AI3011: Lab Assignment Report

Lab Assignment 08

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Declaration

I, Pratik, certify that this project is my own work, based on my personal study and research and that I have acknowledged all material and sources used in its preparation, whether they be books, articles, reports, lecture notes, and any other kind of document, electronic or personal communication. I also certify that this project has not previously been submitted for assessment in any academic capacity and that I have not copied in part or whole or otherwise plagiarised the work of other persons. I confirm that I have identified and declared all possible conflicts that I may have.

Dated: 13 - 03 - 2023

Pratik Rana

Answers

Q1: Provide three applications of Semi-supervised learning.
Ans. Three Applications:

- Speech recognition
- Image classification
- Classify sentiments in text data

Q2: What are the three assumptions of Semi-supervised learning?
Ans. Three Assumptions:

- Cluster assumption: Points that are close to each other in the input space are likely to belong to the same class.
- Manifold assumption: The data lie approximately on a low-dimensional manifold embedded in the input space.
- Continuity assumption: The decision boundary between classes is smooth and doesn't change abruptly within small neighbourhoods.

Q3: What is the significance of each of the above three assumptions in Semi-supervised Learning?
Ans. Significance of using the above three assumptions in Semi-supervised Learning:

- Cluster assumption helps in leveraging unlabelled data by assuming that points close to each other are likely to belong to the same class.
- Manifold assumption aids in extrapolating information from unlabelled data by assuming that the data distribution lies on a low-dimensional manifold.
- Continuity assumption assists in making predictions smoother and more accurate by assuming that the decision boundary between classes doesn't change abruptly.

Q4: How does the Co-training method differ from the Self-training method of Semi-supervised learning? Which one usually performs better for accuracy and such performance metrics?
Ans.

- Co-training uses **multiple views** of the data and trains separate classifiers on each view, while Self-training iteratively trains a single classifier on the entire dataset, including both labelled and unlabelled data.
- Co-training requires initial labelled data for each view, while Self-training starts with a small amount of labelled data and **iteratively** adds pseudo-labelled data.
- Co-training **performs better** when there are multiple informative views of the data, while Self-training may perform better when the dataset has a clear structure and the classifier can effectively exploit the unlabelled data.

Q5: How to evaluate the performance of a semi-supervised learning method while training?
Ans. Monitoring performance metrics such as accuracy, precision, recall, and F1 score on a validation set. Cross-validation and hold-out validation are common evaluation techniques.

References:

