Assignment (1)

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Part 1: K-NNClassifier

1. Load and Balance Data

In [1]:
```
import pandas as pd
from sklearn.utils import shuffle

# Load the dataset (in Pandas DataFrame)
column_names = ['0','1', '2', '3', '4', '5', '6', '7', '8', '9', 'class']
data = pd.read_csv('magic04.csv', names = column_names, index_col = False)
# Show dimensions of loaded data to make sure that data are fully loaded
print("data shape:", data.shape)
# Show First 5 Examples
data.head(5)
```

```
data shape: (19020, 11)
```

Out[1]:

	0	1	2	3	4	5	6	7	8	9	class
0	28.7967	16.0021	2.6449	0.3918	0.1982	27.7004	22.0110	-8.2027	40.0920	81.8828	g
1	31.6036	11.7235	2.5185	0.5303	0.3773	26.2722	23.8238	-9.9574	6.3609	205.2610	g
2	162.0520	136.0310	4.0612	0.0374	0.0187	116.7410	-64.8580	-45.2160	76.9600	256.7880	g
3	23.8172	9.5728	2.3385	0.6147	0.3922	27.2107	-6.4633	-7.1513	10.4490	116.7370	g
4	75.1362	30.9205	3.1611	0.3168	0.1832	-5.5277	28.5525	21.8393	4.6480	356.4620	g

In [2]:
```
# Separate data into gamma and hadron classes
gamma_data = data[data['class'] == 'g']
hadron_data = data[data['class'] == 'h']
# Show dimensions of gamma data
print("gamma_data shape:", gamma_data.shape)
# Show First 5 Examples of gamma_data
gamma_data.head(5)
```

```
gamma_data shape: (12332, 11)
```

Out[2]:

	0	1	2	3	4	5	6	7	8	9	class
0	28.7967	16.0021	2.6449	0.3918	0.1982	27.7004	22.0110	-8.2027	40.0920	81.8828	g
1	31.6036	11.7235	2.5185	0.5303	0.3773	26.2722	23.8238	-9.9574	6.3609	205.2610	g
2	162.0520	136.0310	4.0612	0.0374	0.0187	116.7410	-64.8580	-45.2160	76.9600	256.7880	g
3	23.8172	9.5728	2.3385	0.6147	0.3922	27.2107	-6.4633	-7.1513	10.4490	116.7370	g
4	75.1362	30.9205	3.1611	0.3168	0.1832	-5.5277	28.5525	21.8393	4.6480	356.4620	g

In [3]:
```
# Show dimensions of hadron data
print("hadron_data shape:", hadron_data.shape)
# Show First 5 Examples of hadron_data
hadron_data.head(5)
```

```
hadron_data shape: (6688, 11)
```

Out[3]:

	0	1	2	3	4	5	6	7	8	9	class
12332	93.7035	37.9432	3.1454	0.1680	0.1011	53.2566	89.0566	11.8175	14.1224	231.9028	h
12333	102.0005	22.0017	3.3161	0.1064	0.0724	-54.0862	43.0553	-15.0647	88.4636	274.9392	h
12334	100.2775	21.8784	3.1100	0.3120	0.1446	-48.1834	57.6547	-9.6341	20.7848	346.4330	h
12335	91.6558	18.8293	2.7097	0.4386	0.3420	-52.6841	-97.8373	-17.0955	63.8834	130.7998	h
12336	38.0195	12.6736	2.8747	0.4084	0.1928	-51.4840	8.3471	7.9620	24.5402	163.8674	h

In [4]:
```
# Balance the dataset by randomly selecting gamma events (to prevent bias)
gamma_data = shuffle(gamma_data).iloc[:6688]
# Show dimensions of gamma data after elemination
print("gamma_data shape:", gamma_data.shape)
# Show First 5 Examples of gamma_data after elimination
gamma_data.head(5)
```

```
gamma_data shape: (6688, 11)
```

Out[4]:

