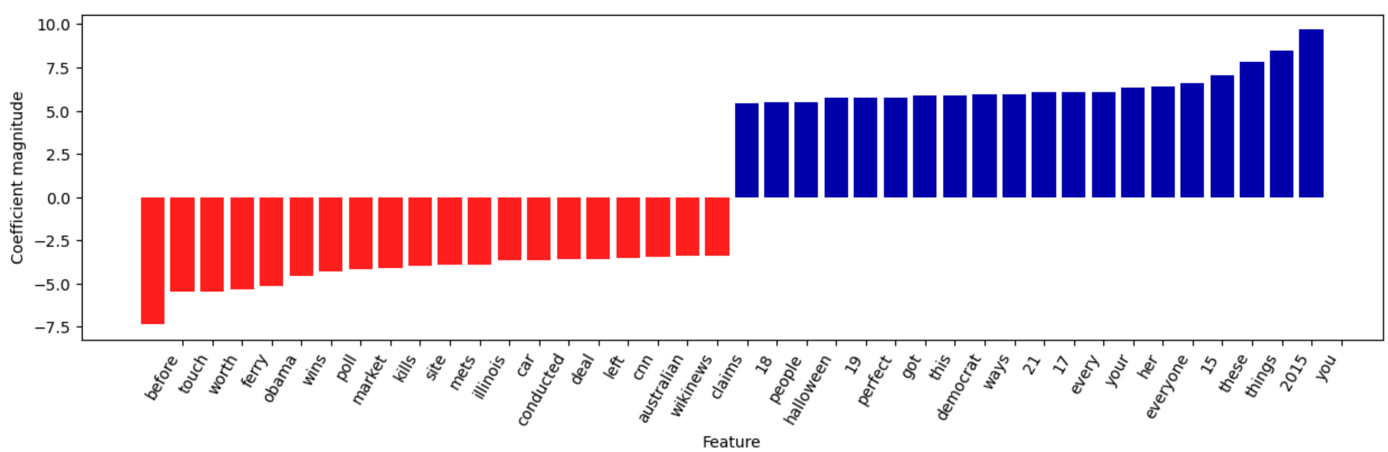
```
grid.fit(X_train, y_train)
```

```
▸ GridSearchCV
▸ best_estimator_: LogisticRegression
    ▸ LogisticRegression
```

```
print("Best Parameters:", grid.best_params_)
print("Best score: ", grid.best_score_)
best_model = grid.best_estimator_
y_pred = best_model.predict(X_test)
score = f1_score(y_test, y_pred)
print("F1 score: ", score)
```

```
Best Parameters: {'C': 100}
Best score:  0.9630477889888389
F1 score:  0.9588615163836403
```

```
visualize_coefficients(best_model.coef_[0], cv.get_feature_names_out(), n_top_features=20)
```