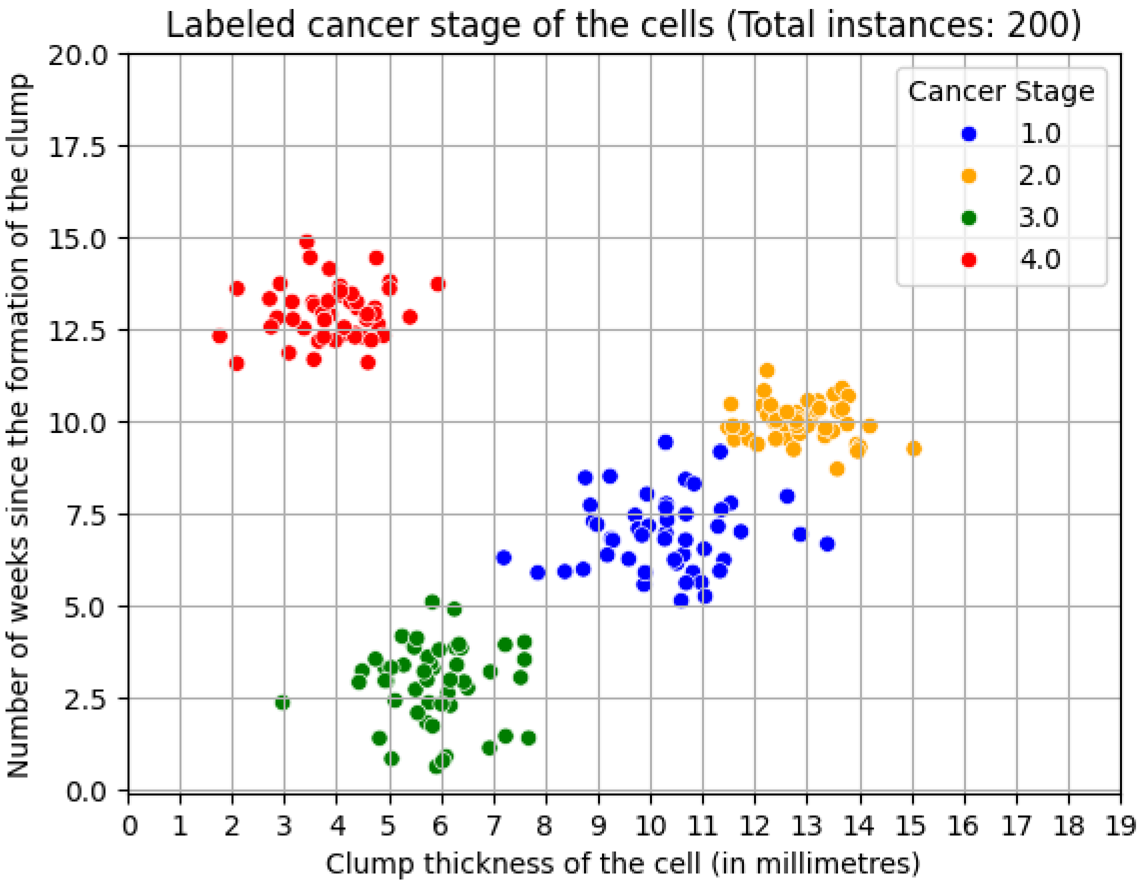
1. **Lecture Slides**

Plots:

In [ ]:
```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
from sklearn.semi_supervised import SelfTrainingClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import confusion_matrix, classification_report, accu
```

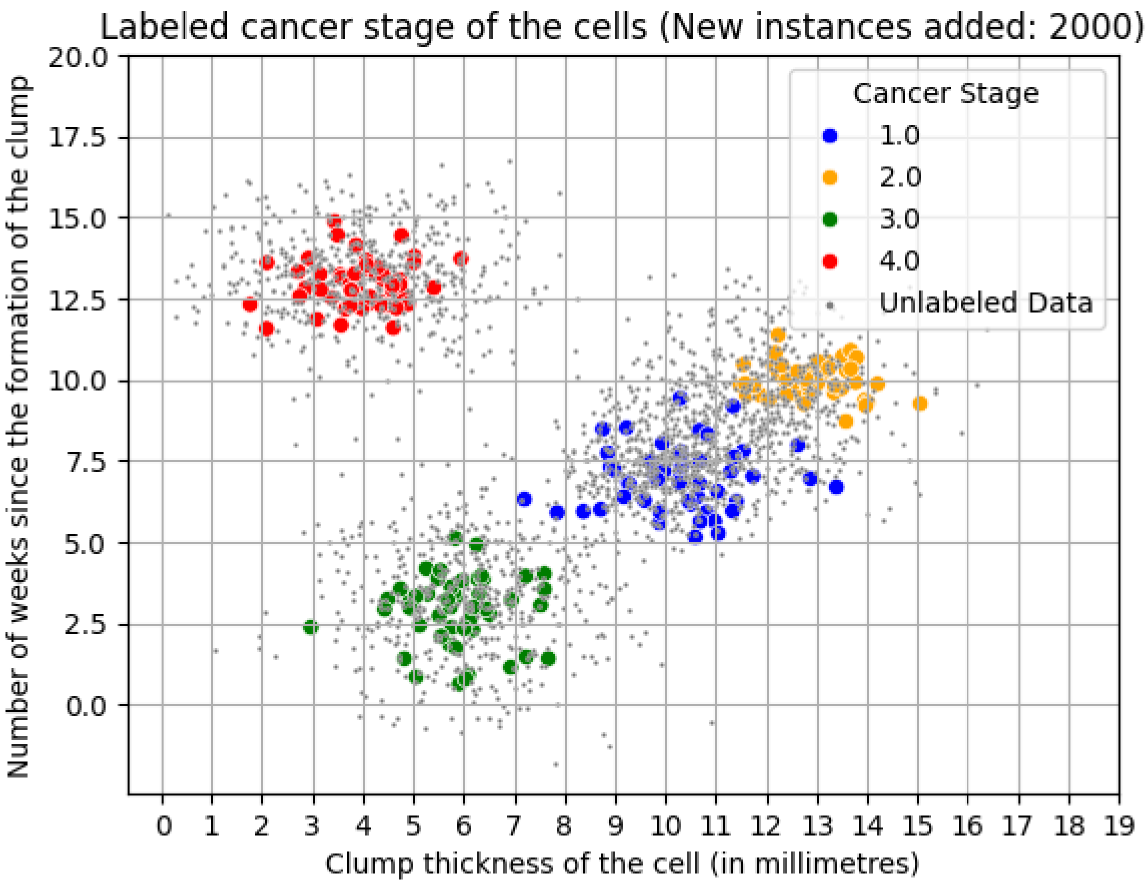
In [ ]:
```
df=pd.read_excel("data 1.xlsx")
palette={1: 'blue', 2:'orange', 3: 'green', 4:'red'}
```

