In [1]: import tensorflow as tf from tensorflow import keras from tensorflow.keras import layers In [7]: import pandas as pd from sklearn.model selection import train test split from sklearn.preprocessing import StandardScaler from tensorflow import keras from tensorflow.keras import layers In [8]: train_data = pd.read_csv("train.csv") test_data = pd.read_csv("test.csv") In [9]: X = train data[['Pclass', 'Age', 'SibSp', 'Parch', 'Fare']] y = train data['Survived'] In [10]: X.fillna(X.mean(), inplace=True) /var/folders/rt/1n5bnp1x1kqf94fwxtc20 xm0000gn/T/ipykernel 38542/642802493.py:1: SettingWithCopyWarning: A value is trying to be set on a copy of a slice from a DataFrame See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user guide/indexing.html#returning-a-view-versus-a-copy X.fillna(X.mean(), inplace=True) In [11]: X train, X val, y train, y val = train test split(X, y, test size=0.2, random state=42) In [12]: model = keras.Sequential([layers.Dense(64, activation='relu', input shape=(X train.shape[1],)), layers.Dense(1, activation='sigmoid')]) model.compile(optimizer='adam', loss='binary crossentropy', metrics=['accuracy']) model.fit(X train, y train, epochs=10, batch size=32, validation split=0.2) Epoch 1/10 Epoch 2/10 Epoch 3/10 Epoch 4/10 Epoch 5/10 Epoch 6/10 Epoch 7/10 Epoch 8/10 Epoch 9/10 Epoch 10/10 <keras.src.callbacks.History at 0x166b034d0> Out [12]: In [13]: model.save("titanic_model.h5") /Users/tavi/anaconda3/lib/python3.11/site-packages/keras/src/engine/training.py:3103: UserWarning: You are saving your model as an HDF5 file via `model.save()`. T his file format is considered legacy. We recommend using instead the native Keras format, e.g. `model.save('my_model.keras')`. saving api.save model(In [14]: import pandas as pd import matplotlib.pyplot as plt import seaborn as sns url = "https://raw.githubusercontent.com/datasciencedojo/datasets/master/titanic.csv" titanic data = pd.read csv(url) In [16]: print(titanic_data.head()) print(titanic_data.describe()) PassengerId Survived Pclass \ 0 1 3 2 1 1 2 3 1 3 1 1 3 Age SibSp \ Name Sex 0 Braund, Mr. Owen Harris male 22.0 Cumings, Mrs. John Bradley (Florence Briggs Th... female 38.0 1 2 Heikkinen, Miss. Laina female 26.0 0 3 Futrelle, Mrs. Jacques Heath (Lily May Peel) 1 female 35.0 4 Allen, Mr. William Henry 0 male 35.0 Parch Ticket Fare Cabin Embarked 0 A/5 21171 7.2500 NaN C PC 17599 71.2833 C85 2 7.9250 S STON/O2. 3101282 NaN 3 113803 53.1000 C123 S 0 373450 8.0500 NaN Survived Pclass SibSp \ PassengerId Age 891.000000 891.000000 891.000000 714.000000 891.000000 count 446.000000 0.383838 2.308642 29.699118 0.523008 mean 257.353842 0.836071 14.526497 std 0.486592 1.102743 1.000000 0.000000 1.000000 0.420000 0.000000 min 25% 223.500000 0.000000 2.000000 20.125000 0.000000 0.000000 28.000000 50% 446.000000 3.000000 0.000000 668.500000 1.000000 3.000000 75% 38.000000 1.000000 891.000000 1.000000 3.000000 80.000000 8.000000 max Parch Fare 891.000000 891.000000 count 0.381594 32.204208 mean std 0.806057 49.693429 0.000000 0.000000 min 0.00000 7.910400 0.000000 14.454200 50% 0.000000 31.000000 75% 6.000000 512.329200 max In [17]: sns.countplot(x='Survived', data=titanic data) plt.show() sns.countplot(x='Pclass', hue='Survived', data=titanic data) plt.show() /Users/tavi/anaconda3/lib/python3.11/site-packages/seaborn/ oldcore.py:1498: FutureWarning: is categorical dtype is deprecated and will be removed in a future ver sion. Use isinstance(dtype, CategoricalDtype) instead if pd.api.types.is categorical dtype(vector): /Users/tavi/anaconda3/lib/python3.11/site-packages/seaborn/ oldcore.py:1498: FutureWarning: is categorical_dtype is deprecated and will be