Supervised Land Cover Classification using Google Earth Engine and JavaScript (Experiment Replication)

```
In []: import ee
        ee.Authenticate()
        %pip install folium
In []: # Import the Earth Engine library and Folium for mapping
        import ee
        import folium
        # Initialize Earth Engine
        ee.Initialize()
        # Load a Landsat 8 image by its asset ID
        image = ee.Image('LANDSAT/LC08/C01/T1_T0A/LC08_044034_20140318')
        # Define a visualization parameter for the image (e.g., bands and color)
        visParams = {
          'bands': ['B4', 'B3', 'B2'], # Red, Green, Blue bands
          'max': 0.3 # Adjust this value for image brightness
        # Create a map centered on the image
        map = folium.Map(location=[image.geometry().centroid().coordinates().get
                                   image.geometry().centroid().coordinates().get
        # Add the Landsat image as a tile layer from Earth Engine
        tile_url = image.getMapId(visParams)
        folium.TileLayer(
            tiles=tile_url['tile_fetcher'].url_format,
            attr='Google Earth Engine',
            overlay=True,
            name='Landsat Image'
        ).add_to(map)
        # Display the map
        map
```



Sampling Image and Creating Training and Testing Sets

```
In [ ]: image = ee.Image('LANDSAT/LC08/C01/T1_T0A/LC08_044034_20140318')
        # Define a region of interest (replace with your region)
        region = ee.Geometry.Rectangle(-122.085, 37.422, -121.774, 37.703)
        # Sample the image at the points and add a random column
        points = image.sample(
            region=region,
            scale=30,
            numPixels=5000,
            seed=0,
            geometries=True # Set this to False to ignore geometries
        ).randomColumn('random')
        # Make a training-testing split
        training = points.filter(ee.Filter.lt('random', 0.7))
        testing = points.filter(ee.Filter.gte('random', 0.7))
        # Print the number of points in each split for verification
        print('Number of points in training:', training.size().getInfo())
        print('Number of points in testing:', testing.size().getInfo())
```

Number of points in training: 3473 Number of points in testing: 1527

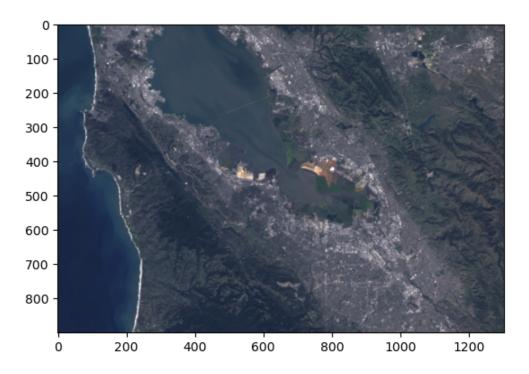
K-means clusterer and train it on our training set. Creates a clusterer object using the Weka K-Means algorithm with 15 clusters. This code trains a classifier using the CART (Classification and Regression Trees) algorithm from the smile library. The code performs clustering using the K-Means algorithm and then uses the resulting clusters as labels to train a classifier. The trained classifier is then used to classify the input image, producing an output image with class labels for each pixel.

```
In []: # Instantiate the clusterer and train it
    clusterer = ee.Clusterer.wekaKMeans(15).train(training)

# Train a classifier using the clusters as labels
    trained = ee.Classifier.smileCart().train(
        features=training,
        classProperty='cluster',
        inputProperties=image.bandNames()
)
output = image.classify(trained)
```

Load image, convert to grayscale, standardize the data, apply spectral clustering,

```
In [ ]: import numpy as np
        import matplotlib.pyplot as plt
        from skimage import io
        from sklearn.cluster import SpectralClustering
        from sklearn.preprocessing import StandardScaler
        # Load the image
        image path = '/Users/johnwishart/Desktop/IST718/pic.png'
        original_image = io.imread(image_path)
        # Convert the color image to grayscale
        image_2d = np.mean(original_image, axis=2)
        # Standardize the data for spectral clustering
        scaler = StandardScaler()
        image_2d_scaled = scaler.fit_transform(image_2d)
        # Define spectral clustering parameters (you can adjust these)
        n_clusters = 15 # Number of clusters
        # Apply spectral clustering
        spectral = SpectralClustering(n clusters=n clusters, affinity='nearest no
        labels = spectral.fit_predict(image_2d_scaled)
        # display the image
        plt.imshow(original_image)
        plt.show()
```



```
In [ ]: # Overlay cluster labels on the original image
                           # Convert the color image to grayscale
                           image_2d = np.mean(original_image, axis=2)
                           # Standardize the data for spectral clustering
                           scaler = StandardScaler()
                           image_2d_scaled = scaler.fit_transform(image_2d)
                           # Define spectral clustering parameters (you can adjust these)
                           n_clusters = 15  # Number of clusters
                           # Apply spectral clustering
                           spectral = SpectralClustering(n_clusters=n_clusters, affinity='nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_nearest_ne
                           labels = spectral.fit_predict(image_2d_scaled)
                           # Display the image with cluster labels overlaid
                           fig, ax = plt.subplots()
                           ax.imshow(original_image)
                           # Create a color map for the clusters
                           color_map = plt.cm.get_cmap('hsv', n_clusters)
                           # Overlay the cluster labels on top of the image
                           for cluster in range(n_clusters):
                                        cluster_pixels = original_image[labels == cluster]
                                        ax.scatter(cluster_pixels[:, 1], cluster_pixels[:, 0], color=color_ma
                           plt.show()
```

/var/folders/hs/qnv8rj497vj3bn3xsct8ktp40000gn/T/ipykernel_30317/2039751
341.py:22: MatplotlibDeprecationWarning: The get_cmap function was depre
cated in Matplotlib 3.7 and will be removed two minor releases later. Us
e ``matplotlib.colormaps[name]`` or ``matplotlib.colormaps.get_cmap(obj)
`` instead.
 color_map = plt.cm.get_cmap('hsv', n_clusters)



Idea and code excerpts from

https://medium.com/@northamericangeoscientistsorg/supervised-land-cover-classification-using-google-earth-engine-and-javascript-9f7740d84863