In [ ]:
```
sns.scatterplot(data=df, x='Clump thickness', y='No of week', hue=df['Can
plt.grid(True)
plt.xlabel("Clump thickness of the cell (in millimetres)")
plt.ylabel("Number of weeks since the formation of the clump")
plt.title("Labeled cancer stage of the cells (Total instances: 200)")
plt.xticks(np.arange(0, 20))
plt.yticks(np.arange(0, 21, 2.5))
plt.legend(title='Cancer Stage', loc='upper right')
plt.show()
```



In [ ]:
```
sns.scatterplot(data=df, x='Clump thickness', y='No of week', hue=df['Can
sns.scatterplot(data=df, x='Clump thickness_new', y='No of week_new', col
plt.scatter([], [], color='grey', label='Unlabeled Data', s=3)
plt.grid(True)
plt.xlabel("Clump thickness of the cell (in millimetres)")
plt.ylabel("Number of weeks since the formation of the clump")
plt.title("Labeled cancer stage of the cells (New instances added: 2000)"
plt.xticks(np.arange(0, 20))
plt.yticks(np.arange(0, 21, 2.5))
```

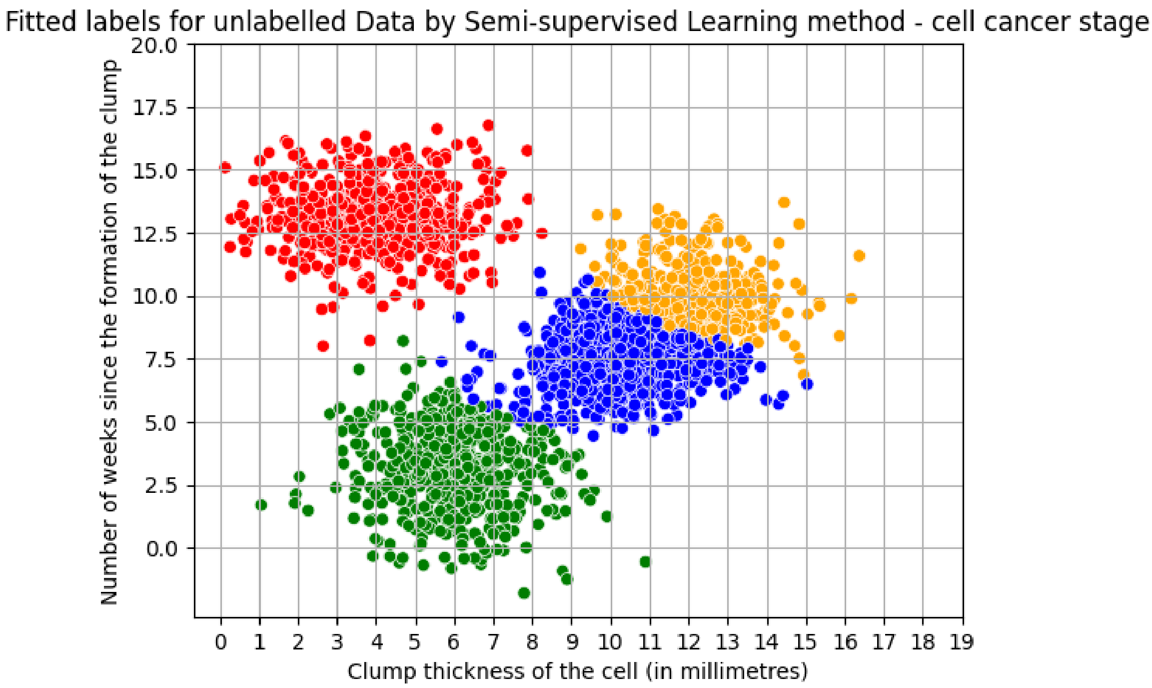
```
plt.legend(title='Cancer Stage', loc='upper right')
plt.show()
```