	0	1	2	3	4	5	6	7	8	9	class
4981	38.2736	17.2842	2.7451	0.2608	0.1466	39.1278	8.7000	14.2626	0.4229	188.455	g
8847	21.6208	16.5914	2.6698	0.4257	0.2620	27.3897	9.4802	10.3581	34.2210	230.005	g
2976	59.9630	15.0103	2.9146	0.3007	0.1686	-72.8926	47.3335	11.0761	2.5920	257.817	g
11544	36.9596	16.6503	2.7723	0.2838	0.1512	-4.0322	-28.5974	-10.5973	10.1152	250.027	g
11508	55.9692	23.7766	3.0408	0.2021	0.1033	71.9799	24.7609	13.5666	3.2503	175.683	g

In [5]:

```
# Combine gamma and hadron data to form the balanced dataset and Shuffle the balanced dataset to be random scat
final_data = shuffle(pd.concat([gamma_data, hadron_data]))
# Show dimensions of final data
print("final_data shape:", final_data.shape)
# Show First 5 Examples of final data
final_data.head(5)
```

```
final_data shape: (13376, 11)
```

Out[5]:

	0	1	2	3	4	5	6	7	8	9	class
6212	26.9109	16.0899	2.7612	0.3813	0.2071	5.0224	-16.0850	-12.1486	16.3000	229.6880	g
12886	119.9750	74.8536	3.5262	0.1906	0.1376	-47.4358	-119.0453	69.0948	86.3852	385.3241	h
2666	26.2642	19.6444	2.6395	0.3601	0.2099	7.0801	10.4091	-14.9864	26.9440	93.3478	g
9437	12.7729	11.5667	2.2978	0.7204	0.3955	-15.3926	8.3552	10.2195	35.8442	96.9367	g
13934	24.8923	17.9013	2.7702	0.3803	0.2126	39.5991	-17.8956	-13.7780	70.7260	237.9777	h

2. Split the data into training (70%), validation (15%), and testing (15%)

In [6]:

```
from sklearn.model_selection import train_test_split

# First, We Splited the data into training (70%) and the rest (30%)
train_set, cv_and_test = train_test_split(final_data, test_size = 0.3, random_state = 42)

# Then We Splited the 30% into  crossvalidation set and testing set
cv_set, test_set = train_test_split(cv_and_test, test_size = 0.5, random_state = 42)

# Display the shapes of the resulting sets
print("Training set shape:", train_set.shape)
print("Validation set shape:", cv_set.shape)
print("Testing set shape:", test_set.shape)
```

```
Training set shape: (9363, 11)
Validation set shape: (2006, 11)
Testing set shape: (2007, 11)
```

3. Apply K-NN Classifier to final_data while varying the hyperparameter K

In [7]:

```
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, confusion_matrix
# Initialize dictionaries to store metrics for different k values
metrics = {'k': [], 'accuracy': [], 'precision': [], 'recall': [], 'f1_score': []}
```

