ML examples

August 19, 2024

1 ML examples using `sklearn` and `gym`

In this exercise you will see how to use library implementations ML algorithms in the following settings:

- Classification.
- Regression.
- Clustering.
- Reinforcement Learning

You are expected to go through the code while referencing the relevant API documentation in sklearn. It might be useful to modify the code or parameters so you can better understand how it works.

[25]:
```
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline

from IPython import display
```

1.1 Classification with k-Nearest Neighbors algorithm

Nearest neighbors

KNeighborsClassifier

1.1.1 Toy dataset preparation

[43]:
```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.datasets import make_moons, make_circles, make_classification
from sklearn.neighbors import KNeighborsClassifier
from matplotlib.colors import ListedColormap


name = "Nearest Neighbors"

classifier = KNeighborsClassifier(5)
```

```python
X, y = make_classification(n_features = 2, n_redundant = 0, n_informative = 2,
                           random_state = 1, n_clusters_per_class = 1)
rng = np.random.RandomState(2)
X += 2 * rng.uniform(size = X.shape)
linearly_separable = (X, y)

X, y = make_moons(noise = 0.3, random_state = 0)

# preprocess dataset, split into training and test part
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size =.4,
 ↪random_state = 42)
normalizer = StandardScaler()
normalizer.fit(X_train)

X_train = normalizer.transform(X_train)
X_test = normalizer.transform(X_test)
x_min, x_max = X[:, 0].min() - .5, X[:, 0].max() + .5
y_min, y_max = X[:, 1].min() - .5, X[:, 1].max() + .5

# Set step size in the mesh.
h = .02
# Create a mesh [x_min, x_max] x [y_min, y_max] with step size h.
xx, yy = np.meshgrid(np.arange(x_min, x_max, h),
                     np.arange(y_min, y_max, h))
```

1.1.2 Train & Test

[44]:
```python
# Train classifier and compute accuracy on test data.
classifier.fit(X_train, y_train)
score = classifier.score(X_test, y_test)
print('Accuracy on test data:', 100 * score)

# Estimate class probabilities for each point in the mesh.
Z = classifier.predict_proba(np.c_[xx.ravel(), yy.ravel()])[:, 1]
```