In [ ]:

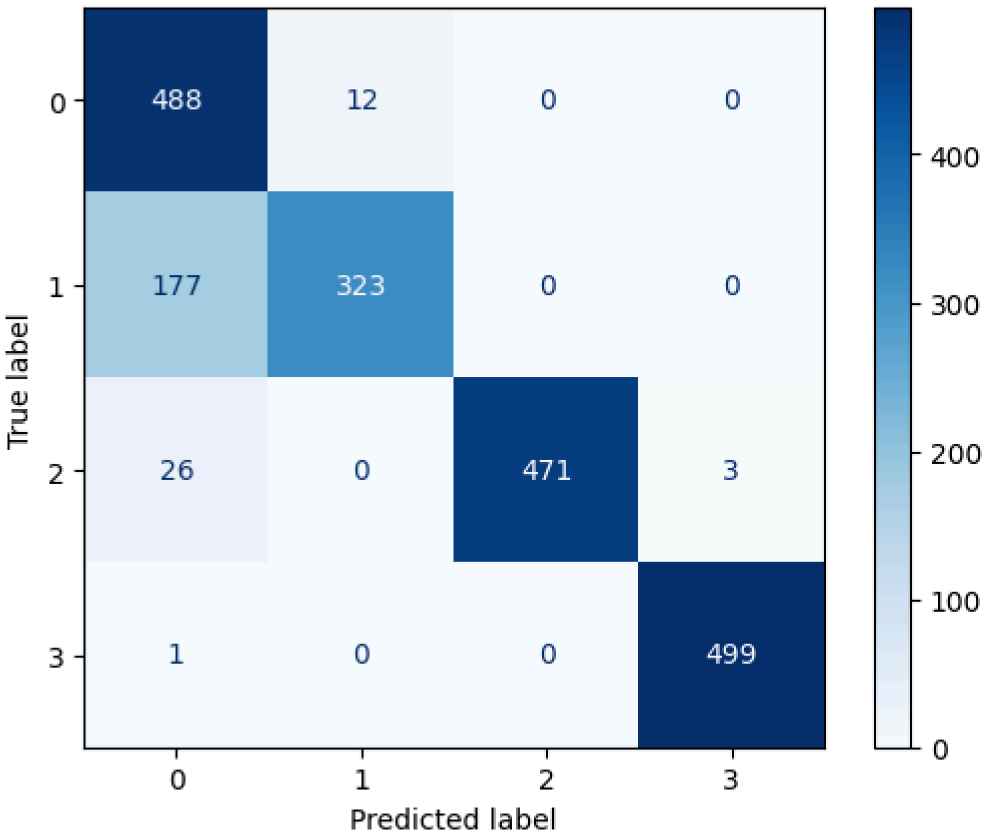
```
x=df[['Clump thickness', 'No of week']][:200]
y=df['Cancer stage'][:200]

knn=KNeighborsClassifier()
ssm=SelfTrainingClassifier(base_estimator=knn)
ssm.fit(x, y)

sns.scatterplot(data=df, x='Clump thickness', y='No of week', hue=df['Can
df[['Clump thickness', 'No of week']]=df[['Clump thickness_new', 'No of w

y_train=df[['Clump thickness', 'No of week']]
y_pred=ssm.predict(y_train)

sns.scatterplot(data=df, x='Clump thickness', y='No of week', hue=y_pred,
plt.grid(True)
plt.xlabel("Clump thickness of the cell (in millimetres)")
plt.ylabel("Number of weeks since the formation of the clump")
plt.title("Fitted labels for unlabelled Data by Semi-supervised Learning
plt.xticks(np.arange(0, 20))
plt.yticks(np.arange(0, 21, 2.5))
plt.legend().set_visible(False)
plt.show()
```

```
/home/pratik/.local/lib/python3.10/site-packages/sklearn/semi_supervised/_
self_training.py:217: UserWarning: y contains no unlabeled samples
  warnings.warn("y contains no unlabeled samples", UserWarning)
```



In [ ]:
```
cm=confusion_matrix(df['True cancer stage'], y_pred)

ConfusionMatrixDisplay(cm).plot(cmap="Blues")
```

