Module 2 Lab Exercise: Tools Used in Machine Learning

Learning Objectives

By the end of this lab, you will be able to:

- Set up and navigate Jupyter Notebook, Google Colab, and VS Code environments
- Install and import essential Python libraries for machine learning
- Create and format professional documentation using Markdown
- Initialize a GitHub repository for your ML projects
- Understand the basic workflow of data science tools

Prerequisites

- Basic understanding of what machine learning is (Module 1)
- Access to internet for downloading tools and datasets
- A Google account (for Colab) or local Python installation

Part 1: Environment Setup and Tool Overview

What are the main tools we'll use in this course?

Jupyter Notebook/Google Colab: Interactive computing environments where you can write code, see results immediately, and document your work with text and visualizations.

Python Libraries: Pre-written code packages that make machine learning tasks easier:

- **Pandas**: For working with data (like Excel, but more powerful)
- **NumPy**: For mathematical operations on arrays of numbers
- **Matplotlib**: For creating charts and graphs
- **Scikit-learn**: The main library for machine learning algorithms

GitHub: A platform to store, share, and collaborate on code projects

VS Code: A powerful text editor for writing and debugging code

Let's start by setting up our environment!

Environment Setup Instructions

Option 1: Google Colab (Recommended for Beginners)

1. Go to colab.research.google.com
2. Sign in with your Google account
3. Click "New Notebook"
4. You're ready to go! Libraries are pre-installed.

Option 2: Local Jupyter Notebook

1. Install Python from python.org
2. Open terminal/command prompt
3. Run: `pip install jupyter pandas numpy matplotlib scikit-learn`
4. Run: `jupyter notebook`
5. Create a new notebook

Option 3: VS Code

1. Download VS Code from code.visualstudio.com
2. Install Python extension
3. Install Jupyter extension
4. Create a new .ipynb file

For this lab, we recommend starting with Google Colab as it requires no installation.

```python
# Install required libraries (uncomment if needed)
# !pip install pandas numpy matplotlib scikit-learn

# Import libraries with standard aliases
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn import datasets
import warnings
warnings.filterwarnings('ignore')  # Hide warning messages for cleaner output

print("✅ All libraries imported successfully!")
print(f"Pandas version: {pd.__version__}")
print(f"NumPy version: {np.__version__}")
```

```
✅ All libraries imported successfully!
Pandas version: 2.2.2
NumPy version: 2.0.2
```

Part 2: Loading and Exploring Your First Dataset

We'll use the famous Iris dataset - a classic dataset for beginners. It contains measurements of iris flowers from three different species.

```python
# Load a simple dataset (Iris flowers - a classic beginner dataset)
from sklearn.datasets import load_iris

# Load the data
iris = load_iris()
print("Dataset loaded successfully!")
print(f"Dataset shape: {iris.data.shape}")
print(f"Features: {iris.feature_names}")
print(f"Target classes: {iris.target_names}")
```

```
Dataset loaded successfully!
Dataset shape: (150, 4)
Features: ['sepal length (cm)', 'sepal width (cm)', 'petal length (cm)', 'petal width (cm)']
Target classes: ['setosa' 'versicolor' 'virginica']
```

```python
# Convert to pandas DataFrame for easier handling
df = pd.DataFrame(iris.data, columns=iris.feature_names)
df['species'] = iris.target_names[iris.target]

# Display first few rows
print("First 5 rows of our dataset:")
print(df.head())

print("\nDataset info:")
print(df.info())
```

```
First 5 rows of our dataset:
   sepal length (cm)  sepal width (cm)  petal length (cm)  petal width (cm)  \
0                5.1               3.5                1.4               0.2
1                4.9               3.0                1.4               0.2
2                4.7               3.2                1.3               0.2
3                4.6               3.1                1.5               0.2
4                5.0               3.6                1.4               0.2

  species
0  setosa
1  setosa
2  setosa
3  setosa
4  setosa

Dataset info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 5 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   sepal length (cm)  150 non-null    float64
 1   sepal width (cm)   150 non-null    float64
 2   petal length (cm)  150 non-null    float64
 3   petal width (cm)   150 non-null    float64
 4   species            150 non-null    object
dtypes: float64(4), object(1)
```

```
memory usage: 6.0+ KB
None
```

Part 3: Creating Your First Visualization

Data visualization is crucial in machine learning. Let's create a simple plot to understand our data.

