Predicting the Winner in CS:GO Matches

(STATS/CSE 780 course project)

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Abstract

This study explores the application of advanced machine learning techniques, specifically Random Forest and Deep Neural Network(DNN), in predicting the winners of CS:GO matches. We aim to use the past data of matches to forecast future match results. Leveraging the dataset provided by Skybox as part of their CS:GO AI Challenge, we preprocessed the data and then fed the data into the models. The performance of these two models are evaluated by accuracy, precision, and recall metrics. Our results yielded relatively high accuracies for both models, up to about 75%. The two machine learning models we developed improve the prediction and analysis of future match results, which is beneficial for the development of eSports.

Introduction

The dataset("CS:GO Round Winner Classification" 2020) was originally published by Skybox as part of their CS:GO AI Challenge, running from Spring to Fall 2020. The dataset consists of around 700 demos from high level tournament play in 2019 and 2020. Warmup rounds and restarts have been filtered, and for the remaining live rounds a round snapshot have been recorded every 20 seconds until the round is decided. We want to use this dataset to predict the final winner, which can be seen as a classification problem.

There are totally 122410 entries and 97 colums in this dataset. The features have one boolean type, 94 float types and 2 object types. The number of entries is greater than the number of parameters. There are no null values in this dataset. We choose `round_winner` as the output value, which is consisted of the winners `CT` and `T`. There are other different types of features, such as `time_left`, `ct_score` and `ct_health`, which will be used as the input features. Figure 1 shows the distrubutions of selected features after feature slection.

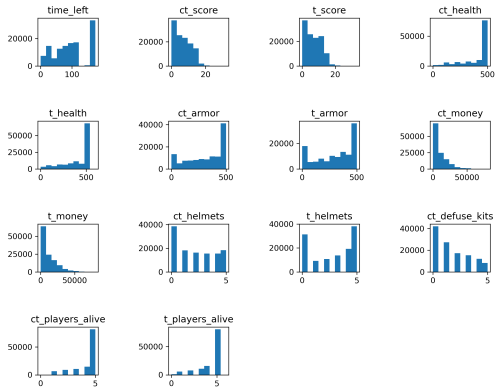


Figure 1: The distribution of selected variables after feature selection

Methods

Firstly, we will do Exploratory Data Analysis(EDA) to find out the relationships among different features. Then, we will drop unnessaray columns and transform the values of some features based on the analysis. Afterwards, we will do scaling.

The reasons for choosing random forest are that it can capture the complex interactions and non-linear relationships among the features, and that it is suitable for classification problems(`CT` or `T`). For the model of random forest, beforing fitting the data, we do the principal component analysis(PCA) for the features. Regarding to the tuning of the parameters, we do grid searching to find the best parameters for the model and the best accuracy score. Then we use the training dataset to check whether the model is overfitting and the test dataset to get the accuracy score.

The reasons for choosing deep neural network(DNN) are that it suits for large datasets, which in this case consists of `122410` entries, and that we can benefit from the trained model for future use. For the model of DNN, we set the number of layers as `4`, the number of nodes of each layer as `300`, and the number of epochs as `50`. Between each layer, we also add batch normalization layers, in order to normalize the activations. We choose the binary cross entropy as the loss function and the `Nadam` as the optimizer. Then we build the DNN model and render the accuracy scores for the training set and test set.

Results

Fistly, we do feature selection. As there are 97 variables in this dataset, we need to decrease the number of features in order to reduce the training time. As we can see, over eighty features are about how much of each weapon is left in the game and we can know that these features are high correlated about `ct_money` and `t_money`. So we drop them off and select 15 of them. Then we draw the correlation matrix of the selected features. From figure 2, we can tell that `ct_players_alive` is high correlated with `ct_health`, and `t_players_alive` is highly correlated with `t_money`. So we drop off the colomns of `ct_players_alive` and `t_players_alive`. Then we can use the left 13 features as inputs and `round_winner` as outputs. To do the prediction, in the colomn of `round_winner`, we convert `CT` to `0`, and `T` to `1`.