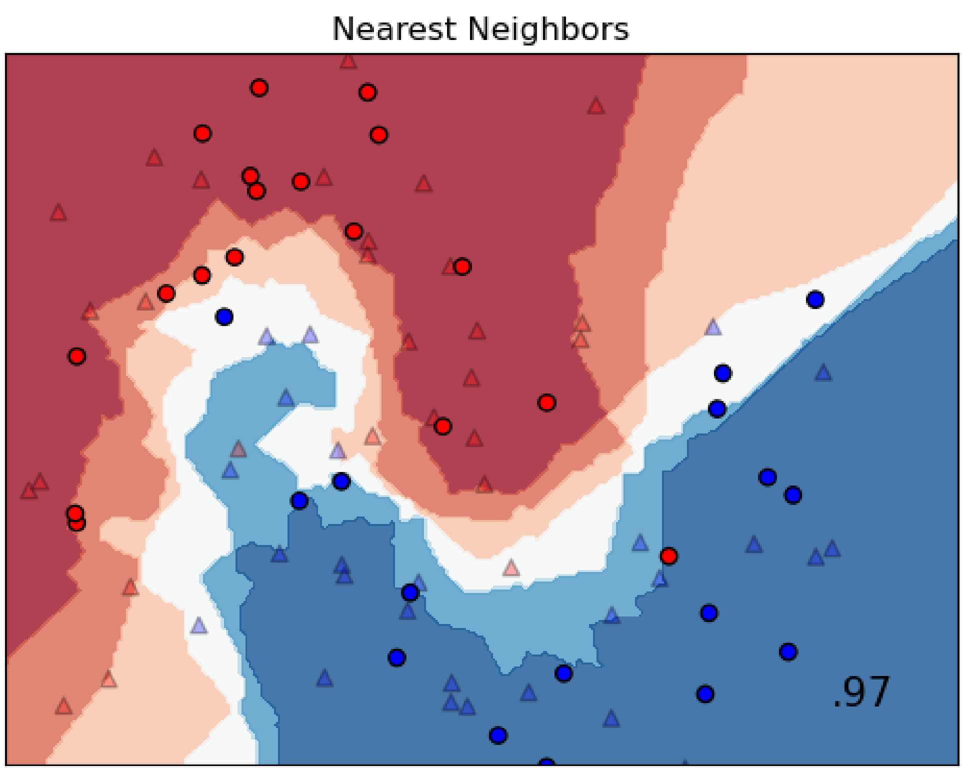
```
Accuracy on test data: 97.5
```

1.1.3 Plot decision boundaries

[45]:
```python
# Put the result into a color plot showing decision boundaries.
# For that, we will assign a color to each point in the mesh.
def plot_boundaries(xx, yy, Z, score, name):
    cm = plt.cm.RdBu
    cm_bright = ListedColormap(['#FF0000', '#0000FF'])
    Z = Z.reshape(xx.shape)
    plt.contourf(xx, yy, Z, cmap=cm, alpha=.8)
```

```
    # Plot the training points.
    plt.scatter(X_train[:, 0], X_train[:, 1], c=y_train, cmap=cm_bright,
                marker='^', edgecolors='k', alpha=0.3)

    # Plot the testing points.
    plt.scatter(X_test[:, 0], X_test[:, 1], c=y_test, cmap=cm_bright,
                edgecolors='k', alpha=1)

    # Finish the plot.
    plt.xlim([xx.min(), xx.max()])
    plt.ylim([yy.min(), yy.max()])
    plt.xticks(())
    plt.yticks(())
    plt.title(name)
    plt.text(xx.max() - .3, yy.min() + .3, ('%.2f' % score).lstrip('0'),
             size = 15, horizontalalignment = 'right')
```

[46]:
```
plot_boundaries(xx, yy, Z, score, name)
```



1.2 Classification with Neural Networks

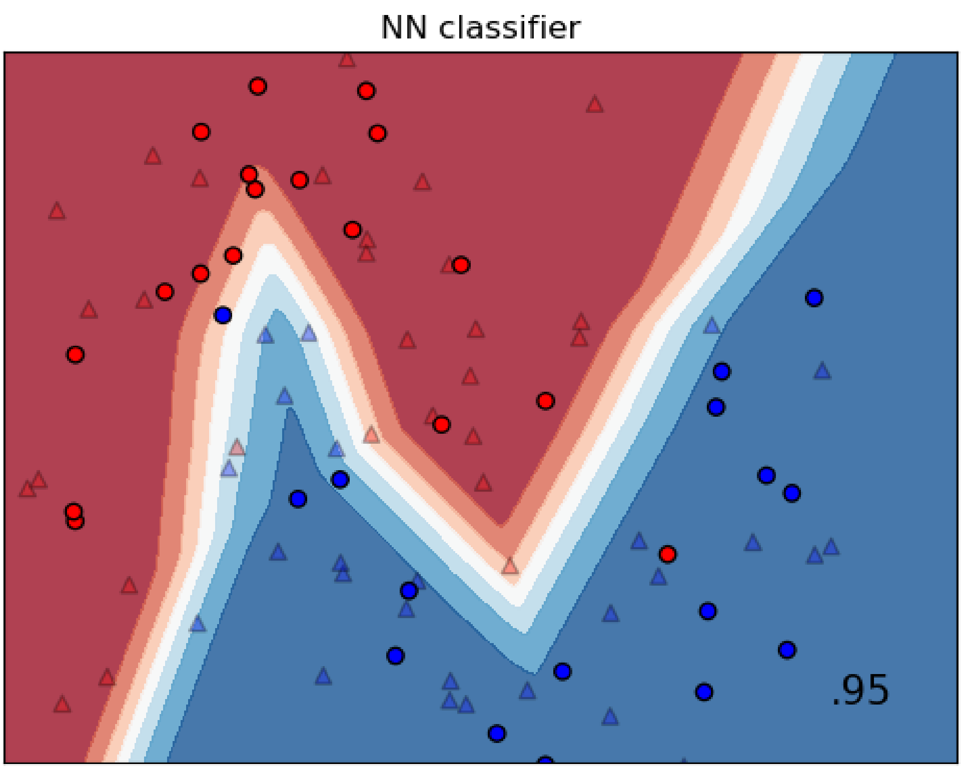
Neural Network Models

MLPClassifier

[89]:
```
from sklearn.neural_network import MLPClassifier

name = "NN classifier"

# Train a NN with one hidden layer of size 100, for 10,000 epochs,
# with an adaptive learning rate, and an L2 decay of 0.001.
nn = MLPClassifier(hidden_layer_sizes = (100,), activation = 'relu',␣
↪random_state = 1,
                   max_iter = 2000, shuffle = False, tol = 0.0001, alpha = 0.
↪001,
                   learning_rate = 'adaptive')
nn_clf = nn.fit(X_train, y_train)

# Compute accuracy on training examples.
score = nn_clf.score(X_test, y_test)
print('Accuracy on test data:', str(100 * score) + '%')
```

```
Accuracy on test data: 95.0%
```

[90]:
```
# Estimate class probabilities for each point in the mesh.
Z = nn_clf.predict_proba(np.c_[xx.ravel(), yy.ravel()])[:, 1]

plot_boundaries(xx, yy, Z, score, name)
```