In [8]:

```
from sklearn.neighbors import KNeighborsClassifier

# Initialize K values
k_values = [1, 3, 5, 7, 9, 11, 13, 15, 20, 30, 50, 60, 80, 100, 200, 300, 500, 650, 720, 800, 1000]

for k in k_values:
    classifier = KNeighborsClassifier(n_neighbors = k)

    # Train the classifier on the training data
    X_train = train_set.drop('class', axis=1) # Remove 'class' column (label)
    y_train = train_set['class']

    # Fit Model 1
    classifier.fit(X_train, y_train)

    # Make prediction on the cross validation set
    prediction = classifier.predict(cv_set.drop(columns=['class']))

    # Calculate metrics
    accuracy = accuracy_score(cv_set['class'], prediction)
    precision = precision_score(cv_set['class'], prediction, pos_label='g')
    recall = recall_score(cv_set['class'], prediction, pos_label='g')
    f1 = f1_score(cv_set['class'], prediction, pos_label='g')
    conf_matrix = confusion_matrix(cv_set['class'], prediction)

    # Store the metrics for this k = 1
    metrics['k'].append(k)
    metrics['accuracy'].append(accuracy)
    metrics['precision'].append(precision)
```

```python
    metrics['recall'].append(recall)
    metrics['f1_score'].append(f1)

    # Print the metrics for the current model
    print(f"Model with k = {k} Metrics:")
    print(f"Accuracy: {accuracy}")
    print(f"Precision: {precision}")
    print(f"Recall: {recall}")
    print(f"F1-Score: {f1}")
    print("Confusion Matrix:")
    print(conf_matrix)
    print("-------------------------------------")
```

```
Model with k = 1 Metrics:
Accuracy: 0.7392821535393819
Precision: 0.7253588516746412
Recall: 0.7625754527162978
F1-Score: 0.7435017165277098
Confusion Matrix:
[[758 236]
 [287 725]]
-------------------------------------
Model with k = 3 Metrics:
Accuracy: 0.7577268195413759
Precision: 0.7351851851851852
Recall: 0.7987927565392354
F1-Score: 0.7656702025072325
Confusion Matrix:
[[794 200]
 [286 726]]
-------------------------------------
Model with k = 5 Metrics:
Accuracy: 0.7622133599202393
Precision: 0.7305976806422837
Recall: 0.823943661971831
F1-Score: 0.774468085106383
Confusion Matrix:
[[819 175]
 [302 710]]
-------------------------------------
Model with k = 7 Metrics:
Accuracy: 0.7517447657028913
Precision: 0.7164048865619547
Recall: 0.8259557344064387
F1-Score: 0.7672897196261682
Confusion Matrix:
[[821 173]
 [325 687]]
-------------------------------------
Model with k = 9 Metrics:
Accuracy: 0.752741774675972
Precision: 0.718421052631579
Recall: 0.823943661971831
F1-Score: 0.767572633552015
Confusion Matrix:
[[819 175]
 [321 691]]
-------------------------------------
Model with k = 11 Metrics:
Accuracy: 0.7562313060817547
Precision: 0.7209098862642169
Recall: 0.8289738430583501
F1-Score: 0.7711745437529246
Confusion Matrix:
[[824 170]
 [319 693]]
-------------------------------------
Model with k = 13 Metrics:
Accuracy: 0.7562313060817547
Precision: 0.7182368193604148
Recall: 0.8360160965794768
F1-Score: 0.7726638772663877
Confusion Matrix:
[[831 163]
 [326 686]]
-------------------------------------
Model with k = 15 Metrics:
Accuracy: 0.7572283150548355
Precision: 0.7179707652622528
Recall: 0.8400402414486922
F1-Score: 0.7742234585071859
Confusion Matrix:
[[835 159]
 [328 684]]
-------------------------------------
Model with k = 20 Metrics:
Accuracy: 0.7462612163509471
Precision: 0.6989335520918786
Recall: 0.8571428571428571
```

```
F1-Score: 0.7699954812471758
Confusion Matrix:
[[852 142]
 [367 645]]
--------------------------------------
Model with k = 30 Metrics:
Accuracy: 0.7477567298105683
Precision: 0.7
Recall: 0.8591549295774648
F1-Score: 0.7714543812104788
Confusion Matrix:
[[854 140]
 [366 646]]
--------------------------------------
Model with k = 50 Metrics:
Accuracy: 0.7462612163509471
Precision: 0.7022518765638032
Recall: 0.8470824949698189
F1-Score: 0.7678978568171455
Confusion Matrix:
[[842 152]
 [357 655]]
--------------------------------------
Model with k = 60 Metrics:
Accuracy: 0.7427716849451645
Precision: 0.6978476821192053
Recall: 0.8480885311871227
F1-Score: 0.7656675749318801
Confusion Matrix:
[[843 151]
 [365 647]]
--------------------------------------
Model with k = 80 Metrics:
Accuracy: 0.7437686939182453
Precision: 0.698019801980198
Recall: 0.8511066398390342
F1-Score: 0.7669990933816864
Confusion Matrix:
[[846 148]
 [366 646]]
--------------------------------------
Model with k = 100 Metrics:
Accuracy: 0.7417746759720838
Precision: 0.6941272430668842
Recall: 0.8561368209255533
F1-Score: 0.7666666666666668
Confusion Matrix:
[[851 143]
 [375 637]]
--------------------------------------
Model with k = 200 Metrics:
Accuracy: 0.7318045862412762
Precision: 0.6832797427652733
Recall: 0.8551307847082495
F1-Score: 0.7596067917783734
Confusion Matrix:
[[850 144]
 [394 618]]
--------------------------------------
Model with k = 300 Metrics:
Accuracy: 0.7238285144566301
Precision: 0.6740506329113924
Recall: 0.8571428571428571
F1-Score: 0.7546501328609388
Confusion Matrix:
[[852 142]
 [412 600]]
--------------------------------------
Model with k = 500 Metrics:
Accuracy: 0.7108673978065803
Precision: 0.6594761171032357
Recall: 0.8611670020120724
F1-Score: 0.7469458987783595
Confusion Matrix:
[[856 138]
 [442 570]]
--------------------------------------
Model with k = 650 Metrics:
Accuracy: 0.7043868394815553
Precision: 0.6506386175807664
Recall: 0.8712273641851107
F1-Score: 0.7449462365591398
Confusion Matrix:
[[866 128]
 [465 547]]
--------------------------------------
Model with k = 720 Metrics:
Accuracy: 0.7013958125623131
Precision: 0.6474981329350261
```

```
Recall: 0.8722334004024145
F1-Score: 0.743249035576511
Confusion Matrix:
[[867 127]
 [472 540]]
--------------------------------------
Model with k = 800 Metrics:
Accuracy: 0.6984047856430707
Precision: 0.6437546193643755
Recall: 0.8762575452716298
F1-Score: 0.742224115892629
Confusion Matrix:
[[871 123]
 [482 530]]
--------------------------------------
Model with k = 1000 Metrics:
Accuracy: 0.6884346959122633
Precision: 0.6320687186828919
Recall: 0.8883299798792756
F1-Score: 0.7386030949393559
Confusion Matrix:
[[883 111]
 [514 498]]
--------------------------------------
```