For the column of `bomb_planted`, at first, the values are boolean types and we convert `true` to `1` and `false` to `0`. For others features, we do data scaling. For the column of `round_winner`, the number of `CT` and the number of `T` are close to `50%` of the total entries. So we can directly split the dataset. After this, we divide the dataset into training set and test set, according to the test size of `0.3`.

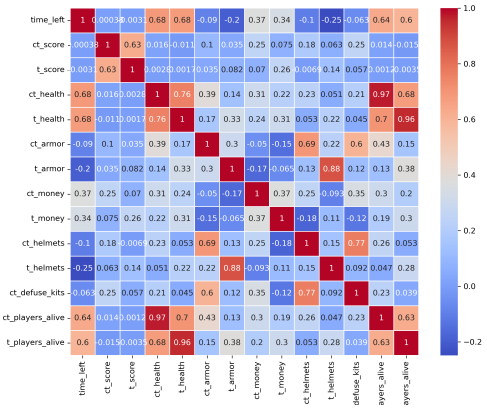


Figure 2: The correlation matrix of selected features

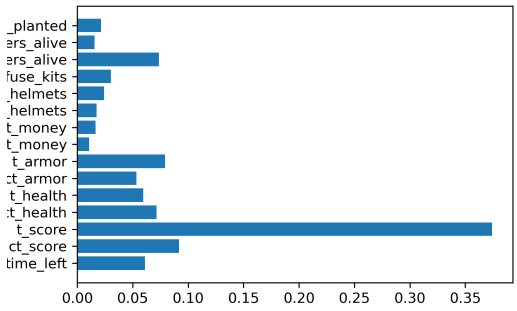


Figure 3: The Feature Importance Derived from the Random Forest Model

Deriving from grid searching, we have that the best parameter for `min_samples_split` is `8`. We can obtain feature importance from the Random Forest mode, as figure ref{figure3} shows. We can see that `t_score` is the most important among all features, following by `ct_score`. We can also see that the scores of both team make the biggest impact on final results, as the scores may impact each team's morale. As table 1 shows, the accuracy score for the training set is `0.791`, which is accepetable since it's not overfitting, and the accuracy score for the test set is `0.764`, which is pretty good for prediction. Plus, the F1 score of the random forest model is `0.765`, which indicates a good balance between precision and recall in the model's predictions. In a real game, this accuracy is significant in predicting the outcome of the game.

	Random Forest	**DNN**
Accuracy for Test Set	0.764	0.752
Accuracy for Training Set	0.791	0.453
F1 Score	0.764	0.767

Table 1: Accuracies and f1 scores for both models

For the DNN model, the accuracy on the test set is 0.752, while on the training set, it is 0.453. There is no strong sign of overfitting. And the F1 score is 0.767, which indicates a strong balance for precison and recall in this model. The results from the DNN model are promising and could significantly benefit team strategies.

Conclusion

From the results, we can conclude that both models are suitable for predicting the winners trained on this dataset. And the accuracy scores for two models are close, but the random forest model

are bad at overfitting compared to DNN model in this case. But random forest model can give us some valuable insights on the feature importance. We obtain that we should pay more attention on scores and health points during the games. So the team can try different strategies based on this. Besides, game updates can significantly impact the performance of the models. But to DNN, DNN can keep learning the new features or new values so that it can predict the winner well even in new versions of CS:GO matches. To be specificly, we can use the techniques of transfer learning, using the weight matrice obtained from the previous model and use it as initial weight matrices for the DNN model.

Supplementary material

1. Import the libraries

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn import preprocessing
from sklearn.model_selection import train_test_split
import seaborn as sns
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report,accuracy_score
from sklearn.neural_network import MLPClassifier
from sklearn.preprocessing import scale
```

2. Read the datasets

