Project ARI3205 Interpretable AI for Deep Learning Models *(Part 3.2)*

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Importing Necessary Libraries

In [7]:

```python
# Check and install required libraries from the libraries.json file
import json

# Read the libraries from the text file
with open('../Libraries/Part3.2_Lib.json', 'r') as file:
    libraries = json.load(file)

# ANSI escape codes for colored output
GREEN = "\033[92m"  # Green text
RED = "\033[91m"    # Red text
RESET = "\033[0m"   # Reset to default color

# Function to check and install libraries
def check_and_install_libraries(libraries):
    for lib, import_name in libraries.items():
        try:
            # Attempt to import the library
            __import__(import_name)
            print(f"[{GREEN}✓{RESET}] Library '{lib}' is already installed.")
        except ImportError:
            # If import fails, try to install the library
            print(f"[{RED}✗{RESET}] Library '{lib}' is not installed. Installin
            %pip install {lib}

# Execute the function to check and install libraries
check_and_install_libraries(libraries)

# Import necessary libraries for data analysis and modeling
import warnings
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Input
from tensorflow.keras.optimizers import Adam
from sklearn.preprocessing import StandardScaler,  OneHotEncoder
from sklearn.impute import SimpleImputer
from sklearn.neural_network import MLPClassifier
# For MMD-Critic
from mmd_critic import MMDCritic
from mmd_critic.kernels import RBFKernel
from sklearn.decomposition import PCA


# Suppress specific warnings
warnings.filterwarnings("ignore", message="X does not have valid feature names")
warnings.filterwarnings("ignore", category=RuntimeWarning)
warnings.filterwarnings("ignore", category=UserWarning)
```

```
[✓] Library 'tensorflow' is already installed.
[✓] Library 'scikit-learn' is already installed.
[✓] Library 'matplotlib' is already installed.
[✓] Library 'seaborn' is already installed.
[✓] Library 'pandas' is already installed.
[✓] Library 'numpy' is already installed.
[✓] Library 'alibi' is already installed.
[✓] Library 'statsmodels' is already installed.
[✓] Library 'mmd-critic' is already installed.
```

