Random_Forest_Tie_Breaking_Strategy

June 22, 2025

[1]:
```python
import pandas as pd
import numpy as np
from sklearn.model_selection import GroupShuffleSplit, RandomizedSearchCV
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.decomposition import PCA
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.linear_model import Ridge
from sklearn.ensemble import RandomForestRegressor
from sklearn.svm import SVR
from sklearn.metrics import r2_score, mean_absolute_error, mean_squared_error
import matplotlib.pyplot as plt
import seaborn as sns
import joblib
import torch
from transformers import RobertaTokenizer, RobertaModel
from sklearn.base import BaseEstimator, TransformerMixin
from xgboost import XGBRegressor
```

[2]:
```python
df = pd.read_csv('/content/Dataset.csv')
```

[3]:
```python
df['Rank_Normalized'] = df.groupby('User ID')['Rank'].transform(lambda x: (x -
 ↪x.min()) / (x.max() - x.min()))
```

[4]:
```python
features = ['Business Value', 'Urgency', 'Stakeholder Priority', 'Complexity',
 ↪'Effort Estimation', 'Task ID', 'User ID', 'Tasks']
X = df[features]
y = df['Rank_Normalized']
```

[5]:
```python
gss = GroupShuffleSplit(n_splits=1, test_size=0.2, random_state=42)
train_idx, test_idx = next(gss.split(X, y, groups=df['User ID']))
X_train, X_test = X.iloc[train_idx], X.iloc[test_idx]
y_train, y_test = y.iloc[train_idx], y.iloc[test_idx]
```

[6]:
```python
print(f"Training set size: {X_train.shape[0]} samples")
print(f"Test set size: {X_test.shape[0]} samples")
```

```
Training set size: 1191 samples
```

```
Test set size: 355 samples
```

[7]:
```
class RobertaEmbedder(BaseEstimator, TransformerMixin):
    def __init__(self, model_name='roberta-base', max_length=32):
        self.model_name = model_name
        self.tokenizer = RobertaTokenizer.from_pretrained(model_name)
        self.model = RobertaModel.from_pretrained(model_name)
        self.max_length = max_length

    def fit(self, X, y=None):
        return self

    def transform(self, X):
        self.model.eval()
        embeddings = []
        with torch.no_grad():
            for text in X:
                inputs = self.tokenizer(text, return_tensors='pt',␣
 ↪max_length=self.max_length, truncation=True, padding='max_length')
                outputs = self.model(**inputs)
                embeddings.append(outputs.last_hidden_state[:, 0, :].squeeze().
 ↪numpy())
        return np.vstack(embeddings)

    def get_params(self, deep=True):
        return {"model_name": self.model_name, "max_length": self.max_length}

    def set_params(self, **parameters):
        for parameter, value in parameters.items():
            setattr(self, parameter, value)
        return self
```

[8]:
```
text_features = ['Tasks']
categorical_features = ['Task ID', 'User ID']
numerical_features = ['Business Value', 'Urgency', 'Stakeholder Priority',␣
 ↪'Complexity', 'Effort Estimation']
```

[9]:
```
text_pipeline = Pipeline([
    ('embedder', RobertaEmbedder()),
    ('pca', PCA(n_components=16))
])

categorical_pipeline = Pipeline([
    ('onehot', OneHotEncoder(handle_unknown='ignore'))
])

numerical_pipeline = Pipeline([
```

```
    ('scaler', StandardScaler())
])

preprocessor = ColumnTransformer([
    ('text', text_pipeline, 'Tasks'),
    ('cat', categorical_pipeline, categorical_features),
    ('num', numerical_pipeline, numerical_features)
])
```

```
/usr/local/lib/python3.11/dist-packages/huggingface_hub/utils/_auth.py:94:
UserWarning:
The secret `HF_TOKEN` does not exist in your Colab secrets.
To authenticate with the Hugging Face Hub, create a token in your settings tab
(https://huggingface.co/settings/tokens), set it as secret in your Google Colab
and restart your session.
You will be able to reuse this secret in all of your notebooks.
Please note that authentication is recommended but still optional to access
public models or datasets.
  warnings.warn(
```

```
tokenizer_config.json:   0%|          | 0.00/25.0 [00:00<?, ?B/s]

vocab.json:   0%|          | 0.00/899k [00:00<?, ?B/s]

merges.txt:   0%|          | 0.00/456k [00:00<?, ?B/s]

tokenizer.json:   0%|          | 0.00/1.36M [00:00<?, ?B/s]

config.json:   0%|          | 0.00/481 [00:00<?, ?B/s]

model.safetensors:   0%|          | 0.00/499M [00:00<?, ?B/s]
```

```
Some weights of RobertaModel were not initialized from the model checkpoint at
roberta-base and are newly initialized: ['pooler.dense.bias',
'pooler.dense.weight']
You should probably TRAIN this model on a down-stream task to be able to use it
for predictions and inference.
```