LogisticRegression + TfidVectorizer + GridSearchCV

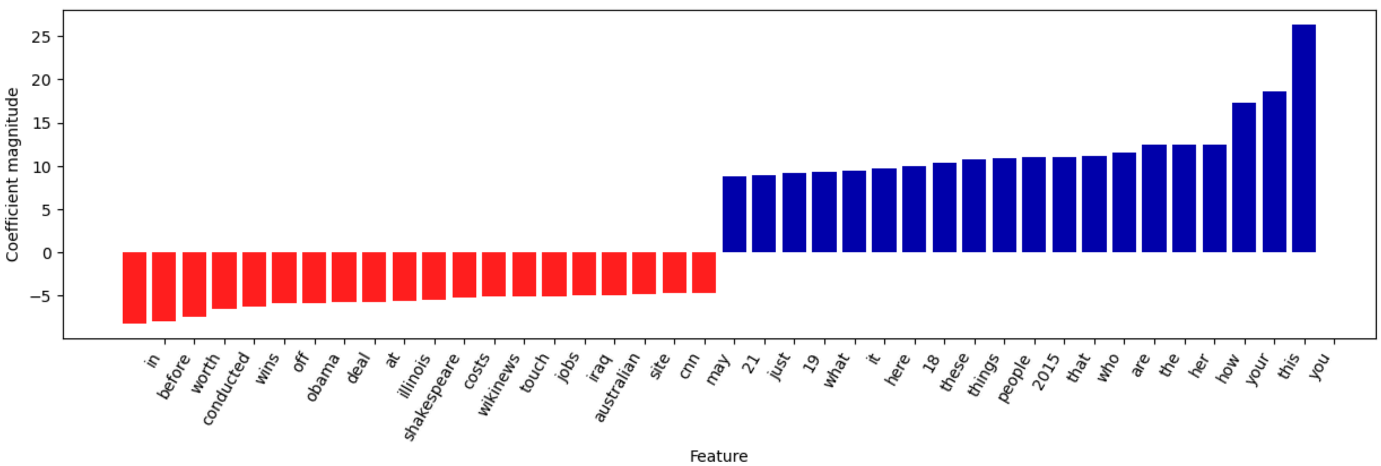
```
from sklearn.feature_extraction.text import TfidfVectorizer
tf = TfidfVectorizer()
X_tf = pd.DataFrame(tf.fit_transform(text_data["headline"]).toarray())
```

```
X_train, X_test, y_train, y_test = train_test_split(X_tf, y, train_size=0.2, random_state=110)
X_train.shape
```

```
(4995, 20332)
```

```
param_grid = {
    'C': [0.1, 1, 10, 100],
}
lr = LogisticRegression()
grid = GridSearchCV(lr, param_grid, cv=5, scoring = 'f1')
grid.fit(X_train, y_train)
print("Best Parameters:", grid.best_params_)
print("Best score: ", grid.best_score_)
best_model = grid.best_estimator_
y_pred = best_model.predict(X_test)
score = f1_score(y_test, y_pred)
print("F1 score: ", score)
visualize_coefficients(best_model.coef_[0], cv.get_feature_names_out(), n_top_features=20)
```

```
Best Parameters: {'C': 100}
Best score:  0.9623268177651176
F1 score:  0.9562709731543624
```



LogisticRegression + CountVectorizer + GridSearchCV + Lemmatizer (PorterStemmer)

```
import nltk
from nltk import word_tokenize
from nltk.stem import WordNetLemmatizer
from sklearn.feature_extraction.text import CountVectorizer

stemmer = nltk.stem.PorterStemmer()

class LemmaTokenizer(object):
    def __init__(self):
        self.wnl = WordNetLemmatizer()
    def __call__(self, doc):
        return [self.wnl.lemmatize(t) for t in word_tokenize(doc)]

lv = CountVectorizer(tokenizer=LemmaTokenizer())
X_lv = pd.DataFrame(lv.fit_transform(text_data["headline"]).toarray())
```

```
/opt/anaconda3/lib/python3.10/site-packages/sklearn/feature_extraction/text.py:521: UserWarning: The parameter 'token_patter
  warnings.warn(
```

```
X_train, X_test, y_train, y_test = train_test_split(X_lv, y, train_size=0.2, random_state=110)
X_train.shape
```

```
(4995, 19650)
```

```
param_grid = {
    'C': [0.1, 1, 10, 100],
```

```
}
lr = LogisticRegression()
grid = GridSearchCV(lr, param_grid, cv=5, scoring = 'f1')
grid.fit(X_train, y_train)
print("Best Parameters:", grid.best_params_)
print("Best score: ", grid.best_score_)
best_model = grid.best_estimator_
y_pred = best_model.predict(X_test)
score = f1_score(y_test, y_pred)
print("F1 score: ", score)
```

```
Best Parameters: {'C': 100}
Best score:  0.9664784529506232
F1 score:  0.9615665034892199
```

The Logistic Regression + Grid Search + Lemmetization had the best performance. The best parameters are {'C': 100}. But they are all good.