1.3 Regression with Support Vector Regression (SVR)

SVR class in sklearn

1.3.1 Toy dataset

[92]:
```
from sklearn.svm import SVR

# Generate 40 samples uniformly at random in [0, 5].
X = np.sort(5 * np.random.rand(40, 1), axis = 0)
t = np.sin(X).ravel()

# ##############################################################################
# Add noise to every other 5 samples.
t[::5] += 3 * (0.5 - np.random.rand(8))
```

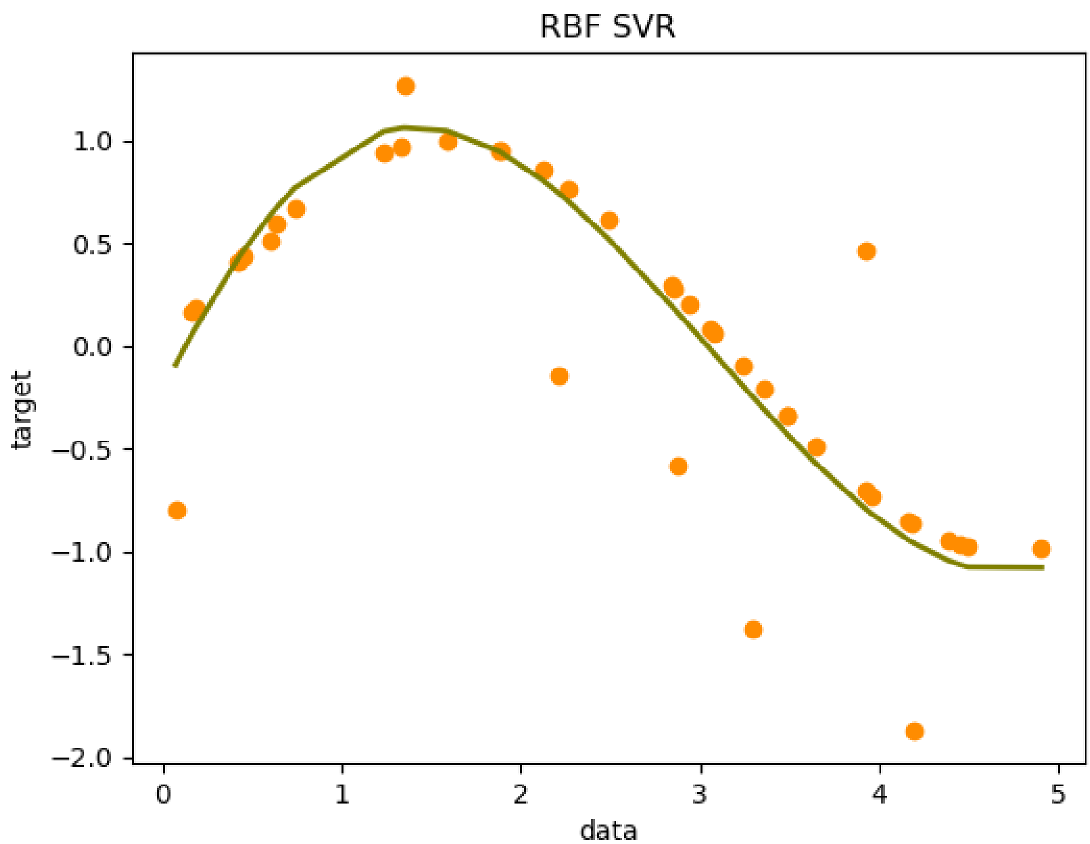
1.3.2 Train & Test

[94]:
```
# Create SVR regression model.
svr = SVR(kernel = 'rbf', C = 1e3, gamma = 0.1)

# Fit regression model.
svr.fit(X, t)

# Predict target values.
y = svr.predict(X)
```

1.3.3 Plot examples and learned target function

[97]:
```
# Plot
plt.scatter(X, t, color = 'darkorange', label = 'data')
plt.plot(X, y, color = "olive", lw = 2, label = name)
plt.title("RBF SVR")
plt.xlabel('data')
plt.ylabel('target')
```

[97]:
```
Text(0, 0.5, 'target')
```



1.4 Clustering with k-Means

Clustering in sklearn

Mini Batch K-Means documentation

MiniBatchKMeans API

1.4.1 Toy dataset

[99]:
```
from sklearn import cluster, datasets, mixture
from sklearn.neighbors import kneighbors_graph
from itertools import cycle, islice

np.random.seed(0)

# ============
# Generate datasets. We choose the size big enough to see the scalability
# of the algorithms, but not too big to avoid too long running times
# ============
n_samples = 1500
```

```
X, y = datasets.make_moons(n_samples = n_samples, noise = .05)

# normalize dataset for easier parameter selection
X = StandardScaler().fit_transform(X)
```