[10]:
```
model = RandomForestRegressor(random_state=42)

pipeline = Pipeline([
    ('preprocessor', preprocessor),
    ('regressor', model)
])
```

[11]:
```
param_distributions = {
    'regressor__n_estimators': [200],
    'regressor__max_depth': [18],
    'regressor__min_samples_split': [2],
    'regressor__min_samples_leaf': [2],
    'regressor__max_features': ['sqrt']
```

```
}
```

[12]:
```
y_train = y_train.replace([np.inf, -np.inf], np.nan)
y_train = y_train.fillna(y_train.mean())
```

[13]:
```
search = RandomizedSearchCV(
    pipeline,
    param_distributions,
    n_iter=5,
    cv=3,
    scoring='r2',
    verbose=2,
    n_jobs=-1,
    random_state=42
)

search.fit(X_train, y_train)
```

```
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You should probably TRAIN this model on a down-stream task to be able to use it
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/usr/local/lib/python3.11/dist-packages/sklearn/model_selection/_search.py:317:
UserWarning: The total space of parameters 1 is smaller than n_iter=5. Running 1
iterations. For exhaustive searches, use GridSearchCV.
  warnings.warn(
```

```
Fitting 3 folds for each of 1 candidates, totalling 3 fits
```

```
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```
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You should probably TRAIN this model on a down-stream task to be able to use it
for predictions and inference.
```

[13]:

```
RandomizedSearchCV(cv=3,
                   estimator=Pipeline(steps=[('preprocessor',
ColumnTransformer(transformers=[('text',
Pipeline(steps=[('embedder',
                 RobertaEmbedder()),
                ('pca',
                 PCA(n_components=16))]),
'Tasks'),
('cat',
Pipeline(steps=[('onehot',
                 OneHotEncoder(handle_unknown='ignore'))]),
['Task '
'ID',
'User '
'ID']),
('num',
Pipeline(steps=[('scaler',
                 StandardScaler())]),
['Bu…
'Stakeholder '
'Priority',
'Complexity',
'Effort '
'Estimation'])])),
                                              ('regressor',
RandomForestRegressor(random_state=42))]),
                   n_iter=5, n_jobs=-1,
                   param_distributions={'regressor__max_depth': [18],
                                        'regressor__max_features': ['sqrt'],
                                        'regressor__min_samples_leaf': [2],
                                        'regressor__min_samples_split': [2],
                                        'regressor__n_estimators': [200]},
                   random_state=42, scoring='r2', verbose=2)
```

[14]:

```python
def inverse_rank(user_ids, normalized_ranks, rank_min, rank_max):
    original_ranks = []
    for user_id, rank in zip(user_ids, normalized_ranks):
        min_rank = rank_min.loc[user_id]
        max_rank = rank_max.loc[user_id]
        original_rank = rank * (max_rank - min_rank) + min_rank
```

```
        original_ranks.append(original_rank)
    return np.array(original_ranks)
```

[15]:
```
rank_min_train = df.iloc[train_idx].groupby('User ID')['Rank'].min()
rank_max_train = df.iloc[train_idx].groupby('User ID')['Rank'].max()
```