Part B: Build a Predictive Neural Network Using Keras

```
data = pd.read_csv("http://vincentarelbundock.github.io/Rdatasets/csv/datasets/iris.csv")
data.head()
data.drop(columns=['rownames'])
```

	Sepal.Length	Sepal.Width	Petal.Length	Petal.Width	Species
0	5.1	3.5	1.4	0.2	setosa
1	4.9	3.0	1.4	0.2	setosa
2	4.7	3.2	1.3	0.2	setosa
3	4.6	3.1	1.5	0.2	setosa
4	5.0	3.6	1.4	0.2	setosa
...	...	...	...	...	...
145	6.7	3.0	5.2	2.3	virginica
146	6.3	2.5	5.0	1.9	virginica
147	6.5	3.0	5.2	2.0	virginica
148	6.2	3.4	5.4	2.3	virginica
149	5.9	3.0	5.1	1.8	virginica

150 rows × 5 columns

```
import tensorflow.keras as keras
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout, Activation
from tensorflow.keras.optimizers import SGD
```

```
data = data.iloc[:,1:]
X = data.loc[:, data.columns != 'Species']
y = data['Species']
X
```

	Sepal.Length	Sepal.Width	Petal.Length	Petal.Width
0	5.1	3.5	1.4	0.2
1	4.9	3.0	1.4	0.2
2	4.7	3.2	1.3	0.2
3	4.6	3.1	1.5	0.2
4	5.0	3.6	1.4	0.2
...	...	...	...	...
145	6.7	3.0	5.2	2.3
146	6.3	2.5	5.0	1.9
147	6.5	3.0	5.2	2.0
148	6.2	3.4	5.4	2.3
149	5.9	3.0	5.1	1.8

150 rows × 4 columns

```
y = keras.utils.to_categorical(data['Species'].map({'setosa': 0, 'versicolor': 1, 'virgi|nica': 2}), num_classes=3)
```

```
/opt/anaconda3/lib/python3.10/site-packages/pandas/core/series.py:1031: RuntimeWarning: invalid value encountered in cast
  arr = np.asarray(values, dtype=dtype)
```

```
model = Sequential()
model.add(Dense(16, activation='relu', input_dim=4))
model.add(Dense(16, activation='relu'))
model.add(Dense(3, activation='softmax'))
```

```
/opt/anaconda3/lib/python3.10/site-packages/keras/src/layers/core/dense.py:87: UserWarning: Do not pass an `input_shape`/`in
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

