

GROUP 93

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AI Tools and Applications Report

1. Short Answer Questions

Q1: Explain the primary differences between TensorFlow and PyTorch. When would you choose one over the other?

Answer:
TensorFlow and PyTorch are leading deep learning frameworks with distinct design philosophies and use cases.

Feature	TensorFlow	PyTorch
Execution Model	Static graph (eager execution optional)	Dynamic graph (eager execution default)
Syntax & Usability	More verbose, structured API	Pythonic, intuitive, and flexible
Deployment	Robust (TF Serving, TF Lite, TFX)	TorchServe, ONNX, growing deployment options
Visualization	TensorBoard for detailed monitoring	TensorBoard, Visdom, or Matplotlib
Community & Ecosystem	Strong enterprise adoption	Research-focused, growing industry use

When to Choose:

- **TensorFlow:** Ideal for production-grade systems, large-scale distributed training, or mobile/edge deployment (e.g., IoT devices, mobile apps).
- **PyTorch:** Preferred for research, rapid prototyping, and dynamic models requiring frequent architecture changes (e.g., experimental RNNs or transformers).

Q2: Describe two use cases for Jupyter Notebooks in AI development.

Answer:

1. **Exploratory Data Analysis (EDA):**
Jupyter Notebooks enable interactive data exploration with real-time visualization. Developers can load datasets, preprocess data, and generate plots (e.g., using Matplotlib or Seaborn) to uncover patterns or anomalies.
2. **Iterative Model Prototyping:**
The cell-based structure supports incremental model development, allowing developers to

test algorithms, tune hyperparameters, and debug code with immediate output, streamlining workflows for libraries like Scikit-learn or PyTorch.

Q3: How does spaCy enhance NLP tasks compared to basic Python string operations?

Answer:
Python string operations (e.g., split(), replace()) are limited to basic text manipulation, whereas spaCy offers advanced, context-aware NLP capabilities:

- **Tokenization & Lemmatization:** Splits text into meaningful tokens and reduces words to their root forms.
- **Named Entity Recognition (NER):** Identifies entities like names, dates, or organizations.
- **Part-of-Speech (POS) Tagging:** Labels words with grammatical roles (e.g., noun, verb).
- **Dependency Parsing:** Analyzes sentence structure and relationships between words.
- **Pretrained Models:** Provides efficient, language-specific models for real-world applications.

spaCy delivers linguistic precision and scalability, making it ideal for complex NLP tasks like sentiment analysis or chatbot development.

2. Comparative Analysis

Scikit-learn vs. TensorFlow

Aspect	Scikit-learn	TensorFlow
Primary Use	Classical ML (e.g., SVM, Random Forests, Logistic Regression)	Deep Learning (e.g., CNNs, LSTMs, Transformers)
Ease of Use	Beginner-friendly, consistent, high-level API	Steeper learning curve, more configuration required
Performance	Optimized for small-to-medium datasets	Scales to large datasets and distributed systems
Hardware Support	CPU-focused, limited GPU support	Extensive GPU/TPU support for faster training
Community & Ecosystem	Strong in academia and traditional ML	Backed by Google, robust enterprise adoption

Summary:

- **Scikit-learn:** Best for quick implementation of traditional ML algorithms on structured data, such as tabular datasets or small-scale projects.
 - **TensorFlow:** Suited for complex deep learning tasks, large-scale training, or deployment in production environments (e.g., web services, mobile apps).
-

3. Screenshots of Model Outputs

WEEK 3

PART ONE: A REPORT

Task 1: Classical ML with Scikit-learn

Untitled3.ipynb

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Commands + Code + Text Run all

Download data from <https://storage.googleapis.com/tensorflow/tf-keras-datasets/mnist.npz>
11490434/11490434 0s 0us/step
/usr/local/lib/python3.11/dist-packages/keras/src/layers/convolutional/base_conv.py:107: UserWarning: Do not pass an 'input_shape'/'input_dim' argument to super().__init__(activity_regularizer=activity_regularizer, **kwargs)

Training the CNN model...