[16]:
```
# Train set evaluation
y_train_pred = search.predict(X_train)
y_train_pred_orig_rank = inverse_rank(X_train['User ID'].values, y_train_pred,␣
 ↪rank_min_train, rank_max_train)
y_train_orig_rank = df.iloc[train_idx]['Rank'].values

print("\n--- Train Set Evaluation ---")
print("R2:", r2_score(y_train_orig_rank, y_train_pred_orig_rank))
print("MAE:", mean_absolute_error(y_train_orig_rank, y_train_pred_orig_rank))
print("MSE:", mean_squared_error(y_train_orig_rank, y_train_pred_orig_rank))
print("RMSE:", np.sqrt(mean_squared_error(y_train_orig_rank,␣
 ↪y_train_pred_orig_rank)))
```

```
--- Train Set Evaluation ---
R2: 0.7191720592112221
MAE: 3.0473688199242037
MSE: 19.13882563431295
RMSE: 4.37479435337399
```

[17]:
```
# Test set prediction
y_pred = search.predict(X_test)
rank_min = df.iloc[test_idx].groupby('User ID')['Rank'].min()
rank_max = df.iloc[test_idx].groupby('User ID')['Rank'].max()
y_pred_orig_rank = inverse_rank(X_test['User ID'].values, y_pred, rank_min,␣
 ↪rank_max)
y_test_orig_rank = df.iloc[test_idx]['Rank'].values

y_pred_orig_rank_rounded = np.round(y_pred_orig_rank).astype(int)
y_test_orig_rank_rounded = y_test_orig_rank.astype(int)
```

[18]:
```
# Create test_results_df, including necessary features for tie-breaking
test_results_df = pd.DataFrame({
    'User ID': X_test['User ID'],
    'Task ID': X_test['Task ID'],
    'Actual_Rank': y_test_orig_rank,
    'Predicted_Rank': y_pred_orig_rank_rounded,
    'Business Value': X_test['Business Value'],
    'Urgency': X_test['Urgency'],
    'Stakeholder Priority': X_test['Stakeholder Priority'],
    'Complexity': X_test['Complexity'],
```

```
    'Effort Estimation': X_test['Effort Estimation']
})
```

[19]:
```
# Tie-breaking before evaluation
def sequential_tie_breaker(group):
    group = group.copy()
    group = group.sort_values(
        by=['Predicted_Rank', 'Business Value', 'Urgency', 'Stakeholder␣
↪Priority', 'Complexity', 'Effort Estimation'],
        ascending=[True, False, False, False, False, False]
    ).reset_index(drop=True)
    group['Adjusted_Predicted_Rank'] = range(1, len(group) + 1)
    return group

test_results_df = test_results_df.groupby('User ID', group_keys=False).
↪apply(sequential_tie_breaker)
```

```
/tmp/ipython-input-19-183209242.py:11: DeprecationWarning:
DataFrameGroupBy.apply operated on the grouping columns. This behavior is
deprecated, and in a future version of pandas the grouping columns will be
excluded from the operation. Either pass `include_groups=False` to exclude the
groupings or explicitly select the grouping columns after groupby to silence
this warning.
  test_results_df = test_results_df.groupby('User ID',
group_keys=False).apply(sequential_tie_breaker)
```

[21]:
```
#Final test set evaluation
adjusted_r2 = r2_score(test_results_df['Actual_Rank'],␣
↪test_results_df['Adjusted_Predicted_Rank'])
adjusted_mae = mean_absolute_error(test_results_df['Actual_Rank'],␣
↪test_results_df['Adjusted_Predicted_Rank'])
adjusted_mse = mean_squared_error(test_results_df['Actual_Rank'],␣
↪test_results_df['Adjusted_Predicted_Rank'])
adjusted_rmse = np.sqrt(adjusted_mse)

print("\n--- Test Set Evaluation (After Tie-Breaking) ---")
print(f"R² Score: {adjusted_r2:.4f}")
print(f"Mean Absolute Error (MAE): {adjusted_mae:.4f}")
print(f"Mean Squared Error (MSE): {adjusted_mse:.4f}")
print(f"Root Mean Squared Error (RMSE): {adjusted_rmse:.4f}")
```

```
--- Test Set Evaluation (After Tie-Breaking) ---
R² Score: 0.9141
Mean Absolute Error (MAE): 1.0141
Mean Squared Error (MSE): 5.0704
Root Mean Squared Error (RMSE): 2.2518
```