```
model.compile(loss='categorical_crossentropy',
              optimizer='sgd',
              metrics=['accuracy'])
```

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y)
print(X_train.shape)
print(y_train.shape)
```

```
(112, 4)
(112, 3)
```

```
model.fit(X_train, y_train,
          epochs=100,
          batch_size=20)
#score = model.evaluate(X, y, batch_size=150) # extract loss and accuracy from test data evaluation
```

```
Epoch 1/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 901us/step - accuracy: 0.4175 - loss: 0.8479
Epoch 2/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 687us/step - accuracy: 0.3207 - loss: 0.7702
Epoch 3/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 779us/step - accuracy: 0.3572 - loss: 0.7269
Epoch 4/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 758us/step - accuracy: 0.4351 - loss: 0.7079
Epoch 5/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 678us/step - accuracy: 0.6489 - loss: 0.6840
Epoch 6/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 696us/step - accuracy: 0.6478 - loss: 0.6808
Epoch 7/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 615us/step - accuracy: 0.6853 - loss: 0.6550
Epoch 8/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 781us/step - accuracy: 0.6511 - loss: 0.6635
Epoch 9/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.6760 - loss: 0.6384
Epoch 10/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 853us/step - accuracy: 0.6958 - loss: 0.6434
Epoch 11/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 808us/step - accuracy: 0.6841 - loss: 0.6347
Epoch 12/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 782us/step - accuracy: 0.6307 - loss: 0.6366
```

```
Epoch 13/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 652us/step - accuracy: 0.6596 - loss: 0.6169
Epoch 14/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 787us/step - accuracy: 0.6575 - loss: 0.6195
Epoch 15/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 707us/step - accuracy: 0.7918 - loss: 0.6118
Epoch 16/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 700us/step - accuracy: 0.6517 - loss: 0.6146
Epoch 17/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 715us/step - accuracy: 0.6949 - loss: 0.5706
Epoch 18/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 807us/step - accuracy: 0.7979 - loss: 0.5973
Epoch 19/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 703us/step - accuracy: 0.6895 - loss: 0.5959
Epoch 20/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 738us/step - accuracy: 0.7365 - loss: 0.5733
Epoch 21/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 710us/step - accuracy: 0.6448 - loss: 0.5582
Epoch 22/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 686us/step - accuracy: 0.7329 - loss: 0.5633
Epoch 23/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 591us/step - accuracy: 0.7365 - loss: 0.5347
Epoch 24/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 785us/step - accuracy: 0.7003 - loss: 0.5453
Epoch 25/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 713us/step - accuracy: 0.6829 - loss: 0.5228
Epoch 26/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 754us/step - accuracy: 0.8253 - loss: 0.5349
Epoch 27/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 748us/step - accuracy: 0.8237 - loss: 0.5289
Epoch 28/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 697us/step - accuracy: 0.6640 - loss: 0.5258
Epoch 29/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 792us/step - accuracy: 0.7189 - loss: 0.4996
```

```
score = model.evaluate(X_test, y_test, batch_size=128)
print(score)
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 51ms/step - accuracy: 0.7368 - loss: 0.3811
[0.3811020255088806, 0.7368420958518982]
```

```
#Second Model
model = Sequential()
model.add(Dense(16, activation='relu', input_dim=4))
model.add(Dense(16, activation='relu'))
model.add(Dense(16, activation='relu'))
model.add(Dense(3, activation='softmax'))

model.compile(loss='categorical_crossentropy',
              optimizer='sgd',
              metrics=['accuracy'])

model.fit(X_train, y_train,
          epochs=100,
          batch_size=20)

score = model.evaluate(X_test, y_test, batch_size=128)
print(score)
```

```
Epoch 1/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 919us/step - accuracy: 0.3807 - loss: 1.0368
/opt/anaconda3/lib/python3.10/site-packages/keras/src/layers/core/dense.py:87: UserWarning: Do not pass an `input_shape`/`in
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
Epoch 2/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 932us/step - accuracy: 0.6998 - loss: 0.7465
Epoch 3/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 628us/step - accuracy: 0.6697 - loss: 0.6915
Epoch 4/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 727us/step - accuracy: 0.6284 - loss: 0.6928
Epoch 5/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 751us/step - accuracy: 0.6715 - loss: 0.6444
Epoch 6/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 674us/step - accuracy: 0.6368 - loss: 0.6646
Epoch 7/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 726us/step - accuracy: 0.6710 - loss: 0.6377
Epoch 8/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 736us/step - accuracy: 0.6372 - loss: 0.6464
Epoch 9/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.6306 - loss: 0.6403
Epoch 10/100
```

```
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 684us/step - accuracy: 0.6592 - loss: 0.6145
Epoch 11/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 748us/step - accuracy: 0.6425 - loss: 0.6245
Epoch 12/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 745us/step - accuracy: 0.6548 - loss: 0.6073