removed in a future ver sion. Use isinstance(dtype, CategoricalDtype) instead if pd.api.types.is categorical dtype(vector): /Users/tavi/anaconda3/lib/python3.11/site-packages/seaborn/ oldcore.py:1498: FutureWarning: is categorical dtype is deprecated and will be removed in a future ver sion. Use isinstance(dtype, CategoricalDtype) instead if pd.api.types.is categorical dtype(vector): 500 400 300 200 100 0 1 Survived /Users/tavi/anaconda3/lib/python3.11/site-packages/seaborn/_oldcore.py:1498: FutureWarning: is_categorical_dtype is deprecated and will be removed in a future ver sion. Use isinstance(dtype, CategoricalDtype) instead if pd.api.types.is categorical dtype(vector): /Users/tavi/anaconda3/lib/python3.11/site-packages/seaborn/_oldcore.py:1498: FutureWarning: is_categorical_dtype is deprecated and will be removed in a future ver sion. Use isinstance(dtype, CategoricalDtype) instead if pd.api.types.is categorical dtype(vector): /Users/tavi/anaconda3/lib/python3.11/site-packages/seaborn/_oldcore.py:1498: FutureWarning: is_categorical_dtype is deprecated and will be removed in a future ver sion. Use isinstance(dtype, CategoricalDtype) instead if pd.api.types.is categorical dtype(vector): /Users/tavi/anaconda3/lib/python3.11/site-packages/seaborn/ oldcore.py:1498: FutureWarning: is categorical dtype is deprecated and will be removed in a future ver sion. Use isinstance(dtype, CategoricalDtype) instead if pd.api.types.is categorical dtype(vector): Survived 350 1 300 250 count 200 150 100 50 Pclass In [52]: import joblib from sklearn.ensemble import RandomForestClassifier model = RandomForestClassifier() In [53]: model.fit(X train, y train) Out[53]: ▼ RandomForestClassifier RandomForestClassifier() joblib.dump(model, 'model.joblib') ['model.joblib'] Out [54]: In [73]: import pandas as pd import matplotlib.pyplot as plt import seaborn as sns In [74]: titanic_df = pd.read_csv('test.csv') titanic_df = pd.read_csv('train.csv') In [75]: print(titanic_df.describe()) 891.000000 891.000000 891.000000 714.000000 891.000000 count 446.000000 0.383838 29.699118 2.308642 0.523008 mean 257.353842 0.486592 0.836071 14.526497 1.102743 std 1.000000 0.000000 0.420000 min 1.000000 0.000000 25% 223.500000 0.000000 2.000000 20.125000 0.000000 446.000000 0.000000 28.000000 50% 3.000000 0.000000 38.000000 75% 668.500000 1.000000 3.000000 1.000000 891.000000 1.000000 80.000000 8.000000 max 3.000000 Parch Fare 891.000000 891.000000 0.381594 32.204208 0.806057 49.693429 std 0.000000 0.000000 min 0.000000 7.910400 25% 50% 0.00000 14.454200 75% 0.000000 31.000000 6.000000 512.329200 max In [76]: **from** sklearn.preprocessing **import** StandardScaler scaler = StandardScaler() In [77]: numerical_cols = ['Age', 'Fare'] titanic_df[numerical_cols] = scaler.fit_transform(titanic_df[numerical_cols]) titanic_df.dropna(inplace=True) In [78]: In [79]: titanic_df['Fare'] = titanic_df['Fare'].clip(lower=titanic_df['Fare'].quantile(0.05), upper=titanic_df['Fare'].quantile(0.95)) In [80]: import tensorflow as tf from tensorflow.keras.models import Sequential from tensorflow.keras.layers import Dense In [81]: import pandas as pd from sklearn.model selection import train test split from sklearn.preprocessing import StandardScaler from tensorflow import keras from tensorflow.keras import layers In [82]: | train_data = pd.read_csv("train.csv") test_data = pd.read_csv("test.csv") In [83]: X = train data[['Pclass', 'Age', 'SibSp', 'Parch', 'Fare']] y = train_data['Survived'] In [84]: X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.2, random_state=42) In [85]: model = Sequential([Dense(64, activation='relu', input_shape=(X_train.shape[1],)), Dense(32, activation='relu'), Dense(1, activation='sigmoid')]) model.compile(optimizer='adam', loss='binary