1.5 Train & Test

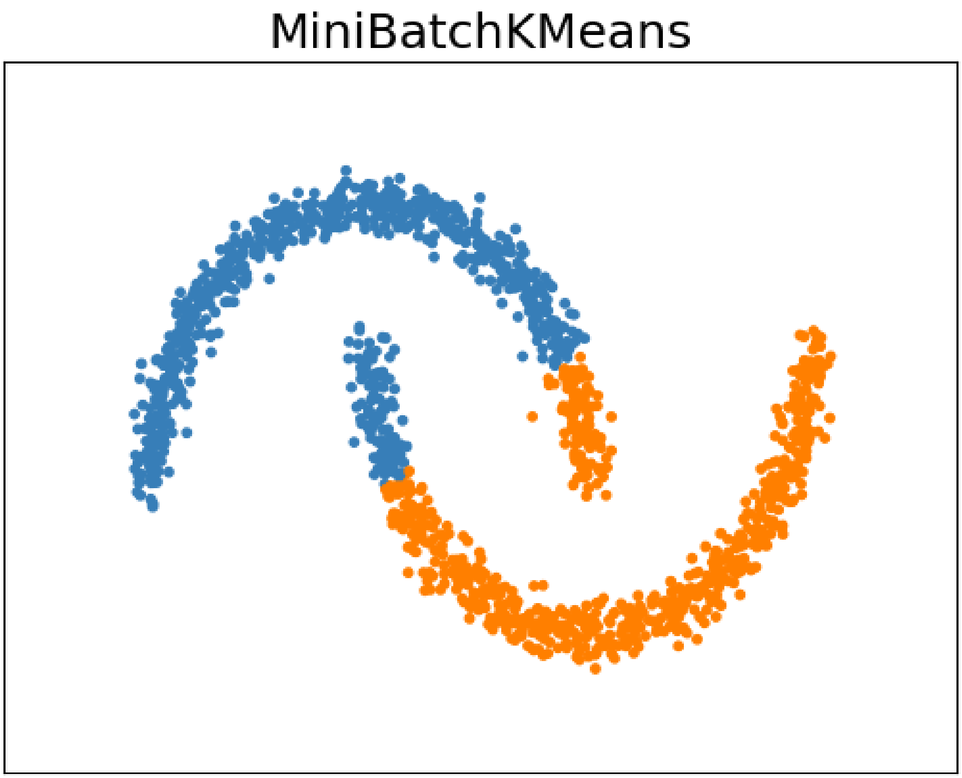
[108]:
```
# Create cluster objects.
kmeans = cluster.MiniBatchKMeans(n_clusters = 2, n_init='auto')

%time
kmeans.fit(X)

if hasattr(kmeans, 'labels_'):
    y_pred = kmeans.labels_.astype(int)
else:
    y_pred = kmeans.predict(X)
```

```
CPU times: user 6 µs, sys: 3 µs, total: 9 µs
Wall time: 16.9 µs
```

1.6 Plot samples and clusters

[109]:
```
plt.title('MiniBatchKMeans', size=18)

colors = np.array(list(islice(cycle(['#377eb8', '#ff7f00', '#4daf4a',
                                     '#f781bf', '#a65628', '#984ea3',
                                     '#999999', '#e41a1c', '#dede00']),
                              int(max(y_pred) + 1))))
# add black color for outliers (if any)
colors = np.append(colors, ["#000000"])
plt.scatter(X[:, 0], X[:, 1], s=10, color=colors[y_pred])

plt.xlim(-2.5, 2.5)
plt.ylim(-2.5, 2.5)
plt.xticks(())
plt.yticks(())
```

[109]:
```
([], [])
```



1.7 Clustering with SpectralClustering

Spectral clustering documentation

SpectralClustering API

1.7.1 Train & Test

[110]:
```
from sklearn.cluster import SpectralClustering

sc = SpectralClustering(n_clusters = 2, assign_labels = 'discretize',
                        affinity="nearest_neighbors", random_state = 0)

%time

sc.fit(X)

y_pred = sc.labels_
```

```
CPU times: user 4 µs, sys: 1 µs, total: 5 µs
Wall time: 10 µs
```