Epoch 13/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 705us/step - accuracy: 0.6553 - loss: 0.6130
Epoch 14/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 759us/step - accuracy: 0.6562 - loss: 0.6051
Epoch 15/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 618us/step - accuracy: 0.6728 - loss: 0.5797
Epoch 16/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 661us/step - accuracy: 0.6737 - loss: 0.5841
Epoch 17/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 679us/step - accuracy: 0.6181 - loss: 0.6181
Epoch 18/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 788us/step - accuracy: 0.6211 - loss: 0.6123
Epoch 19/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 667us/step - accuracy: 0.6636 - loss: 0.5795
Epoch 20/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.6587 - loss: 0.5677
Epoch 21/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 836us/step - accuracy: 0.6248 - loss: 0.5880
Epoch 22/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 727us/step - accuracy: 0.6356 - loss: 0.5747
Epoch 23/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 661us/step - accuracy: 0.6550 - loss: 0.5731
Epoch 24/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 678us/step - accuracy: 0.6387 - loss: 0.5579
Epoch 25/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 763us/step - accuracy: 0.6027 - loss: 0.5950
Epoch 26/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 663us/step - accuracy: 0.6310 - loss: 0.5742
Epoch 27/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 768us/step - accuracy: 0.6527 - loss: 0.5478
Epoch 28/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 681us/step - accuracy: 0.6615 - loss: 0.5360
```

```
#Second Model
model = Sequential()
model.add(Dense(16, activation='relu', input_dim=4))
model.add(Dense(16, activation='relu'))
model.add(Dense(16, activation='relu'))
model.add(Dense(16, activation='relu'))
model.add(Dense(16, activation='relu'))
model.add(Dense(16, activation='relu'))
model.add(Dense(16, activation='relu'))
model.add(Dense(16, activation='relu'))
model.add(Dense(3, activation='softmax'))

model.compile(loss='categorical_crossentropy',
              optimizer='sgd',
              metrics=['accuracy'])

model.fit(X_train, y_train,
          epochs=100,
          batch_size=20)

score = model.evaluate(X_test, y_test, batch_size=128)
print(score)
```

```
Epoch 1/100
/opt/anaconda3/lib/python3.10/site-packages/keras/src/layers/core/dense.py:87: UserWarning: Do not pass an `input_shape`/`in
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 865us/step - accuracy: 0.6235 - loss: 1.0708
Epoch 2/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 663us/step - accuracy: 0.6640 - loss: 1.0219
Epoch 3/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 676us/step - accuracy: 0.6807 - loss: 0.9732
Epoch 4/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 649us/step - accuracy: 0.6618 - loss: 0.9420
Epoch 5/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.7147 - loss: 0.8856
Epoch 6/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 755us/step - accuracy: 0.6543 - loss: 0.8868
Epoch 7/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 745us/step - accuracy: 0.6835 - loss: 0.8448
Epoch 8/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 574us/step - accuracy: 0.5946 - loss: 0.8773
Epoch 9/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 656us/step - accuracy: 0.6449 - loss: 0.8215
Epoch 10/100
```

```
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 648us/step - accuracy: 0.6499 - loss: 0.8024
Epoch 11/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 597us/step - accuracy: 0.6280 - loss: 0.8049
Epoch 12/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 649us/step - accuracy: 0.6430 - loss: 0.7796
Epoch 13/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 538us/step - accuracy: 0.6638 - loss: 0.7492
Epoch 14/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 558us/step - accuracy: 0.6140 - loss: 0.7811
Epoch 15/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 680us/step - accuracy: 0.6577 - loss: 0.7309
Epoch 16/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 749us/step - accuracy: 0.6494 - loss: 0.7309
Epoch 17/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 703us/step - accuracy: 0.6994 - loss: 0.6681
Epoch 18/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 628us/step - accuracy: 0.7153 - loss: 0.6438
Epoch 19/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 727us/step - accuracy: 0.6372 - loss: 0.7174
Epoch 20/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 779us/step - accuracy: 0.6282 - loss: 0.7145
Epoch 21/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 604us/step - accuracy: 0.6524 - loss: 0.6790
Epoch 22/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 779us/step - accuracy: 0.6217 - loss: 0.7016
Epoch 23/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 702us/step - accuracy: 0.6321 - loss: 0.6909
Epoch 24/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 571us/step - accuracy: 0.6882 - loss: 0.6183
Epoch 25/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 600us/step - accuracy: 0.6263 - loss: 0.6715
Epoch 26/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 624us/step - accuracy: 0.6423 - loss: 0.6489
Epoch 27/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 538us/step - accuracy: 0.7005 - loss: 0.5925
Epoch 28/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 715us/step - accuracy: 0.7034 - loss: 0.5783
```

The data with 3 hidden layer has the highest result. Too much hidden layer does not give a better result, but will cause overfitting.

Double-click (or enter) to edit