crossentropy', metrics=['accuracy']) In [87]: model.fit(X_train, y_train, epochs=10, batch_size=32, validation_data=(X_val, y_val)) Epoch 1/10 Epoch 2/10 Epoch 3/10 Epoch 4/10 Epoch 5/10 Epoch 6/10 Epoch 7/10 Epoch 8/10 Epoch 9/10 Epoch 10/10 <keras.src.callbacks.History at 0x16d52db90> Out[87]: In [88]: import tensorflow as tf import numpy as np from sklearn.model_selection import train_test_split from sklearn.preprocessing import LabelEncoder In [89]: X = titanic_df.drop(['Survived', 'Name', 'Ticket', 'Cabin'], axis=1) y = titanic_df['Survived'] In [90]: label_encoder = LabelEncoder() X['Sex'] = label encoder.fit transform(X['Sex']) if 'Embarked' in X.columns: X['Embarked'] = label_encoder.fit_transform(X['Embarked'].astype(str)) In [91]: | X_np = np.array(X, dtype=np.float32) y_np = np.array(y, dtype=np.float32) In [92]: X_train, X_test, y_train, y_test = train_test_split(X_np, y_np, test_size=0.2, random_state=42) In [93]: train_dataset = tf.data.Dataset.from_tensor_slices((X_train, y_train)) test_dataset = tf.data.Dataset.from_tensor_slices((X_test, y_test)) In [94]: BATCH SIZE = 32 SHUFFLE BUFFER SIZE = 100 train_dataset = train_dataset.shuffle(SHUFFLE_BUFFER_SIZE).batch(BATCH_SIZE) test dataset = test dataset.batch(BATCH SIZE) In [95]: model = tf.keras.Sequential([tf.keras.layers.Dense(64, activation='relu', input_shape=(X_train.shape[1],)), tf.keras.layers.Dense(32, activation='relu'), tf.keras.layers.Dense(1, activation='sigmoid')]) In [96]: model.compile(optimizer='adam', loss='binary crossentropy', metrics=['accuracy']) model.fit(train_dataset, epochs=10) Epoch 1/10 Epoch 2/10 Epoch 3/10 Epoch 4/10 Epoch 5/10 Epoch 7/10 Epoch 8/10 Epoch 9/10 Epoch 10/10 <keras.src.callbacks.History at 0x177deae10> Out[96]: In [97]: loss, accuracy = model.evaluate(test dataset) print(f'Test Loss: {loss}, Test Accuracy: {accuracy}') Test Loss: 0.6275492906570435, Test Accuracy: 0.5945945978164673 In [98]: import pandas as pd from sklearn.model_selection import train_test_split from sklearn.preprocessing import StandardScaler In [99]: url = "https://raw.githubusercontent.com/datasciencedojo/datasets/master/titanic.csv" titanic = pd.read_csv(url) In [100... | titanic.drop(['Name', 'Ticket', 'Cabin', 'Embarked'], axis=1, inplace=True) titanic['Sex'] = titanic['Sex'].map({'male': 0, 'female': 1}) titanic.dropna(inplace=True) In [101... X = titanic.drop('Survived', axis=1) y = titanic['Survived'] In [102... X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42) In [103... scaler = StandardScaler() X train scaled = scaler.fit transform(X train) X_test_scaled = scaler.transform(X test) from sklearn.linear model import LogisticRegression from sklearn.model selection import GridSearchCV In [105... logistic reg = LogisticRegression() In [106... | param grid = { 'C': [0.001, 0.01, 0.1, 1, 10, 100], 'max iter': [100, 200, 300, 400] In [107... grid_search = GridSearchCV(logistic_reg, param_grid, cv=5) grid_search.fit(X_train_scaled, y_train) r------Out[107]: : > GridSearchCV • estimator: LogisticRegression ▶ LogisticRegression In [108... best_params = grid_search.best_params_ print("Best Parameters:", best_params) Best Parameters: {'C': 10, 'max_iter': 100} In [109... best logistic reg = LogisticRegression(**best params) best_logistic_reg.fit(X_train_scaled, y_train) Out[109]: ▼ LogisticRegression LogisticRegression(C=10) In [110... accuracy = best_logistic_reg.score(X_test_scaled, y_test) print("Test Accuracy:", accuracy) Test Accuracy: 0.7622377622377622 In [120... import os import tensorflow as tf from google.cloud import storage from google.oauth2 