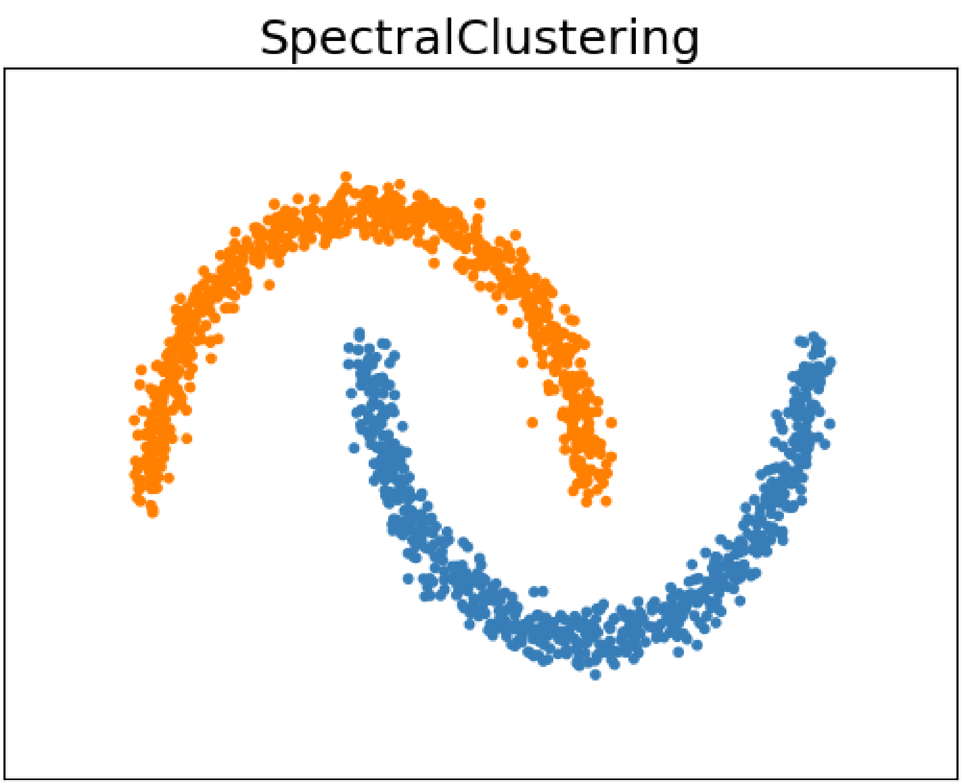
```
/Users/rbunescu/anaconda3/lib/python3.10/site-
packages/sklearn/manifold/_spectral_embedding.py:274: UserWarning: Graph is not
```

```
fully connected, spectral embedding may not work as expected.
  warnings.warn(
```

1.8 Plot samples and clusters

[111]:
```python
plt.title('SpectralClustering', size=18)

colors = np.array(list(islice(cycle(['#377eb8', '#ff7f00', '#4daf4a',
                                     '#f781bf', '#a65628', '#984ea3',
                                     '#999999', '#e41a1c', '#dede00']),
                              int(max(y_pred) + 1))))
# add black color for outliers (if any)
colors = np.append(colors, ["#000000"])
plt.scatter(X[:, 0], X[:, 1], s=10, color=colors[y_pred])

plt.xlim(-2.5, 2.5)
plt.ylim(-2.5, 2.5)
plt.xticks(())
plt.yticks(())
```

[111]: ([], [])



2 Reinforcement Learning

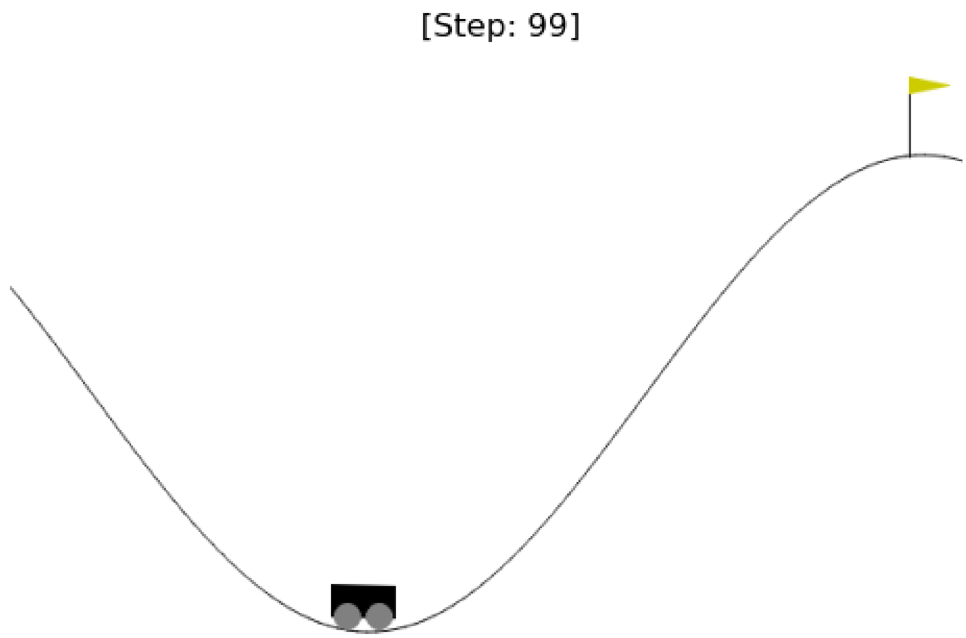
You need to install OpenAI Gymnasium for this exercise by running `pip install gymnasium` on terminal. Please check this link to directly access to the GitHub repo.