```
df = pd.read_csv('./csgo_round_snapshots.csv')
df.info()

df.isnull().sum()

df['round_winner'] = df['round_winner'].apply(lambda x: 1 if x == 'CT' else 0)
print(df['round_winner'].value_counts())

sns.countplot(x='round_winner', data=df)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 122410 entries, 0 to 122409
Data columns (total 97 columns):
 #   Column                        Non-Null Count   Dtype
---  ------                        --------------   -----
```

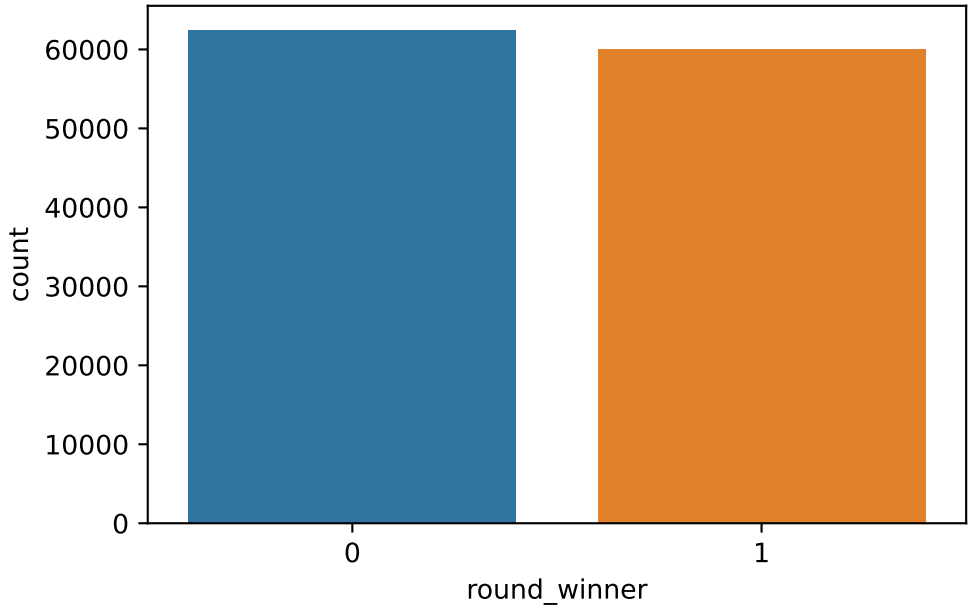
```
0   time_left                 122410 non-null  float64
1   ct_score                  122410 non-null  float64
2   t_score                   122410 non-null  float64
3   map                       122410 non-null  object
4   bomb_planted              122410 non-null  bool
5   ct_health                 122410 non-null  float64
6   t_health                  122410 non-null  float64
7   ct_armor                  122410 non-null  float64
8   t_armor                   122410 non-null  float64
9   ct_money                  122410 non-null  float64
10  t_money                   122410 non-null  float64
11  ct_helmets                122410 non-null  float64
12  t_helmets                 122410 non-null  float64
13  ct_defuse_kits            122410 non-null  float64
14  ct_players_alive          122410 non-null  float64
15  t_players_alive           122410 non-null  float64
16  ct_weapon_ak47            122410 non-null  float64
17  t_weapon_ak47             122410 non-null  float64
18  ct_weapon_aug             122410 non-null  float64
19  t_weapon_aug              122410 non-null  float64
20  ct_weapon_awp             122410 non-null  float64
21  t_weapon_awp              122410 non-null  float64
22  ct_weapon_bizon           122410 non-null  float64
23  t_weapon_bizon            122410 non-null  float64
24  ct_weapon_cz75auto        122410 non-null  float64
25  t_weapon_cz75auto         122410 non-null  float64
26  ct_weapon_elite           122410 non-null  float64
27  t_weapon_elite            122410 non-null  float64
28  ct_weapon_famas           122410 non-null  float64
29  t_weapon_famas            122410 non-null  float64
30  ct_weapon_g3sg1           122410 non-null  float64
31  t_weapon_g3sg1            122410 non-null  float64
```