4. Compare using metrics dataframe generated

In [9]:

```
# Convert the metrics to a DataFrame for easy comparison
metrics_df = pd.DataFrame(metrics)
metrics_df
```

Out[9]:

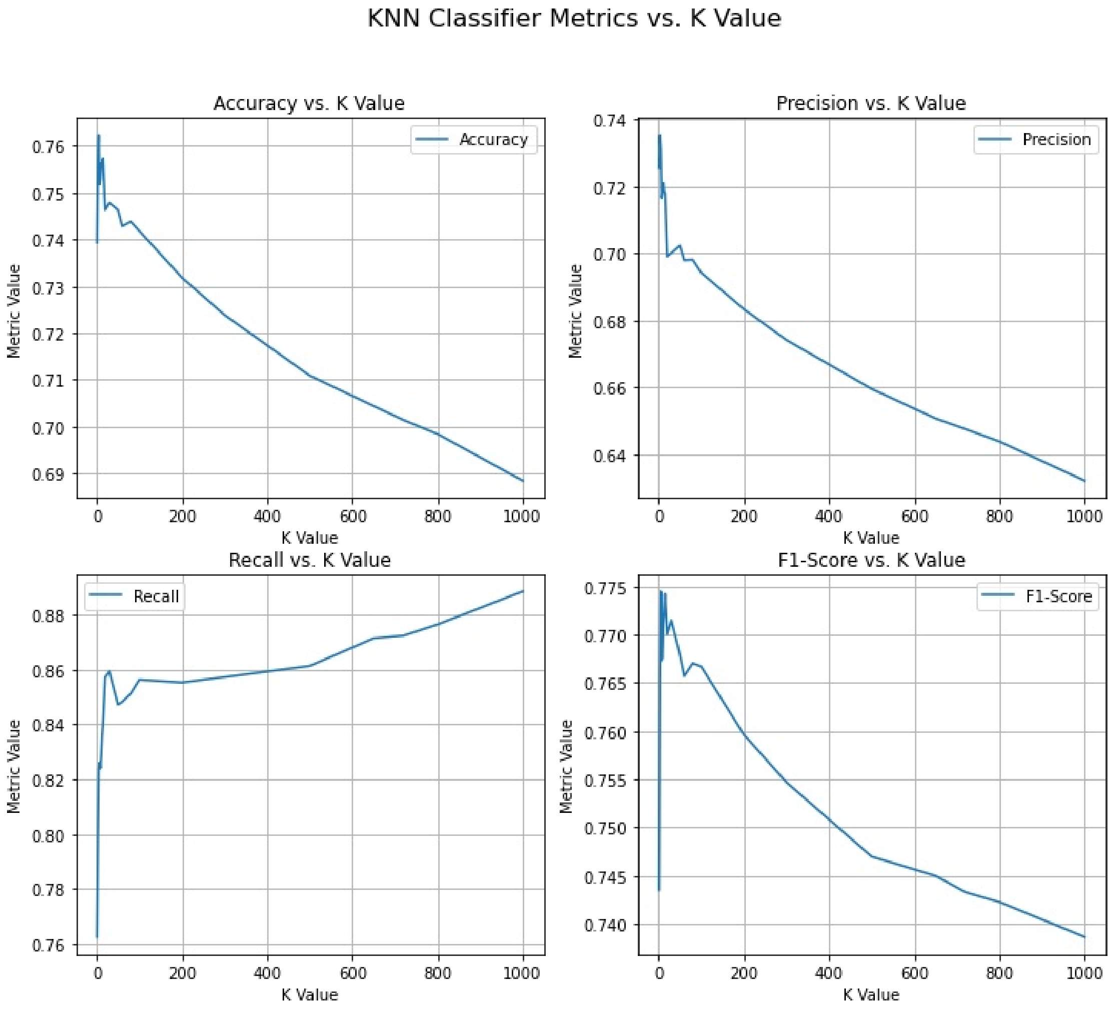
	k	accuracy	precision	recall	f1_score
0	1	0.739282	0.725359	0.762575	0.743502
1	3	0.757727	0.735185	0.798793	0.765670
2	5	0.762213	0.730598	0.823944	0.774468
3	7	0.751745	0.716405	0.825956	0.767290
4	9	0.752742	0.718421	0.823944	0.767573
5	11	0.756231	0.720910	0.828974	0.771175
6	13	0.756231	0.718237	0.836016	0.772664
7	15	0.757228	0.717971	0.840040	0.774223
8	20	0.746261	0.698934	0.857143	0.769995
9	30	0.747757	0.700000	0.859155	0.771454
10	50	0.746261	0.702252	0.847082	0.767898
11	60	0.742772	0.697848	0.848089	0.765668
12	80	0.743769	0.698020	0.851107	0.766999
13	100	0.741775	0.694127	0.856137	0.766667
14	200	0.731805	0.683280	0.855131	0.759607
15	300	0.723829	0.674051	0.857143	0.754650
16	500	0.710867	0.659476	0.861167	0.746946
17	650	0.704387	0.650639	0.871227	0.744946
18	720	0.701396	0.647498	0.872233	0.743249
19	800	0.698405	0.643755	0.876258	0.742224
20	1000	0.688435	0.632069	0.888330	0.738603

5.Compare between models by plotting metrics against k values used

In [10]:

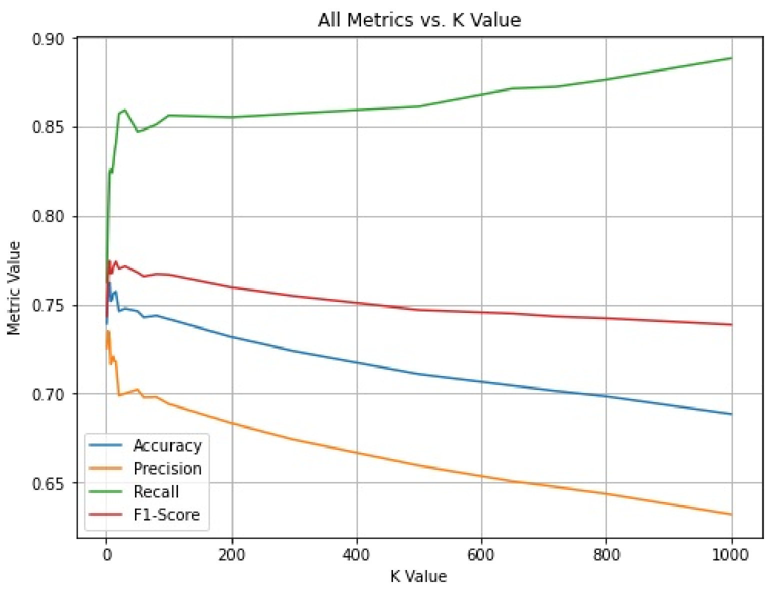
```
import matplotlib.pyplot as plt

# Create subplots for each metric
fig, axs = plt.subplots(2, 2, figsize=(12, 10))
fig.suptitle('KNN Classifier Metrics vs. K Value', fontsize=16)

# Plot individual metrics in subplots
axs[0, 0].plot(metrics['k'], metrics['accuracy'], label='Accuracy')
axs[0, 0].set_title('Accuracy vs. K Value')

axs[0, 1].plot(metrics['k'], metrics['precision'], label='Precision')
axs[0, 1].set_title('Precision vs. K Value')

axs[1, 0].plot(metrics['k'], metrics['recall'], label='Recall')
axs[1, 0].set_title('Recall vs. K Value')
```

```
axs[1, 1].plot(metrics['k'], metrics['f1_score'], label='F1-Score')
axs[1, 1].set_title('F1-Score vs. K Value')

for ax in axs.flat:
    ax.set(xlabel='K Value', ylabel='Metric Value')
    ax.grid()
    ax.legend()
```



In [11]:

```
# plot a combined plot for all metrics
plt.figure(figsize=(8, 6))
plt.plot(metrics['k'], metrics['accuracy'], label='Accuracy')
plt.plot(metrics['k'], metrics['precision'], label='Precision')
plt.plot(metrics['k'], metrics['recall'], label='Recall')
plt.plot(metrics['k'], metrics['f1_score'], label='F1-Score')

plt.xlabel('K Value')
plt.ylabel('Metric Value')
plt.title('All Metrics vs. K Value')
plt.legend()
plt.grid()
```



6.Find best model according to accuracy

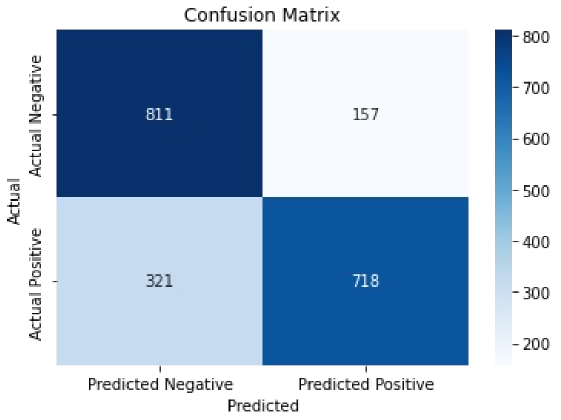
In [12]:
```
# Find the model with the highest accuracy
best_model = metrics_df.loc[metrics_df['accuracy'].idxmax()]

print("Best Model with k={}:".format(best_model['k']))
print("Accuracy: {}".format(best_model['accuracy']))
print("Precision: {}".format(best_model['precision']))
print("Recall: {}".format(best_model['recall']))
print("F1 Score: {}".format(best_model['f1_score']))
```

```
Best Model with k=5.0:
Accuracy: 0.7622133599202393
Precision: 0.7305976806422837
Recall: 0.823943661971831
F1 Score: 0.774468085106383
```