In [8]:

```python
# Define the filenames
train_filename = '../Datasets/Titanic/train.csv'
test_filename = '../Datasets/Titanic/test.csv'
gender_submission_filename = '../Datasets/Titanic/gender_submission.csv'

# Load the datasets
try:
    train_data = pd.read_csv(train_filename)
    test_data = pd.read_csv(test_filename)
    gender_submission_data = pd.read_csv(gender_submission_filename)
    print(f"'{train_filename}' dataset loaded successfully.")
    print(f"'{test_filename}' dataset loaded successfully.")
    print(f"'{gender_submission_filename}' dataset loaded successfully.")
except FileNotFoundError as e:
    print(f"Error: {e.filename} was not found. Please ensure it is in the correc
    exit()
except pd.errors.EmptyDataError as e:
    print(f"Error: {e.filename} is empty.")
    exit()
except pd.errors.ParserError as e:
    print(f"Error: There was a problem parsing {e.filename}. Please check the fi
    exit()

# Dataset insights
print("\nTrain Dataset Overview:")
print(train_data.info())
print("\nTrain Dataset Statistical Summary:")
print(train_data.describe())

print("\nTest Dataset Overview:")
print(test_data.info())
print("\nTest Dataset Statistical Summary:")
print(test_data.describe())

print("\nGender Submission Dataset Overview:")
print(gender_submission_data.info())
```

```
'../Datasets/Titanic/train.csv' dataset loaded successfully.
'../Datasets/Titanic/test.csv' dataset loaded successfully.
'../Datasets/Titanic/gender_submission.csv' dataset loaded successfully.

Train Dataset Overview:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   PassengerId  891 non-null    int64  
 1   Survived     891 non-null    int64  
 2   Pclass       891 non-null    int64  
 3   Name         891 non-null    object 
 4   Sex          891 non-null    object 
 5   Age          714 non-null    float64
 6   SibSp        891 non-null    int64  
 7   Parch        891 non-null    int64  
 8   Ticket       891 non-null    object 
 9   Fare         891 non-null    float64
 10  Cabin        204 non-null    object 
 11  Embarked     889 non-null    object 
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB
None

Train Dataset Statistical Summary:
       PassengerId    Survived      Pclass         Age       SibSp  \
count   891.000000  891.000000  891.000000  714.000000  891.000000   
mean    446.000000    0.383838    2.308642   29.699118    0.523008   
std     257.353842    0.486592    0.836071   14.526497    1.102743   
min       1.000000    0.000000    1.000000    0.420000    0.000000   
25%     223.500000    0.000000    2.000000   20.125000    0.000000   
50%     446.000000    0.000000    3.000000   28.000000    0.000000   
75%     668.500000    1.000000    3.000000   38.000000    1.000000   
max     891.000000    1.000000    3.000000   80.000000    8.000000   

            Parch        Fare  
count  891.000000  891.000000  
mean     0.381594   32.204208  
std      0.806057   49.693429  
min      0.000000    0.000000  
25%      0.000000    7.910400  
50%      0.000000   14.454200  
75%      0.000000   31.000000  
max      6.000000  512.329200  

Test Dataset Overview:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 418 entries, 0 to 417
Data columns (total 11 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   PassengerId  418 non-null    int64  
 1   Pclass       418 non-null    int64  
 2   Name         418 non-null    object 
 3   Sex          418 non-null    object 
 4   Age          332 non-null    float64
 5   SibSp        418 non-null    int64  
 6   Parch        418 non-null    int64  
 7   Ticket       418 non-null    object 
 8   Fare         417 non-null    float64
 9   Cabin        91 non-null     object 
 10  Embarked     418 non-null    object 
dtypes: float64(2), int64(4), object(5)
memory usage: 36.1+ KB
None

Test Dataset Statistical Summary:
       PassengerId      Pclass         Age       SibSp       Parch        Fare
count   418.000000  418.000000  332.000000  418.000000  418.000000  417.000000
mean   1100.500000    2.265550   30.272590    0.447368    0.392344   35.627188
std     120.810458    0.841838   14.181209    0.896760    0.981429   55.907576
min     892.000000    1.000000    0.170000    0.000000    0.000000    0.000000
25%     996.250000    1.000000   21.000000    0.000000    0.000000    7.895800
50%    1100.500000    3.000000   27.000000    0.000000    0.000000   14.454200
75%    1204.750000    3.000000   39.000000    1.000000    0.000000   31.500000
max    1309.000000    3.000000   76.000000    8.000000    9.000000  512.329200

Gender Submission Dataset Overview:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 418 entries, 0 to 417
Data columns (total 2 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   PassengerId  418 non-null    int64
 1   Survived     418 non-null    int64
dtypes: int64(2)
memory usage: 6.7 KB
None
```

Feed-Forward Neural Network

In [9]:

```python
# Load the Titanic dataset
train_data = pd.read_csv('../Datasets/Titanic/train.csv')

# Preprocessing
# Separate features and target
y = train_data['Survived']  # Target
X = train_data.drop(columns=['Survived', 'PassengerId', 'Name', 'Ticket', 'Cabin

# Handle categorical variables with one-hot encoding
categorical_features = ['Sex', 'Embarked']
one_hot_encoder = OneHotEncoder(sparse_output=False, handle_unknown='ignore')
categorical_encoded = one_hot_encoder.fit_transform(X[categorical_features])
categorical_encoded_df = pd.DataFrame(categorical_encoded, columns=one_hot_encod

# Drop original categorical columns and append the encoded columns
X = X.drop(columns=categorical_features)
X = pd.concat([X.reset_index(drop=True), categorical_encoded_df.reset_index(drop

# Handle missing values with mean imputation
imputer = SimpleImputer(strategy='mean')
X_imputed = pd.DataFrame(imputer.fit_transform(X), columns=X.columns)

# Standardize the features
scaler = StandardScaler()
X_scaled = pd.DataFrame(scaler.fit_transform(X_imputed), columns=X.columns)
```

```
# Split the data into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2,
print("Training data shape:", X_train.shape)
print("Test data shape:", X_test.shape)
```

```
Training data shape: (712, 11)
Test data shape: (179, 11)
```