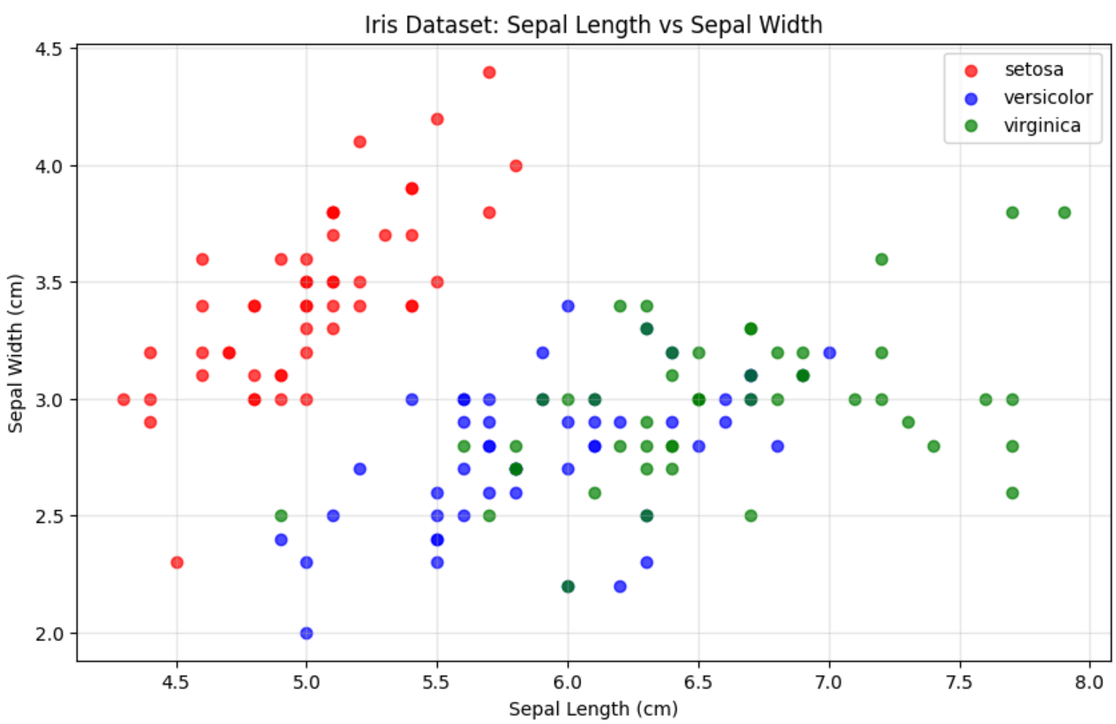
```
# Create a simple scatter plot
plt.figure(figsize=(10, 6))

# Plot sepal length vs sepal width, colored by species
species_colors = {'setosa': 'red', 'versicolor': 'blue', 'virginica': 'green'}

for species in df['species'].unique():
    species_data = df[df['species'] == species]
    plt.scatter(species_data['sepal length (cm)'],
                species_data['sepal width (cm)'],
                c=species_colors[species],
                label=species,
                alpha=0.7)

plt.xlabel('Sepal Length (cm)')
plt.ylabel('Sepal Width (cm)')
plt.title('Iris Dataset: Sepal Length vs Sepal Width')
plt.legend()
plt.grid(True, alpha=0.3)
plt.show()

print("🎉 Congratulations! You've created your first data visualization!")
```




```
🎉 Congratulations! You've created your first data visualization!
```

Part 4: Practice with Basic Data Operations

Let's practice some basic data analysis operations that you'll use throughout the course.

```
# Basic statistical analysis
print("Basic Statistics for Iris Dataset:")
print("=" * 40)

# Calculate mean values for each species
species_means = df.groupby('species').mean()
print("\nMean values by species:")
print(species_means)
```

```
print(species_means)

# Count samples per species
species_counts = df['species'].value_counts()
print("\nSamples per species:")
print(species_counts)
```

```
Basic Statistics for Iris Dataset:
========================================

Mean values by species:
            sepal length (cm)  sepal width (cm)  petal length (cm)  \
species
setosa                  5.006             3.428              1.462
versicolor              5.936             2.770              4.260
virginica               6.588             2.974              5.552

            petal width (cm)
species
setosa                 0.246
versicolor             1.326
virginica              2.026

Samples per species:
species
setosa        50
versicolor    50
virginica     50
Name: count, dtype: int64
```

Part 5: GitHub and Documentation Best Practices

Why GitHub for Machine Learning?