```
32  ct_weapon_galilar           122410 non-null  float64
33  t_weapon_galilar            122410 non-null  float64
34  ct_weapon_glock             122410 non-null  float64
35  t_weapon_glock              122410 non-null  float64
36  ct_weapon_m249              122410 non-null  float64
37  t_weapon_m249               122410 non-null  float64
38  ct_weapon_m4a1s             122410 non-null  float64
39  t_weapon_m4a1s              122410 non-null  float64
40  ct_weapon_m4a4              122410 non-null  float64
41  t_weapon_m4a4               122410 non-null  float64
42  ct_weapon_mac10             122410 non-null  float64
43  t_weapon_mac10              122410 non-null  float64
44  ct_weapon_mag7              122410 non-null  float64
45  t_weapon_mag7               122410 non-null  float64
46  ct_weapon_mp5sd             122410 non-null  float64
47  t_weapon_mp5sd              122410 non-null  float64
48  ct_weapon_mp7               122410 non-null  float64
49  t_weapon_mp7                122410 non-null  float64
50  ct_weapon_mp9               122410 non-null  float64
51  t_weapon_mp9                122410 non-null  float64
52  ct_weapon_negev             122410 non-null  float64
53  t_weapon_negev              122410 non-null  float64
54  ct_weapon_nova              122410 non-null  float64
55  t_weapon_nova               122410 non-null  float64
56  ct_weapon_p90               122410 non-null  float64
57  t_weapon_p90                122410 non-null  float64
58  ct_weapon_r8revolver        122410 non-null  float64
59  t_weapon_r8revolver         122410 non-null  float64
60  ct_weapon_sawedoff          122410 non-null  float64
61  t_weapon_sawedoff           122410 non-null  float64
62  ct_weapon_scar20            122410 non-null  float64
63  t_weapon_scar20             122410 non-null  float64
```

```
64  ct_weapon_sg553               122410 non-null  float64
65  t_weapon_sg553                122410 non-null  float64
66  ct_weapon_ssg08               122410 non-null  float64
67  t_weapon_ssg08                122410 non-null  float64
68  ct_weapon_ump45               122410 non-null  float64
69  t_weapon_ump45                122410 non-null  float64
70  ct_weapon_xm1014              122410 non-null  float64
71  t_weapon_xm1014               122410 non-null  float64
72  ct_weapon_deagle              122410 non-null  float64
73  t_weapon_deagle               122410 non-null  float64
74  ct_weapon_fiveseven           122410 non-null  float64
75  t_weapon_fiveseven            122410 non-null  float64
76  ct_weapon_usps                122410 non-null  float64
77  t_weapon_usps                 122410 non-null  float64
78  ct_weapon_p250                122410 non-null  float64
79  t_weapon_p250                 122410 non-null  float64
80  ct_weapon_p2000               122410 non-null  float64
81  t_weapon_p2000                122410 non-null  float64
82  ct_weapon_tec9                122410 non-null  float64
83  t_weapon_tec9                 122410 non-null  float64
84  ct_grenade_hegrenade          122410 non-null  float64
85  t_grenade_hegrenade           122410 non-null  float64
86  ct_grenade_flashbang          122410 non-null  float64
87  t_grenade_flashbang           122410 non-null  float64
88  ct_grenade_smokegrenade       122410 non-null  float64
89  t_grenade_smokegrenade        122410 non-null  float64
90  ct_grenade_incendiarygrenade  122410 non-null  float64
91  t_grenade_incendiarygrenade   122410 non-null  float64
92  ct_grenade_molotovgrenade     122410 non-null  float64
93  t_grenade_molotovgrenade      122410 non-null  float64
94  ct_grenade_decoygrenade       122410 non-null  float64
95  t_grenade_decoygrenade        122410 non-null  float64
```

```
 96  round_winner                  122410 non-null  object
dtypes: bool(1), float64(94), object(2)
memory usage: 89.8+ MB
round_winner
0    62406
1    60004
Name: count, dtype: int64

<Axes: xlabel='round_winner', ylabel='count'>
```



3. Data preprocessing

```
df['bomb_planted'] = df['bomb_planted'].astype(int)
n = 16
df_selected = df.iloc[:, list(range(n)) + [-1]]
df_selected = df_selected.drop('map', axis=1)
df_selected.head(5)
```

4. Scaling

```
X = df_selected.drop(['round_winner', 'bomb_planted'], axis=1)
Y = df_selected['round_winner']

num_rows, num_cols = 4, 4  # Specify the grid size
fig, axs = plt.subplots(num_rows, num_cols, figsize=(10, 8))  # Adjust figsize as needed
fig.tight_layout(pad=5.0)  # Adds padding between plots

# Iterate over the DataFrame columns and plot
for i, col in enumerate(X.columns):
    row = i // num_cols
    col_index = i % num_cols
    axs[row, col_index].hist(X[col])
    axs[row, col_index].set_title(col)