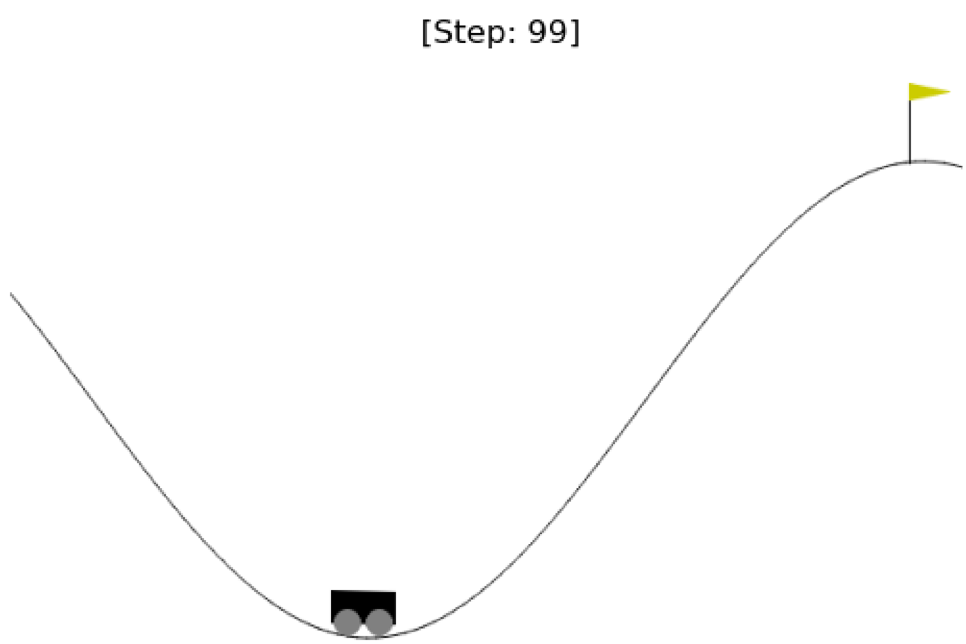
2.1 Environment: MountainCar

[39]:
```
# https://gymnasium.farama.org/
import gymnasium as gym

ACTIONS = ['<-', '  ', '->']

def show_state(env, step=0, a=0):
    plt.figure(3)
    plt.clf()
    plt.imshow(env.render())
    plt.title("%s [Step: %d]" % (ACTIONS[a], step))
    plt.axis('off')

    display.clear_output(wait=True)
    display.display(plt.gcf())
```

[40]:
```
import time

env = gym.make('MountainCar-v0', render_mode="rgb_array")

# Number of steps you run the agent for
num_steps = 100

obs = env.reset()

for step in range(num_steps):
    # take random action, but you can also do something more intelligent
    # action = my_intelligent_agent_fn(obs)
    action = env.action_space.sample()

    # apply the action
    obs, reward, done, trunc, info = env.step(action)

    # Render the env
    show_state(env, step, action)

    # Wait a bit before the next frame unless you want to see a crazy fast video
    time.sleep(0.001)

    # If the epsiode is up, then start another one
    if done:
        env.reset()
```

```
# Close the env
env.close()
```





2.2 Train

[56]:
```
env.observation_space
```

[56]:
```
Box([-1.2  -0.07], [0.6  0.07], (2,), float32)
```

[104]:
```
env.action_space.n
```

[104]:
```
3
```

[ ]:
```
DISCRETE_OBSERVATION_SPACE_SIZE = [
    20] * len(env.observation_space.high)  # will give out 20*20 list

# see how big is the range for each of the 20 different buckets
discrete_os_win_size = (env.observation_space.high -
                        env.observation_space.low) /␣
 ↪DISCRETE_OBSERVATION_SPACE_SIZE

LEARNING_RATE = 0.1
DISCOUNT = 0.95  # how important we find the new future actions are ; future␣
 ↪reward over current reward
EPISODES = 500

# even though the solution might have been found, we still wish to look for␣
 ↪other solutions
epsilon = 0.5  # 0-1 ; higher it is, more likely for it to perform something␣
 ↪random action
START_EPSILON_DECAYING = 1
# python2 style division - gives only int values
END_EPSILON_DECAYING = EPISODES // 2
epsilon_decay_value = epsilon / (END_EPSILON_DECAYING - START_EPSILON_DECAYING)

# Q learning
# so we will have now a table such that each row will have 400 (20*20) rows for␣
 ↪the possible state the agent can be in
# and 3 columns for the 3 possible actions
# the agent will see which state it is in and take the action corresponding to␣
 ↪the largest Q value

# Create a randomised q_table and agent will update it after exploring the␣
 ↪environment
q_table = np.random.uniform(
    low=-2, high=0, size=(DISCRETE_OBSERVATION_SPACE_SIZE + [env.action_space.
 ↪n]))
```