- **Version Control**: Track changes to your code and data
- **Collaboration**: Work with others on projects
- **Portfolio**: Showcase your work to potential employers
- **Backup**: Never lose your work

Basic GitHub Workflow:

1. **Create Repository**: A folder for your project
2. **Clone/Download**: Get the project on your computer
3. **Add Files**: Put your notebooks and data
4. **Commit**: Save a snapshot of your changes
5. **Push**: Upload changes to GitHub

For This Course:

- Create a repository named "ITAI-1371-ML-Labs"
- Upload each lab notebook as you complete it
- Include a README.md file describing your projects

Action Item: After this lab, create your GitHub account and repository.

Assessment: Tool Familiarity Check

Complete the following tasks to demonstrate your understanding of the tools:

```
# Task 1: Create a simple calculation using NumPy
# Calculate the mean and standard deviation of sepal length

sepal_lengths = df['sepal length (cm)']

# Your code here:
mean_sepal_length = np.mean(sepal_lengths)
std_sepal_length = np.std(sepal_lengths)

print(f"Mean sepal length: {mean_sepal_length:.2f} cm")
print(f"Standard deviation: {std_sepal_length:.2f} cm")

# Verification (don't modify)
```

```
assert isinstance(mean_sepal_length, (float, np.floating)), "Mean should be a number"
assert isinstance(std_sepal_length, (float, np.floating)), "Std should be a number"
print("✅ Task 1 completed successfully!")
```

```
Mean sepal length: 5.84 cm
Standard deviation: 0.83 cm
✅ Task 1 completed successfully!
```

Start coding or generate with AI.

```
# Task 2: Create a simple bar chart showing species counts
species_counts = df['species'].value_counts()

plt.figure(figsize=(8, 5))
plt.bar(species_counts.index, species_counts.values, color=['red', 'blue', 'green'])
plt.title('Number of Samples per Species')
plt.xlabel('Species')
plt.ylabel('Count')
plt.show()

print(f"Species distribution: {dict(species_counts)}")
print("✅ Task 2 completed successfully!")
```

```
## Your Analysis and Reflection

**Instructions**: Complete the analysis below by editing this markdown cell.

### My Observations About the Iris Dataset

**Dataset Overview:**
- Number of samples: 150
- Number of features: 4 (sepal length, sepal width, petal length, petal width)
- Number of classes: 3 (setosa, versicolor, virginica)

**Key Findings from the Visualization:**
1. Setosa forms a tight, distinct cluster with shorter sepal length (~4.3–5.8
cm) and wider sepal width (~2.8–4.4 cm), making it visually separable from the
other two classes.

2. Versicolor and virginica overlap noticeably in this sepal-based projection;
they occupy mid-to-long sepal lengths (~5.0–7.5 cm) with widths mostly between
~2.2–3.4 cm, which suggests this feature pair alone won't cleanly separate them.

3. Virginica tends to the largest sepal lengths (often >6.3 cm) with moderate
widths, while versicolor sits in the middle range on both axes—this matches the
mean summaries you computed.

**Questions for Further Investigation:**
-Do petal features (petal length vs petal width) separate versicolor and
virginica better than sepal features? (Common intuition says yes—let's verify
with a scatter plot or a simple baseline classifier.)

- How does dimensionality reduction (e.g., PCA) change class separability, and
which features carry the most variance/information?

**Reflection:**

Working through the plots helped me shift from "making graphs" to asking
testable questions about separability and feature quality. I also realized that
vectorized thinking (NumPy) and label-aware indexing (pandas loc) reduce errors
and make my intent clearer. Most importantly, small diagnostics (shape checks,
counts, quick prints) turned errors into useful signals instead of roadblocks.

---
*Note: This is practice for documenting your machine learning projects
professionally.*
```

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Lab Summary and Next Steps

What You've Accomplished:

✅ Set up your machine learning development environment
✅ Imported and used essential Python libraries
✅ Loaded and explored your first dataset
✅ Created your first data visualization
✅ Practiced professional documentation with Markdown
✅ Learned about GitHub for project management

Preparation for Module 3:

In the next lab, you'll:

- Learn about different types of machine learning
- Build your first simple classifier
- Understand the complete ML workflow
- Work with more complex datasets

Action Items:

1. **Create your GitHub account** and repository
2. **Upload this completed notebook** to your repository
3. **Experiment** with different visualizations using the Iris dataset
4. **Practice** Markdown formatting in a new notebook

Resources for Continued Learning:

- Pandas Documentation
- Matplotlib Gallery
- GitHub Guides
- Jupyter Notebook Tips

Great job completing Module 2! You're now equipped with the essential tools for machine learning. 🎉