7.Calculate confusion matrix of best model according to accuracy

In [13]:
```
import seaborn as sns
import matplotlib.pyplot as plt

# Your previous code for model training and confusion matrix calculation
best_knn = KNeighborsClassifier(n_neighbors=int(best_model['k']))
best_knn.fit(train_set.drop(columns=['class']), train_set['class'])
predictions = best_knn.predict(test_set.drop(columns=['class']))
conf_matrix = confusion_matrix(test_set['class'], predictions)

# Extract the values from the confusion matrix
true_positive = conf_matrix[1][1]
true_negative = conf_matrix[0][0]
false_positive = conf_matrix[0][1]
false_negative = conf_matrix[1][0]

print("Confusion Matrix:")
print(conf_matrix)
print("---------------------------------")
# Print the confusion matrix with labels
print(f'TP (True Positives): {true_positive}')
print(f'TN (True Negatives): {true_negative}')
print(f'FP (False Positives): {false_positive}')
print(f'FN (False Negatives): {false_negative}')

# Visualize the confusion matrix using a heatmap
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues',
            xticklabels=['Predicted Negative', 'Predicted Positive'],
            yticklabels=['Actual Negative', 'Actual Positive'])

plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')

plt.show()
```

```
Confusion Matrix:
[[811 157]
 [321 718]]
---------------------------------
TP (True Positives): 718
TN (True Negatives): 811
FP (False Positives): 157
FN (False Negatives): 321
```



8.Find best model according to F1 Score

In [14]:
```
# Find the model with the highest f1 score
best_model = metrics_df.loc[metrics_df['f1_score'].idxmax()]
```

```
print("Best Model with k={}:".format(best_model['k']))
print("Accuracy: {}".format(best_model['accuracy']))
print("Precision: {}".format(best_model['precision']))
print("Recall: {}".format(best_model['recall']))
print("F1 Score: {}".format(best_model['f1_score']))
```

```
Best Model with k=5.0:
Accuracy: 0.7622133599202393
Precision: 0.7305976806422837
Recall: 0.823943661971831
F1 Score: 0.774468085106383
```

Calculate confusion matrix of best model according to f1 score

In [18]:

```
# Calculate the confusion matrix for the best model
best_knn = KNeighborsClassifier(n_neighbors=int(best_model['k']))
best_knn.fit(train_set.drop(columns=['class']), train_set['class'])
predictions = best_knn.predict(test_set.drop(columns=['class']))
conf_matrix = confusion_matrix(test_set['class'], predictions)

# Extract the values from the confusion matrix
true_positive = conf_matrix[1][1]
true_negative = conf_matrix[0][0]
false_positive = conf_matrix[0][1]
false_negative = conf_matrix[1][0]

print("Confusion Matrix:")
print(conf_matrix)
print("---------------------------------")
# Print the confusion matrix with labels
print(f'TP (True Positives): {true_positive}')
print(f'TN (True Negatives): {true_negative}')
print(f'FP (False Positives): {false_positive}')
print(f'FN (False Negatives): {false_negative}')

# Visualize the confusion matrix using a heatmap
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Reds',
            xticklabels=['Predicted Negative', 'Predicted Positive'],
            yticklabels=['Actual Negative', 'Actual Positive'])

plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')

plt.show()
```

```
Confusion Matrix:
[[811 157]
 [321 718]]
---------------------------------
TP (True Positives): 718
TN (True Negatives): 811
FP (False Positives): 157
FN (False Negatives): 321
```