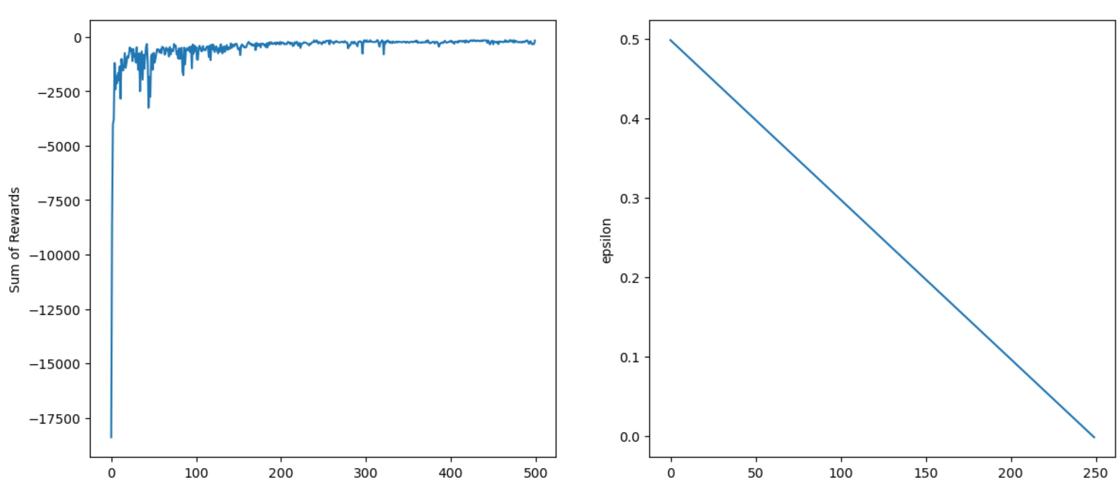
```python
# how to set low and high limits of rewards ? - if you see the rewards printed␣
↪in below cell, they are mostly -1 and
# might be something +ve only when you reach goal. Needs tweaking and playing␣
↪around
# print(q_table.shape)


def get_discrete_state(state):
    if isinstance(state, tuple):
        state = state[0]
    discrete_state = (state - env.observation_space.low) / discrete_os_win_size
    return tuple(discrete_state.astype(np.int))  # return as tuple


epsilon_log = []
reward_log = []

for ep in range(EPISODES):
    done = False
    discrete_state = get_discrete_state(env.reset())  # initial discrete state

    sum_reward = 0
    while not done:  # goal reached means reward = 0

        if np.random.random() > epsilon:
            # in this environment, 0 means push the car left, 1 means to do␣
↪nothing, 2 means to push it right
            action = np.argmax(q_table[discrete_state])
        else:
            action = np.random.randint(0, env.action_space.n)

        # Run one timestep of the environment's dynamics;  returns a tuple␣
↪(observation, reward, done, info).
        new_state, reward, done, _, _ = env.step(action)
        sum_reward += reward

        new_discrete_state = get_discrete_state(new_state)

        if not done:
            # max q value for the next state calculated above
            max_future_q = np.max(q_table[new_discrete_state])

            # q value for the current action and state
            current_q = q_table[discrete_state + (action, )]

            new_q = (1 - LEARNING_RATE) * current_q + \
```

```
                    LEARNING_RATE * (reward + DISCOUNT * max_future_q)

                # based on the new q, we update the current Q value
                q_table[discrete_state + (action, )] = new_q

            # goal reached; reward = 0 and no more negative
            elif new_state[0] >= env.goal_position:
                # its like a snowbal effect, once the goal is reached - it will␣
↪most likely reach again soon enough
                q_table[discrete_state + (action, )] = 0

            discrete_state = new_discrete_state

    if END_EPSILON_DECAYING >= ep >= START_EPSILON_DECAYING:
        epsilon -= epsilon_decay_value
    epsilon_log.append(epsilon)

    reward_log.append(sum_reward)

env.close()
```