In [10]:

```
# Build the feed-forward neural network
model = Sequential([
    Input(shape=(X_train.shape[1],)),  # Define input shape explicitly
    Dense(64, activation='relu'),
    Dense(32, activation='relu'),
    Dense(1, activation='sigmoid')  # Output layer for binary classification
])

# Compile the model
model.compile(optimizer=Adam(learning_rate=0.001), loss='binary_crossentropy', m

# Train the model
history = model.fit(X_train, y_train, validation_split=0.2, epochs=50, batch_siz

# Evaluate the model
test_loss, test_accuracy = model.evaluate(X_test, y_test, verbose=1)
print(f"Test Loss: {test_loss:.4f}, Test Accuracy: {test_accuracy:.4f}")
```

```
Epoch 1/50
18/18 [==============================] - 1s 10ms/step - loss: 0.6789 - accuracy:
0.5923 - val_loss: 0.5875 - val_accuracy: 0.7552
Epoch 2/50
18/18 [==============================] - 0s 3ms/step - loss: 0.5487 - accuracy:
0.7750 - val_loss: 0.4977 - val_accuracy: 0.7832
Epoch 3/50
18/18 [==============================] - 0s 3ms/step - loss: 0.4948 - accuracy:
0.7926 - val_loss: 0.4517 - val_accuracy: 0.7832
Epoch 4/50
18/18 [==============================] - 0s 3ms/step - loss: 0.4670 - accuracy:
0.8014 - val_loss: 0.4337 - val_accuracy: 0.8182
Epoch 5/50
18/18 [==============================] - 0s 3ms/step - loss: 0.4519 - accuracy:
0.8102 - val_loss: 0.4241 - val_accuracy: 0.8252
Epoch 6/50
18/18 [==============================] - 0s 3ms/step - loss: 0.4409 - accuracy:
0.8155 - val_loss: 0.4153 - val_accuracy: 0.8112
Epoch 7/50
18/18 [==============================] - 0s 3ms/step - loss: 0.4289 - accuracy:
0.8278 - val_loss: 0.4136 - val_accuracy: 0.8252
Epoch 8/50
18/18 [==============================] - 0s 3ms/step - loss: 0.4233 - accuracy:
0.8278 - val_loss: 0.4124 - val_accuracy: 0.8182
Epoch 9/50
18/18 [==============================] - 0s 3ms/step - loss: 0.4178 - accuracy:
0.8295 - val_loss: 0.4046 - val_accuracy: 0.8252
Epoch 10/50
18/18 [==============================] - 0s 3ms/step - loss: 0.4112 - accuracy:
0.8330 - val_loss: 0.4047 - val_accuracy: 0.8252
Epoch 11/50
18/18 [==============================] - 0s 3ms/step - loss: 0.4061 - accuracy:
0.8348 - val_loss: 0.4043 - val_accuracy: 0.8252
Epoch 12/50
18/18 [==============================] - 0s 3ms/step - loss: 0.4037 - accuracy:
0.8366 - val_loss: 0.4034 - val_accuracy: 0.8252
Epoch 13/50
18/18 [==============================] - 0s 3ms/step - loss: 0.3981 - accuracy:
0.8366 - val_loss: 0.3985 - val_accuracy: 0.8182
Epoch 14/50
18/18 [==============================] - 0s 3ms/step - loss: 0.3970 - accuracy:
0.8401 - val_loss: 0.3997 - val_accuracy: 0.8322
Epoch 15/50
18/18 [==============================] - 0s 3ms/step - loss: 0.3938 - accuracy:
0.8453 - val_loss: 0.4018 - val_accuracy: 0.8252
Epoch 16/50
18/18 [==============================] - 0s 3ms/step - loss: 0.3903 - accuracy:
0.8436 - val_loss: 0.3958 - val_accuracy: 0.8322
Epoch 17/50
18/18 [==============================] - 0s 3ms/step - loss: 0.3875 - accuracy:
0.8436 - val_loss: 0.3982 - val_accuracy: 0.8252
Epoch 18/50
18/18 [==============================] - 0s 3ms/step - loss: 0.3849 - accuracy:
0.8436 - val_loss: 0.3984 - val_accuracy: 0.8252
Epoch 19/50
18/18 [==============================] - 0s 3ms/step - loss: 0.3822 - accuracy:
0.8436 - val_loss: 0.4014 - val_accuracy: 0.8252
Epoch 20/50
18/18 [==============================] - 0s 3ms/step - loss: 0.3821 - accuracy:
0.8401 - val_loss: 0.3984 - val_accuracy: 0.8182
```

```
Epoch 21/50
18/18 [==============================] - 0s 3ms/step - loss: 0.3781 - accuracy:
0.8471 - val_loss: 0.3986 - val_accuracy: 0.8182
Epoch 22/50
18/18 [==============================] - 0s 3ms/step - loss: 0.3767 - accuracy:
0.8383 - val_loss: 0.3983 - val_accuracy: 0.8112
Epoch 23/50
18/18 [==============================] - 0s 3ms/step - loss: 0.3753 - accuracy:
0.8471 - val_loss: 0.4048 - val_accuracy: 0.8182
Epoch 24/50