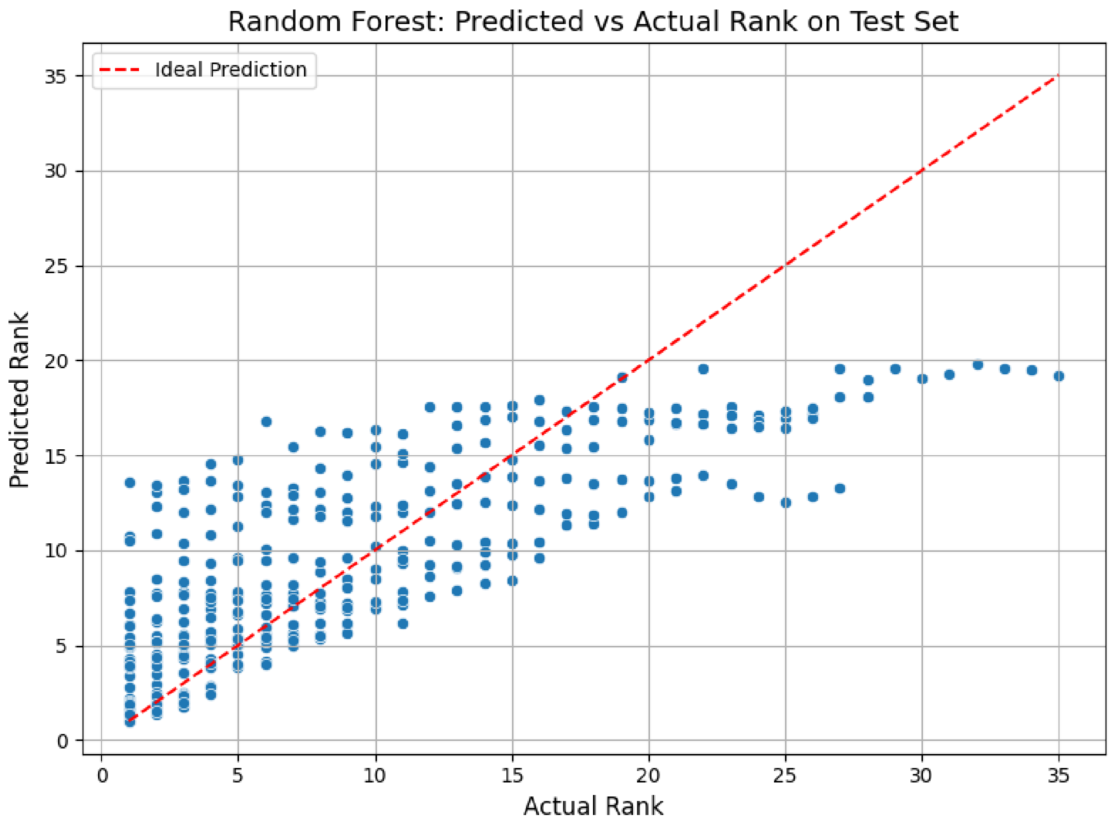
[22]:
```
test_results_df.to_csv("Random Forest_adjusted_unique_ranks.csv", index=False)
```

[24]:
```
from google.colab import files
files.download("Random Forest_adjusted_unique_ranks.csv")
```