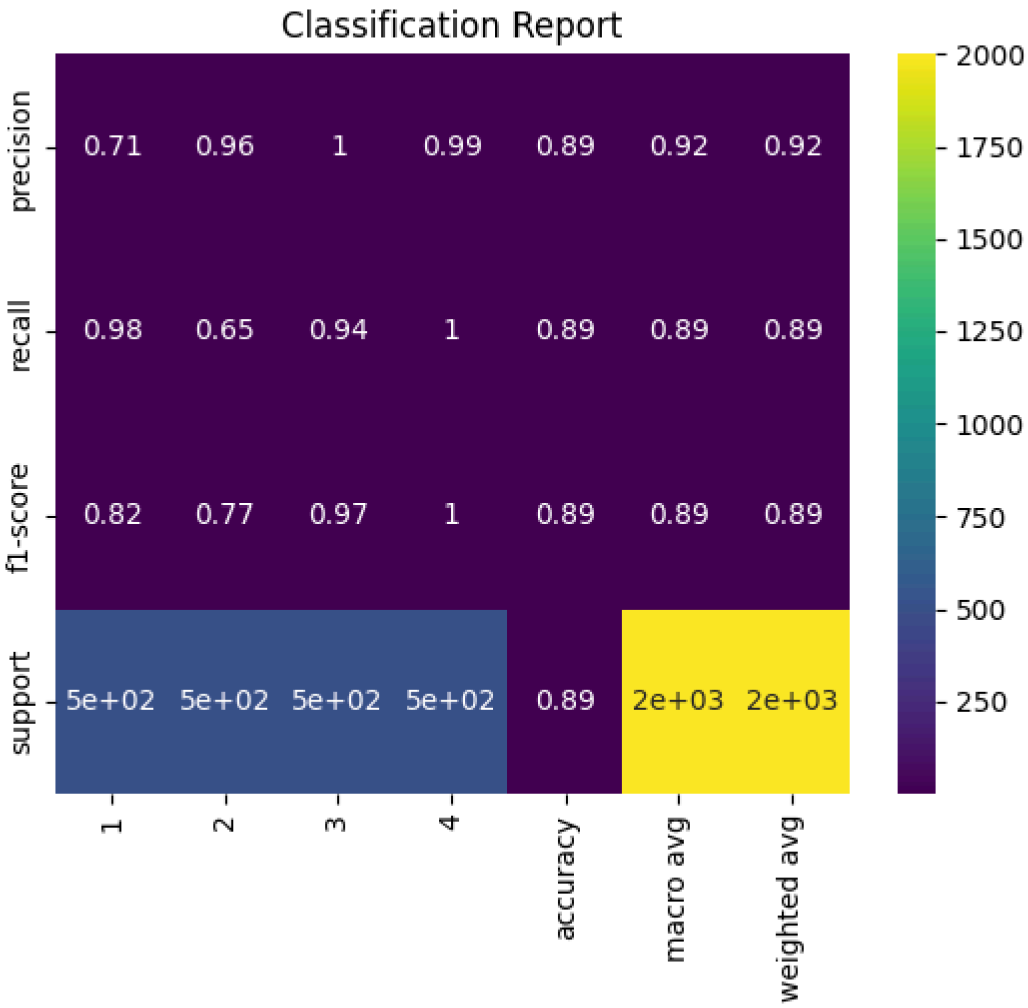
Out[ ]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x78e1
6bdef310>
```



In [ ]:
```
print(f'Classification Report : {classification_report(df["True cancer st
report_dict = classification_report(df["True cancer stage"], y_pred, outp
report_df = pd.DataFrame(report_dict)
sns.heatmap(report_df, annot=True, cmap='viridis')
plt.title('Classification Report')
```

```
plt.show()
print(f'Accuracy Score: {accuracy_score(df["True cancer stage"], y_pred)}
print(f'Balanced Accuracy Score: {balanced_accuracy_score(df["True cancer
```

```
Classification Report :               precision    recall  f1-score   supp
ort

           1       0.71      0.98      0.82       500
           2       0.96      0.65      0.77       500
           3       1.00      0.94      0.97       500
           4       0.99      1.00      1.00       500

    accuracy                           0.89      2000
   macro avg       0.92      0.89      0.89      2000
weighted avg       0.92      0.89      0.89      2000
```




```
Accuracy Score: 0.8905
Balanced Accuracy Score: 0.8905000000000001
```