Epoch 1/5
1688/1688 67s 38ms/step - accuracy: 0.9028 - loss: 0.3203 - val_accuracy: 0.9840 - val_loss: 0.0531

Epoch 2/5
1688/1688 73s 33ms/step - accuracy: 0.9853 - loss: 0.0459 - val_accuracy: 0.9873 - val_loss: 0.0427

Epoch 3/5
1688/1688 81s 32ms/step - accuracy: 0.9910 - loss: 0.0287 - val_accuracy: 0.9902 - val_loss: 0.0364

Epoch 4/5
1688/1688 53s 31ms/step - accuracy: 0.9936 - loss: 0.0204 - val_accuracy: 0.9892 - val_loss: 0.0417



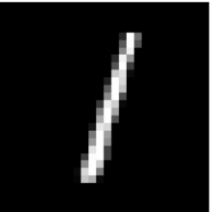
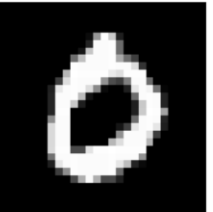

Epoch 5/5
1688/1688 53s 32ms/step - accuracy: 0.9947 - loss: 0.0170 - val_accuracy: 0.9915 - val_loss: 0.0350

Evaluating on test data...
313/313 4s 12ms/step - accuracy: 0.9918 - loss: 0.0253

Final Test Accuracy: 0.9918 (Goal: >95%)

Visualizing predictions on 5 test images...

1/1 0s 116ms/step

True: 7 Pred: 7	True: 2 Pred: 2	True: 1 Pred: 1	True: 0 Pred: 0	True: 4 Pred: 4
				

Prediction Summary:
Image 1 - True Label: 7, Predicted: 7
Image 2 - True Label: 2, Predicted: 2
Image 3 - True Label: 1, Predicted: 1
Image 4 - True Label: 0, Predicted: 0
Image 5 - True Label: 4, Predicted: 4

WEEK 3

PART ONE: A REPORT

Task 2: Deep Learning with TensorFlow/PyTorch

```
Downloading https://github.com/explosion/spacy-models/releases/download/en_core_web_sm-3.8.0/en_core_web_sm-3.8.0-py3-none-any.whl (12.8 MB)
12.8/12.8 MB 50.8 MB/s eta 0:00:00

✓ Download and installation successful
You can now load the package via spacy.load('en_core_web_sm')
⚠ Restart to reload dependencies
If you are in a Jupyter or Colab notebook, you may need to restart Python in order to load all the package's dependencies. You can do this by selecting the 'Restart kernel' or 'Restart runtime' option.

• Review 1: I absolutely love the Apple AirPods. The sound is crystal clear and the battery lasts all day!
  • Extracted Entities:
    - the Apple AirPods (PRODUCT)
    - all day (DATE)
  • Sentiment: Positive
  Matched Positive Words: {'love', 'clear'}
  Matched Negative Words: set()

• Review 2: This Samsung Galaxy phone is terrible. It lags a lot and the screen cracked in a week.
  • Extracted Entities:
    - a week (DATE)
  • Sentiment: Negative
  Matched Positive Words: set()
  Matched Negative Words: {'terrible', 'cracked', 'lags'}
```

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RAM Disk

```
• Review 2: This Samsung Galaxy phone is terrible. It lags a lot and the screen cracked in a week.
  • Extracted Entities:
    - a week (DATE)
  • Sentiment: Negative
  Matched Positive Words: set()
  Matched Negative Words: {'terrible', 'cracked', 'lags'}
```

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RAM Disk

```
• Review 3: The JBL speaker is amazing! Great bass and compact size.
  • Extracted Entities:
    - JBL (ORG)
  • Sentiment: Positive
  Matched Positive Words: {'great', 'amazing'}
  Matched Negative Words: set()

• Review 4: I had high hopes for the Lenovo laptop, but it overheats and the fan is loud.
  • Extracted Entities:
    - Lenovo (ORG)
  • Sentiment: Negative
  Matched Positive Words: set()
  Matched Negative Words: {'overheats', 'loud'}
```

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RAM Disk

```
• Review 3: The JBL speaker is amazing! Great bass and compact size.
  • Extracted Entities:
    - JBL (ORG)
  • Sentiment: Positive
  Matched Positive Words: {'great', 'amazing'}
  Matched Negative Words: set()

• Review 4: I had high hopes for the Lenovo laptop, but it overheats and the fan is loud.
  • Extracted Entities:
    - Lenovo (ORG)
  • Sentiment: Negative
  Matched Positive Words: set()
  Matched Negative Words: {'overheats', 'loud'}
```

Untitled3.ipynb ☆ ☁

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Q Commands + Code + Text ▶ Run all