18/18 [==============================] - 0s 3ms/step - loss: 0.3736 - accuracy:
0.8453 - val_loss: 0.3941 - val_accuracy: 0.8252
Epoch 25/50
18/18 [==============================] - 0s 3ms/step - loss: 0.3710 - accuracy:
0.8489 - val_loss: 0.3997 - val_accuracy: 0.8182
Epoch 26/50
18/18 [==============================] - 0s 3ms/step - loss: 0.3708 - accuracy:
0.8418 - val_loss: 0.3985 - val_accuracy: 0.8182
Epoch 27/50
18/18 [==============================] - 0s 5ms/step - loss: 0.3693 - accuracy:
0.8401 - val_loss: 0.3957 - val_accuracy: 0.8252
Epoch 28/50
18/18 [==============================] - 0s 3ms/step - loss: 0.3688 - accuracy:
0.8453 - val_loss: 0.4022 - val_accuracy: 0.8252
Epoch 29/50
18/18 [==============================] - 0s 3ms/step - loss: 0.3667 - accuracy:
0.8471 - val_loss: 0.3971 - val_accuracy: 0.8252
Epoch 30/50
18/18 [==============================] - 0s 3ms/step - loss: 0.3645 - accuracy:
0.8436 - val_loss: 0.4006 - val_accuracy: 0.8182
Epoch 31/50
18/18 [==============================] - 0s 3ms/step - loss: 0.3631 - accuracy:
0.8471 - val_loss: 0.3967 - val_accuracy: 0.8322
Epoch 32/50
18/18 [==============================] - 0s 4ms/step - loss: 0.3623 - accuracy:
0.8489 - val_loss: 0.3934 - val_accuracy: 0.8322
Epoch 33/50
18/18 [==============================] - 0s 3ms/step - loss: 0.3627 - accuracy:
0.8383 - val_loss: 0.4075 - val_accuracy: 0.8322
Epoch 34/50
18/18 [==============================] - 0s 3ms/step - loss: 0.3604 - accuracy:
0.8436 - val_loss: 0.3973 - val_accuracy: 0.8252
Epoch 35/50
18/18 [==============================] - 0s 3ms/step - loss: 0.3586 - accuracy:
0.8471 - val_loss: 0.3953 - val_accuracy: 0.8322
Epoch 36/50
18/18 [==============================] - 0s 3ms/step - loss: 0.3567 - accuracy:
0.8489 - val_loss: 0.4053 - val_accuracy: 0.8322
Epoch 37/50
18/18 [==============================] - 0s 3ms/step - loss: 0.3539 - accuracy:
0.8489 - val_loss: 0.4014 - val_accuracy: 0.8322
Epoch 38/50
18/18 [==============================] - 0s 3ms/step - loss: 0.3540 - accuracy:
0.8506 - val_loss: 0.3966 - val_accuracy: 0.8392
Epoch 39/50
18/18 [==============================] - 0s 3ms/step - loss: 0.3519 - accuracy:
0.8489 - val_loss: 0.4024 - val_accuracy: 0.8252
Epoch 40/50
18/18 [==============================] - 0s 3ms/step - loss: 0.3517 - accuracy:
0.8436 - val_loss: 0.4021 - val_accuracy: 0.8252
```

```
Epoch 41/50
18/18 [==============================] - 0s 3ms/step - loss: 0.3506 - accuracy:
0.8453 - val_loss: 0.3942 - val_accuracy: 0.8392
Epoch 42/50
18/18 [==============================] - 0s 3ms/step - loss: 0.3503 - accuracy:
0.8506 - val_loss: 0.3976 - val_accuracy: 0.8392
Epoch 43/50
18/18 [==============================] - 0s 3ms/step - loss: 0.3480 - accuracy:
0.8541 - val_loss: 0.4034 - val_accuracy: 0.8252
Epoch 44/50
18/18 [==============================] - 0s 3ms/step - loss: 0.3492 - accuracy:
0.8489 - val_loss: 0.4037 - val_accuracy: 0.8392
Epoch 45/50
18/18 [==============================] - 0s 3ms/step - loss: 0.3511 - accuracy:
0.8418 - val_loss: 0.4072 - val_accuracy: 0.8252
Epoch 46/50
18/18 [==============================] - 0s 3ms/step - loss: 0.3467 - accuracy:
0.8471 - val_loss: 0.4000 - val_accuracy: 0.8252
Epoch 47/50
18/18 [==============================] - 0s 3ms/step - loss: 0.3447 - accuracy:
0.8436 - val_loss: 0.4007 - val_accuracy: 0.8392
Epoch 48/50
18/18 [==============================] - 0s 3ms/step - loss: 0.3444 - accuracy:
0.8453 - val_loss: 0.4037 - val_accuracy: 0.8392
Epoch 49/50
18/18 [==============================] - 0s 3ms/step - loss: 0.3453 - accuracy:
0.8524 - val_loss: 0.3952 - val_accuracy: 0.8392
Epoch 50/50
18/18 [==============================] - 0s 3ms/step - loss: 0.3450 - accuracy:
0.8541 - val_loss: 0.4129 - val_accuracy: 0.8112
6/6 [==============================] - 0s 2ms/step - loss: 0.4448 - accuracy: 0.8
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Test Loss: 0.4448, Test Accuracy: 0.8212
```