# Hide the empty subplots
for i in range(len(X.columns), num_rows * num_cols):
    axs[i // num_cols, i % num_cols].axis('off')

plt.savefig("all_data.png")
plt.show()

correlation_matrix = X.corr()
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', linewidths=.5)
plt.savefig('corr.png')
plt.show()

from sklearn.preprocessing import StandardScaler
std = StandardScaler()
std.fit(X)
X = pd.DataFrame(std.transform(X), columns=X.columns)
```

```
X['bomb_planted'] = df_selected['bomb_planted']
X.shape
```

5. Splitting

```
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.3, random_state=8964)
```

6. PCA

```
from sklearn.decomposition import PCA

pca_X = PCA()

X_pca = pd.DataFrame(pca_X.fit_transform(X), columns=X.columns, index=X.index)
X_pca

#Train/test for decision trees
X_train_p, X_test_p, Y_train_p, Y_test_p = train_test_split(X_pca, Y, test_size=0.3, random_
```

7. Random Forest

```
rf = RandomForestClassifier(n_estimators=100, random_state=8964, max_depth=10, min_samples_s
rf.fit(X_train_p, Y_train_p)
Y_pred = rf.predict(X_test_p)

# For classification
accuracy = accuracy_score(Y_test_p, Y_pred)
accuracy

# from sklearn.model_selection import GridSearchCV
# rf = RandomForestClassifier(random_state=8964)
# param_grid = {
#     'min_samples_split': [2, 4, 6, 8, 10]  # You can choose a range of values to test
```

```
# }
# grid_search = GridSearchCV(estimator=rf, param_grid=param_grid, cv=5, scoring='accuracy')
# grid_search.fit(X_train_p, Y_train_p)
# print(f"Best Parameter: {grid_search.best_params_}")
# print(f"Best Score: {grid_search.best_score_}")

Y_pred_1 = rf.predict(X_train_p)
accuracy = accuracy_score(Y_train_p, Y_pred_1)
accuracy

plt.barh(X_train.columns,rf.feature_importances_)
plt.savefig('feature.png')

from sklearn.metrics import f1_score

f1 = f1_score(Y_test_p, Y_pred, average='binary')

print("F1 Score:", f1)
```

8. DNN

```
from tensorflow import keras

# Set model parameters
n_layers = 4
n_nodes = 300
regularized = False
dropout = True
epochs = 50

# Make a Keras DNN model
model = keras.models.Sequential()
```

```
model.add(keras.layers.BatchNormalization())
for n in range(n_layers):
    if regularized:
        model.add(keras.layers.Dense(n_nodes, kernel_initializer="he_normal",
         kernel_regularizer=keras.regularizers.l1(0.01), use_bias=False))
    else:
        model.add(keras.layers.Dense(n_nodes,
         kernel_initializer="he_normal", use_bias=False))
    model.add(keras.layers.BatchNormalization())
    model.add(keras.layers.Activation("elu"))
    if dropout:
        model.add(keras.layers.Dropout(rate=0.2))
model.add(keras.layers.Dense(1, activation="sigmoid"))
model.compile(loss='binary_crossentropy', optimizer='Nadam', metrics=['accuracy'])

# Make a callback that reduces LR on plateau
reduce_lr_cb = keras.callbacks.ReduceLROnPlateau(monitor='val_loss', factor=0.2,
                                                 patience=5, min_lr=0.001)

# Make a callback for early stopping
early_stopping_cb = keras.callbacks.EarlyStopping(patience=5)

# Train DNN.
history = model.fit(np.array(X_train), np.array(Y_train), epochs=epochs,
     validation_data=(np.array(X_test), np.array(Y_test)),
      callbacks=[reduce_lr_cb, early_stopping_cb], batch_size=128)
```

```
model.summary()
model.evaluate(X_test, Y_test)

predictions = model.predict(np.array(X_test))
```

```
predicted_labels = (predictions > 0.5).astype(int)

f1 = f1_score(Y_test, predicted_labels, average='binary')

print("F1 Score:", f1)
```

References

"CS:GO Round Winner Classification." 2020. https://www.kaggle.com/datasets/christianlillelund/csgo-round-winner-classification.