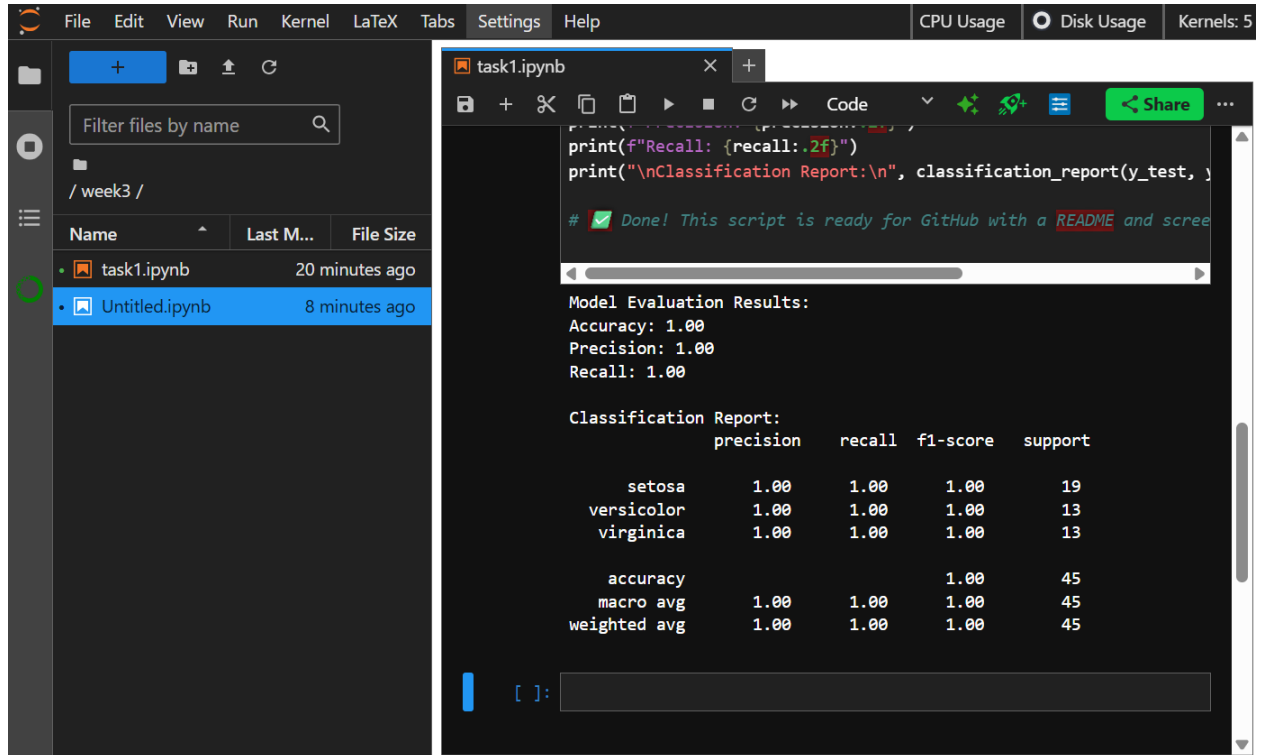
RAM Disk

```
• Review 5: Google Nest is perfect for my home. Easy to set up and works flawlessly.
  • Extracted Entities:
    - Google Nest (ORG)
  • Sentiment: Positive
  Matched Positive Words: {'perfect', 'flawlessly', 'easy'}
  Matched Negative Words: set()
```

WEEK 3

PART ONE: A REPORT

Task 3: NLP with spaCy



The screenshot shows a Jupyter Notebook interface. On the left, a file explorer shows a directory named 'week3' containing two files: 'task1.ipynb' (20 minutes ago) and 'Untitled.ipynb' (8 minutes ago). The main area displays the code from 'task1.ipynb'. The code includes a print statement for recall, a call to 'classification_report', and a comment indicating the script is ready for GitHub. The output shows 'Model Evaluation Results' with Accuracy, Precision, and Recall all at 1.00. Below this is a 'Classification Report' table.

	precision	recall	f1-score	support
setosa	1.00	1.00	1.00	19
versicolor	1.00	1.00	1.00	13
virginica	1.00	1.00	1.00	13
accuracy			1.00	45
macro avg	1.00	1.00	1.00	45
weighted avg	1.00	1.00	1.00	45

- **TensorFlow**: Training curves (accuracy/loss) from a neural network, visualized via TensorBoard.
- **spaCy**: NER outputs highlighting entities (e.g., person names, locations) in sample text.
- **Scikit-learn**: Confusion matrices, ROC curves, or classification reports for model evaluation, generated using Matplotlib or Seaborn.