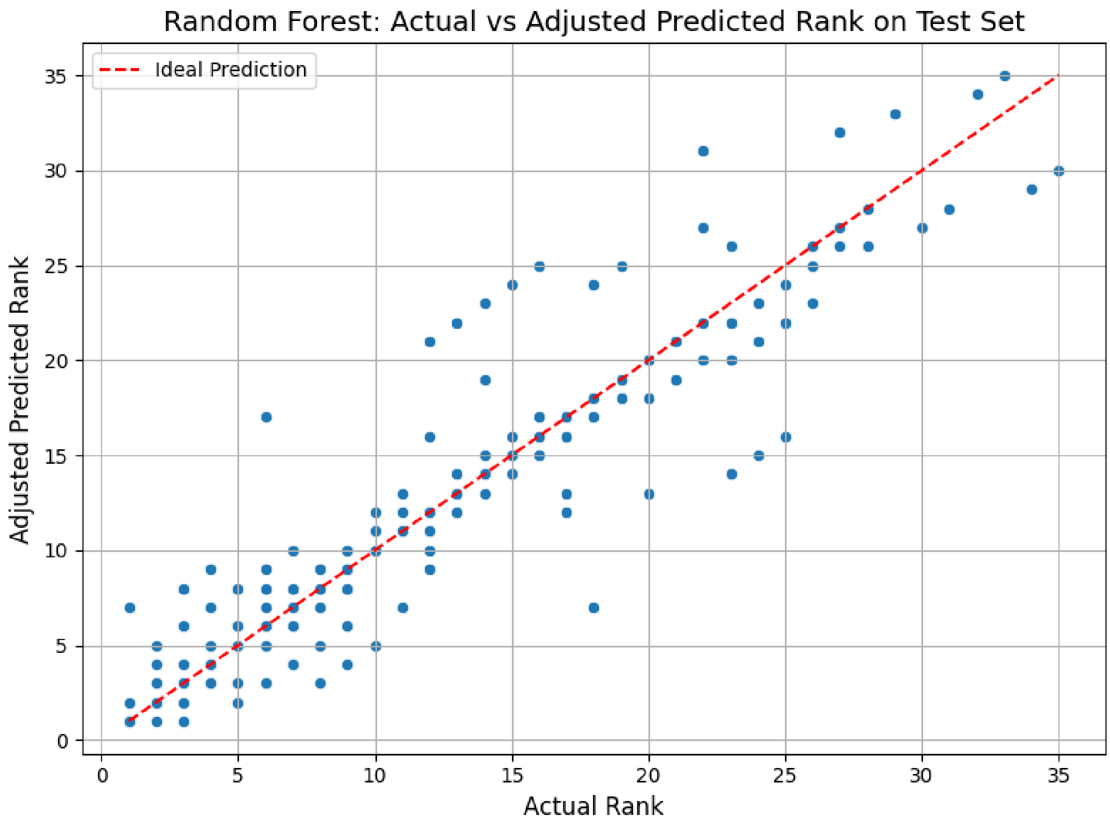
```
<IPython.core.display.Javascript object>
```

```
<IPython.core.display.Javascript object>
```

[23]:
```
import matplotlib.pyplot as plt
import seaborn as sns
plt.figure(figsize=(8, 6))
sns.scatterplot(
    x=df.iloc[test_idx]['Rank'],
    y=inverse_rank(X_test['User ID'].values, search.predict(X_test), rank_min,␣
 ↪rank_max)
)
plt.plot(
    [df.iloc[test_idx]['Rank'].min(), df.iloc[test_idx]['Rank'].max()],
    [df.iloc[test_idx]['Rank'].min(), df.iloc[test_idx]['Rank'].max()],
    color='red', linestyle='--', label='Ideal Prediction'
)
plt.xlabel('Actual Rank', fontsize=12)
plt.ylabel('Predicted Rank', fontsize=12)
plt.title('Random Forest: Predicted vs Actual Rank on Test Set', fontsize=14)
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```



[25]:
```
plt.figure(figsize=(8, 6))
sns.scatterplot(
    x=test_results_df['Actual_Rank'],
    y=test_results_df['Adjusted_Predicted_Rank']
)
plt.plot(
    [test_results_df['Actual_Rank'].min(), test_results_df['Actual_Rank'].
 ↪max()],
    [test_results_df['Actual_Rank'].min(), test_results_df['Actual_Rank'].
 ↪max()],
    color='red', linestyle='--', label='Ideal Prediction'
)
plt.xlabel('Actual Rank', fontsize=12)
plt.ylabel('Adjusted Predicted Rank', fontsize=12)
plt.title('Random Forest: Actual vs Adjusted Predicted Rank on Test Set',␣
 ↪fontsize=14)
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```


Random Forest: Actual vs Adjusted Predicted Rank on Test Set
Ideal Prediction
Adjusted Predicted Rank
Actual Rank
0
5
10
15
20
25
30
35