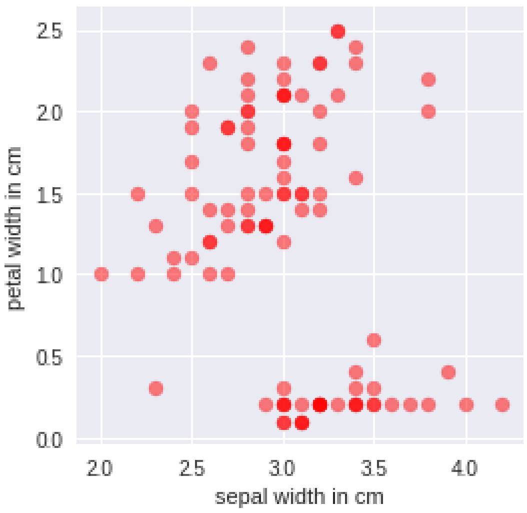
```python
from keras.models import Sequential
from keras.layers import Dense
import numpy as np
import matplotlib.pyplot as plt

# Import the iris dataset's first four columns
# Metadata: https://github.com/badriadhikari/2019-Spring-AI/blob/master/supplement
#  Column 2. sepal width in cm (load as col 0)
#  Column 3. petal length in cm (load as col 1)
#  Column 4. petal width in cm (load as col 2)
dataset = np.genfromtxt("https://raw.githubusercontent.com/badriadhikari/2019-Spri

print('')
print(dataset.shape)
print('')
print(dataset[0:5])
```

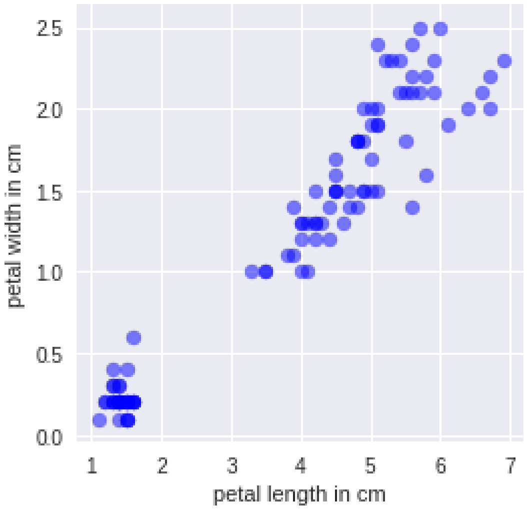
```
Using TensorFlow backend.

(150, 3)

[[3.5 1.4 0.2]
 [3.  1.4 0.2]
 [3.2 1.3 0.2]
 [3.1 1.5 0.2]
 [3.6 1.4 0.2]]
```

```python
# Q1. Why is shuffling important before splitting?
np.random.shuffle(dataset)
print('')
print(dataset[0:5])
# Say, we would like to predict petal width (col4) using
#   sepal width (col2) and petal length (col3)
train = dataset[:100]
valid = dataset[100:]
print('')
print(train.shape)
print('')
print(valid.shape)
```

```

[[3.1 1.5 0.1]
 [3.  4.2 1.5]
 [3.  5.5 2.1]
 [2.8 5.6 2.1]
 [3.3 1.4 0.2]]

(100, 3)

(50, 3)
```

```python
#Q2. Which of the two input features seems more useful
#    for predicting petal width?
plt.figure(figsize=(4,4))
plt.scatter(train[:, 0], train[:, 2], color = 'r', alpha = 0.5)
plt.xlabel('sepal width in cm')
plt.ylabel('petal width in cm')
plt.show()
plt.figure(figsize=(4,4))
plt.scatter(train[:, 1], train[:, 2], color = 'b', alpha = 0.5)
plt.xlabel('petal length in cm')
plt.ylabel('petal width in cm')
plt.show()
```





```
train_input = train[:, 0:2] # col 2 & 3
train_output = train[:, 2] # col 4
valid_input = valid[:, 0:2]
valid_output = valid[:, 2]

print('')
print(train_input[0:5])
print('')
print(train_output[0:5])
```

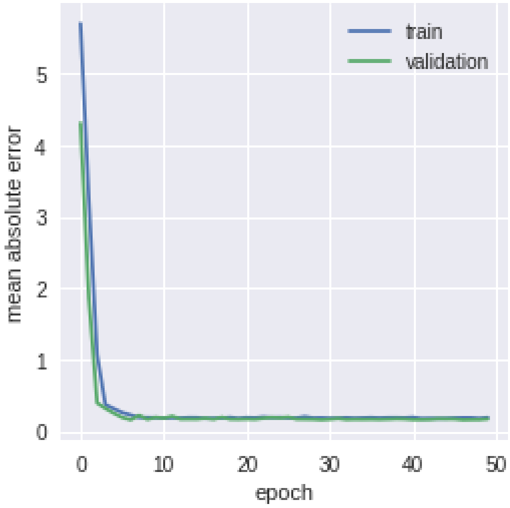
```
[[3.1 1.5]
 [3.  4.2]
 [3.  5.5]
 [2.8 5.6]
 [3.3 1.4]]

[0.1 1.5 2.1 2.1 0.2]
```

```
#Q3. Why is the number of parameters = 3?
model = Sequential()
```

```
model.add(Dense(1, input_dim = len(train_input[0]), activation='linear'))
print(model.summary())

# Changing 'mae' to 'mse' should improve the smoothness of
#  the learning curve and possibly the overall errors
model.compile(loss='mae', optimizer='sgd', metrics=['mae'])

# Verbose = 0 shows no updates, can be changed to 1 or 2
history = model.fit(train_input, train_output, epochs=50,
                    verbose = 0, batch_size=10,
                    validation_data = (valid_input, valid_output))

```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_1 (Dense)              (None, 1)                 3         
=================================================================
Total params: 3
Trainable params: 3
Non-trainable params: 0
_________________________________________________________________
None
```

```
#Q4. Why eventually validation MAE is not
#    always less than train MAE?
plt.figure(figsize=(4,4))
plt.plot(history.history['mean_absolute_error'])
plt.plot(history.history['val_mean_absolute_error'])
plt.ylabel('mean absolute error')
plt.xlabel('epoch')
plt.legend(['train', 'validation'], loc='upper right')
plt.show()
```



```
#Q5. Are these predictions reasonable?
np.set_printoptions(precision = 2)
print ('True Validation Data:')
print(valid_output[0:5])
prediction = model.predict(valid_input)
print ('Prediction:')
print(prediction[0:5].T)
```