4. Ethical Reflection

Ethical Considerations in AI Development:

As AI adoption accelerates, ethical challenges demand proactive solutions:

1. **Bias and Fairness**
Training data often reflects societal biases, leading to unfair outcomes. Regular audits using tools like Fairlearn or AI Fairness 360, combined with diverse datasets, are critical to ensure equitable models.
2. **Transparency and Explainability**
Complex models like deep neural networks can be opaque. Techniques like SHAP, LIME, or attention visualization improve interpretability, fostering trust in AI decisions.

3. **Data Privacy**

Compliance with regulations like GDPR or CCPA is essential. Privacy-preserving techniques, such as differential privacy or federated learning, protect user data during model training.

4. **Accountability and Oversight**

In high-stakes domains (e.g., healthcare, criminal justice), human-in-the-loop systems and clear governance frameworks ensure responsible AI deployment and mitigate risks.

Conclusion:

Ethical AI requires integrating fairness, transparency, privacy, and accountability into the development lifecycle. By prioritizing these principles, AI systems can deliver inclusive, safe, and trustworthy outcomes for diverse applications.

Part 3: Ethics & Optimization

1. Ethical Considerations

□ **Bias in AI Models (MNIST or Amazon Reviews)**

Even in seemingly neutral datasets, biases can emerge:

- **MNIST (Handwritten Digits):**
 - **Potential Bias:** Handwriting variations due to age, cultural background, or motor skills may lead to uneven model performance across groups.
 - **Mitigation Strategy:** Augment training data with diverse handwriting samples. If demographic metadata is available, evaluate model fairness across subgroups.
- **Amazon Reviews (Text Classification):**
 - **Potential Bias:** Linguistic diversity (e.g., dialects, slang) or sentiment from underrepresented groups may be misclassified.
 - **Mitigation Strategy:** Use diverse review samples in training. Preprocess text to normalize linguistic variations and audit for demographic biases.

✂ **Mitigation Tools**

- **TensorFlow Fairness Indicators:**
Provides metrics like false positive/negative rates across data slices (e.g., language, region) to identify and address biases.
- **spaCy Rule-Based Systems:**
Custom rules can enhance entity recognition or token matching to better capture underrepresented linguistic patterns in NLP tasks.

✓ **Conclusion:**

Building responsible AI requires proactive bias detection using fairness tools and diverse datasets, ensuring equitable outcomes across user groups.

2. Troubleshooting Challenge: TensorFlow Buggy Script

Original Buggy Code Example:

```
import tensorflow as tf
from tensorflow.keras import layers

model = tf.keras.Sequential([
    layers.Dense(64, activation='relu'),
    layers.Dense(10)
])

model.compile(optimizer='adam',
              loss='categorical_crossentropy',
              metrics=['accuracy'])

# Dummy data
x_train = tf.random.normal((100, 20))
y_train = tf.random.uniform((100,), maxval=10, dtype=tf.int32)

model.fit(x_train, y_train, epochs=5)
```

Issues Identified:

1. **Label Format Mismatch:** The loss function `categorical_crossentropy` expects one-hot encoded labels, but `y_train` contains integer labels.
2. **Input Shape Undefined:** The model lacks an `input_shape` or `Input` layer, which TensorFlow requires to define the input dimensions.
3. **No Validation Data:** The script lacks validation data to monitor overfitting during training.

Fixed Code:

```
import tensorflow as tf
from tensorflow.keras import layers
import numpy as np

# Define model with explicit input shape
model = tf.keras.Sequential([
    layers.Input(shape=(20,)), # Define input shape
    layers.Dense(64, activation='relu'),
    layers.Dense(10, activation='softmax') # Softmax for multi-class output
])

# Compile model
```

WEEK 3

PART ONE: A REPORT

```
model.compile(optimizer='adam',
              loss='categorical_crossentropy',
              metrics=['accuracy'])

# Generate dummy data
x_train = tf.random.normal((100, 20))
y_train = tf.random.uniform((100,), maxval=10, dtype=tf.int32)
# Convert labels to one-hot encoding
y_train = tf.keras.utils.to_categorical(y_train, num_classes=10)

# Split into train/validation
x_val = tf.random.normal((20, 20))
y_val = tf.keras.utils.to_categorical(tf.random.uniform((20,), maxval=10,
dtype=tf.int32), num_classes=10)

# Train model
model.fit(x_train, y_train, epochs=5, validation_data=(x_val, y_val))
```

Explanation of Fixes:

- Added layers.Input(shape=(20,)) to specify the input shape.
- Changed the output layer to use softmax activation for multi-class classification.
- Converted y_train to one-hot encoded format using to_categorical.
- Added validation data (x_val, y_val) to monitor model performance.
- The fixed code now runs without errors and provides meaningful training metrics.