Surrogate Model - MLPClassifier

In [11]:

```python
# Train a surrogate model (MLPClassifier)
surrogate_model = MLPClassifier(hidden_layer_sizes=(32,), activation='logistic',
print('Accuracy (MLPClassifier): ' + str(surrogate_model.score(X_train, y_train)
```

```
Accuracy (MLPClassifier): 0.800561797752809
```

Part 3.2

Set up Prototypes and Criticisms

In [12]:

```python
# Cell 5: Integrate MMD-Critic to obtain prototypes and criticisms
# We will use PCA to reduce the dimensionality of X_train to 2D for visualisatio

pca = PCA(n_components=2)
X_train_pca = pca.fit_transform(X_train)
X_list = X_train_pca.tolist()

# Set the number of prototypes and criticisms you want to extract
n_prototypes = 5
n_criticisms = 5
```

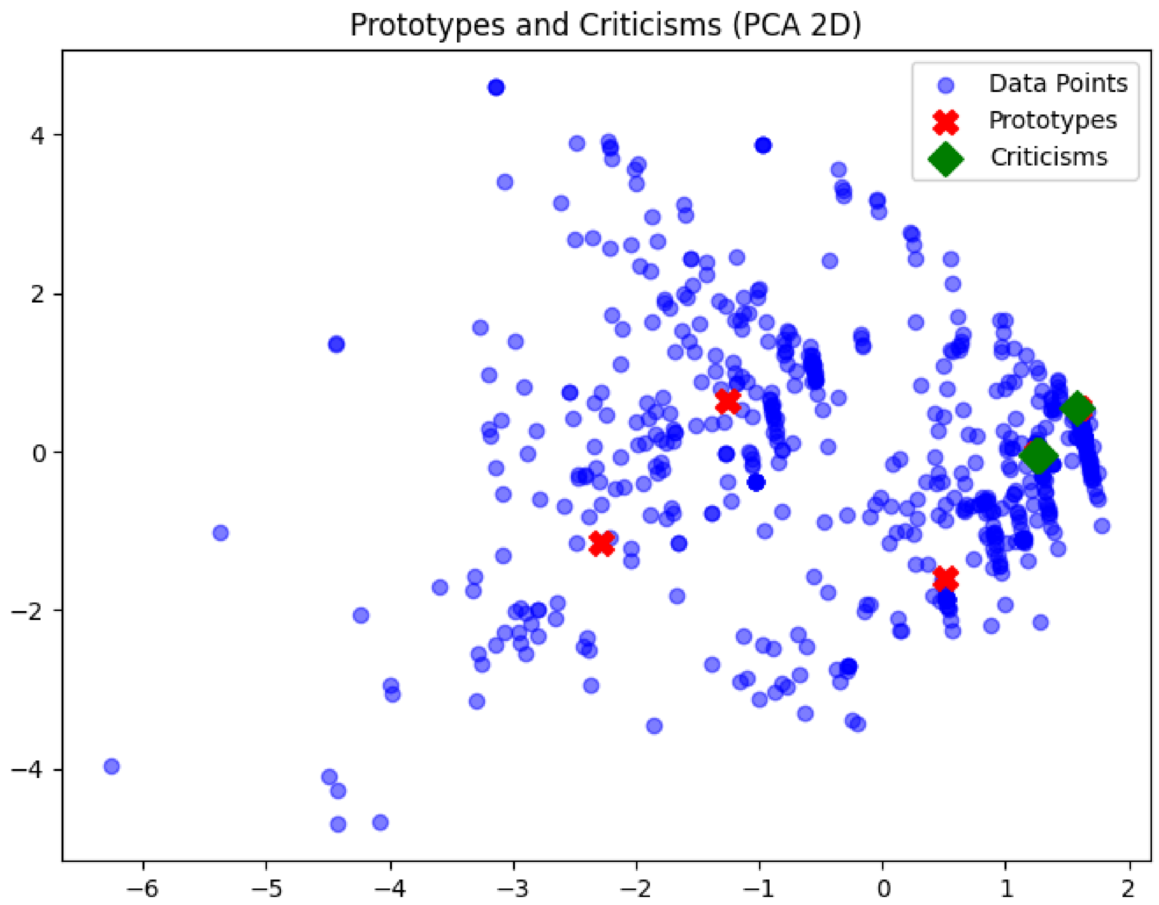
```python
# Initialise MMD-Critic with two RBF kernels using different bandwidths
critic = MMDCritic(X_list, RBFKernel(1), RBFKernel(0.025))

# Select prototypes
prototypes, _ = critic.select_prototypes(n_prototypes)

# Select criticisms
criticisms, _ = critic.select_criticisms(n_criticisms, prototypes)

# Convert everything back to NumPy arrays for plotting
prototypes = np.array(prototypes)
criticisms = np.array(criticisms)
X_train_pca = np.array(X_list)

# Plot the data points, prototypes, and criticisms
plt.figure(figsize=(8, 6))
plt.scatter(
    X_train_pca[:, 0],
    X_train_pca[:, 1],
    c='blue',
    alpha=0.5,
    label='Data Points'
)
plt.scatter(
    prototypes[:, 0],
    prototypes[:, 1],
    c='red',
    label='Prototypes',
    marker='X',
    s=100
)
plt.scatter(
    criticisms[:, 0],
    criticisms[:, 1],
    c='green',
    label='Criticisms',
    marker='D',
    s=100
)
plt.title("Prototypes and Criticisms (PCA 2D)")
plt.legend()
plt.show()
```