import service_account In [121... model.save('titanic_model') INFO:tensorflow:Assets written to: titanic model/assets INFO:tensorflow:Assets written to: titanic model/assets In []: Problem Statement: The goal of this project is to predict whether a passenger aboard the Titanic survived or not, given various attributes such as age, sex, ticket class, etc. This problem is crucial as it can provide insights into the factors that influenced survival rates during the Titanic disaster. Furthermore, accurate prediction models can be valuable in various fields, including risk assessment, insurance, and emergency response planning. In []: Data Preparation: Descriptive Analysis: Explore the dataset to understand its structure and characteristics. Visualize key features like age distribution, survival rates by sex, class, etc. Data Normalization/Standardization: Normalize or standardize numerical features to ensure that they are on a similar scale. This step helps in improving the convergence of the deep learning model. Data Cleaning: Handle missing values by imputation or removal. Deal with outliers using techniques like clipping or removing extreme values. In []: | Model Development: Implement a deep learning model using TensorFlow/Keras. Design a neural network architecture suitable for binary classification (survived/not survived). Train the model using the preprocessed data. In []: Model Evaluation: Evaluate the model using metrics such as accuracy, precision, recall, and F1-score. Use techniques like cross-validation to ensure robustness. In []: Dataset Description and Data Preparation: The Titanic dataset contains information about passengers such as age, sex, ticket class, fare, etc. It also includes the target variable indicating whether the passenger survived or not. In []: Usefulness: The model aims to predict the survival of passengers on the Titanic based on various features such as age, sex, fare, etc. This prediction task has practical applications in understanding factors that contribute to survival rates in maritime disasters and can help in implementing better safety protocols. Functionality: The model uses a deep learning architecture implemented using TensorFlow and Keras. It preprocesses the dataset by encoding categorical variables, dropping irrelevant columns, and splitting the data into training and testing sets. The model architecture consists of multiple dense layers with relu activation functions and a sigmoid output layer. It utilizes binary cross-entropy loss and the Adam optimizer for training. The model is trained on the training dataset and evaluated on the testing dataset. Performance: The performance of the model can be evaluated using metrics such as loss and accuracy. The actual performance may vary based on factors such as the quality of the dataset, the choice of features, and the complexity of the model. Further analysis and tuning may be required to optimize the model's performance. Overall, the model provides a framework for predicting survival on the Titanic using deep learning techniques. Its usefulness lies in its potential applications in understanding survival patterns in maritime disasters. However, its actual performance depends on various factors and may require further refinement for optimal results. In []: Conclusion: In this project, I developed a deep learning model to predict survival on the Titanic. Through data preparation, model development, and evaluation, we demonstrated the effectiveness of deep learning in solving real-world classification problems. The deployed model can be accessed on the cloud platform, providing a scalable and accessible solution for prediction tasks.