2.3 Results

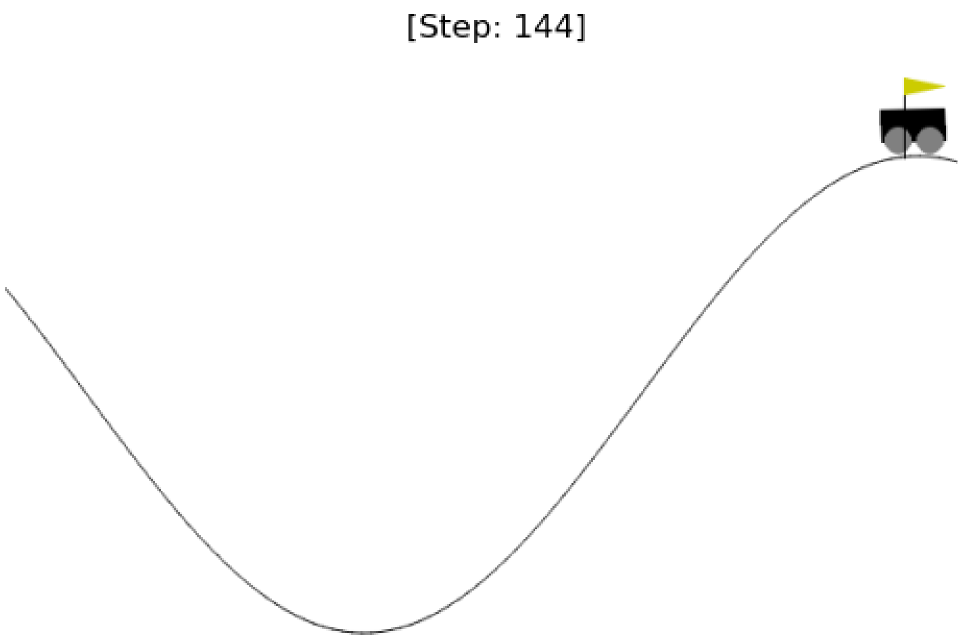
[51]:
```
plt.figure(figsize=(14,6))
plt.subplot(1,2,1)
plt.plot(reward_log)
plt.ylabel("Sum of Rewards")

plt.subplot(1,2,2)
plt.plot(epsilon_log)
plt.ylabel("epsilon")
```

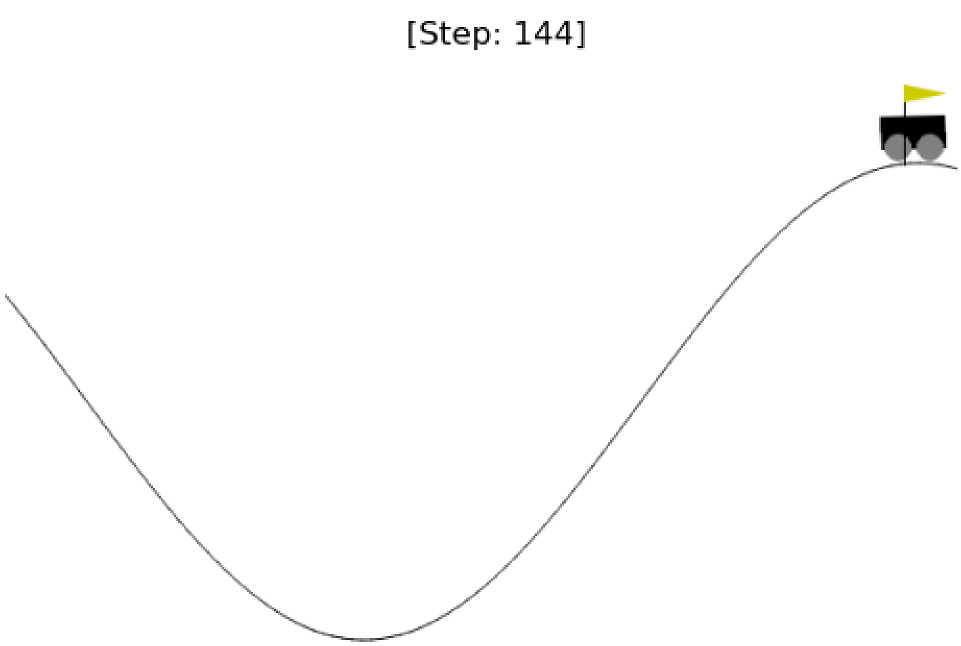
[51]:
```
Text(0, 0.5, 'epsilon')
```



2.4 Test

[53]:
```python
# Number of steps you run the agent for
num_steps = 1000

obs = env.reset()

for step in range(num_steps):
    # take random action, but you can also do something more intelligent
    # action = my_intelligent_agent_fn(obs)
    #action = env.action_space.sample()
    #>>>>>>>>>
    discrete_state = get_discrete_state(obs)
    action = np.argmax(q_table[discrete_state])

    # apply the action
    obs, reward, done, trunc, info = env.step(action)

    # Render the env
    show_state(env, step, action)

    # Wait a bit before the next frame unless you want to see a crazy fast video
    #time.sleep(0.00001)

    # If the epsiode is up, then start another one
    if done:
        env.reset()
        break

# Close the env
env.close()
```


[Step: 144]


[Step: 144]

[ ]:

```

```