This graph illustrates the result of applying MMD-Critic to identify prototypes and criticisms within the dataset. The blue circles represent the data points once they have been projected into two dimensions using PCA. The points marked with red crosses are the selected prototypes, which serve as representative samples of the dataset's main patterns or clusters. In contrast, the green diamonds denote the identified criticisms, which highlight data points that are not well explained or captured by the prototypes.

By examining the locations of these prototypes, one can observe the typical examples of the dataset that best characterise the underlying distribution. Conversely, the criticisms provide insight into observations that may be outliers or less typical, suggesting areas where the model's performance or the dataset's coverage might warrant further investigation.

3.2 b

Prototypes and criticisms are important tools in interpretable AI because they offer a way to understand a dataset and model performance beyond standard metrics. Prototypes highlight examples that capture the most prominent patterns in the dataset, effectively showing what "typical" instances look like. This helps one see how the model generalises by referencing samples deemed highly representative of the underlying data distribution.

Criticisms, on the other hand, draw attention to points that originate from these representative samples, potentially indicating outliers or subsets of data that do not conform to main trends. Identifying such points can prompt further inspection of whether the model handles these "unusual" cases effectively or whether the dataset requires augmentation or refinement. Together, prototypes and criticisms facilitate a more nuanced understanding of model decisions and data coverage, supporting informed decisions about model reliability and fairness.