Factors Influencing Steam Game Success: A Predictive Analysis of Positive Ratings

In this project, we aim to analyze what factors may have contributed to a positive rate of the game on Steam using a comprehensive dataset of information on games. We will investigate the relationship between several game variances (price, developer, game type..etc) and the positive rate percentage. By using the technique we learned from this course, we wish to find the key factors that contribute the most to game success and develop a model to predict the game's potential positive rate depending on its features.

Loading and Visualizing the Data

Download the Steam games dataset from Kaggle.

We first get a glimpse of the data within each spreadsheet. This helps to get a feel for what the datasets look like before further analysis.

The dataset contains various features such as appid, genre, developer, release date, price, user ratings, etc.

```
import pandas as pd
steam_requirements_data = pd.read_csv('/content/steam_requirements_data.csv', encoding='latin-1')
steamspy_tag_data = pd.read_csv('/content/steamspy_tag_data.csv')
steam_data = pd.read_csv('/content/steam.csv')
```

```
datasets_overview = {
    "steam_requirements_data": steam_requirements_data.head(),
    "steamspy_tag_data": steamspy_tag_data.head(),
    "steam_data": steam_data.head()
}
datasets_overview
```

```
 4     50      0     77     0   0          0         0   0             0

    3d_vision  ...  warhammer_40k  web_publishing  werewolves  western  \
 0          0  ...              0               0           0        0
 1          0  ...              0               0           0        0
 2          0  ...              0               0           0        0
 3          0  ...              0               0           0        0
 4          0  ...              0               0           0        0

    word_game  world_war_i  world_war_ii  wrestling  zombies  e_sports
 0          0            0             0          0        0       550
 1          0            0             0          0        0         0
 2          0            5           122          0        0         0
```

```
   negative_ratings  average_playtime  median_playtime             owners  \
0              3339             17612              317  10000000-20000000
1               633               277               62   5000000-10000000
2               398               187               34   5000000-10000000
3               267               258              184   5000000-10000000
4               288               624              415   5000000-10000000

   price
0   7.19
1   3.99
2   3.99
3   3.99
4   3.99  }
```

```
column_names = {
    "steam_data": steam_data.columns.tolist(),
    "steamspy_tag_data": steamspy_tag_data.columns.tolist(),
    "steam_requirements_data": steam_requirements_data.columns.tolist(),
}
column_names
```

```
       'linear',
       'local_co_op',
       'local_multiplayer',
       'logic',
       'loot',
       'lore_rich',
       'lovecraftian',
       'mmorpg',
       'moba',
       'magic',
       'management',
       'mars',
       'martial_arts',
       'massively_multiplayer',
       'masterpiece',
       'match_3',
       'mature',
       'mechs',
       'medieval',
       'memes',
       'metroidvania',
       'military',
       'mini_golf',
       'minigames',
       'minimalist',
       'mining',
       'mod',
       'moddable',
       'modern',
       'motocross',
       'motorbike',
       'mouse_only',
       'movie',
       'multiplayer',
       'multiple_endings',
       'music',
       'music_based_procedural_generation',
       'mystery',
       'mystery_dungeon',
       'mythology',
       'nsfw',
       'narration',
       'naval',
       'ninja',
       'noir',
       'nonlinear',
       'nudity',
       'offroad',
       'old_school',
       'on_rails_shooter',
       'online_co_op',
       'open_world',
       'otome',
       'parkour',
       'parody_',
       'party_based_rpg',
       'perma_death',
       'philisophical',
       'photo_editing',
```

```
merged_df = pd.merge(
    steam_data,
    steamspy_tag_data,
```

```
    on='appid',
    how='left',
    suffixes=('', '_tags')
)

final_merged_df = pd.merge(
    merged_df,
    steam_requirements_data,
    on='appid',
    how='left',
    suffixes=('', '_req')
)

# Check for any missing values after merge
missing_values = final_merged_df.isnull().sum()
print("\nMissing values in merged dataset:")
print(missing_values[missing_values > 0])

# Save the merged dataset
final_merged_df.to_csv('merged_steam_data.csv', index=False)
print("\nMerged dataset has been saved as 'merged_steam_data.csv'")

print(f"\nFinal merged dataset rows: {len(final_merged_df)}")
```

```
Missing values in merged dataset:
developer                1
publisher               14
pc_requirements         13
mac_requirements        13
linux_requirements      13
minimum                 18
recommended          13057
dtype: int64

Merged dataset has been saved as 'merged_steam_data.csv'

Final merged dataset rows: 27075
```

```
import numpy as np
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.ensemble import RandomForestRegressor
from sklearn.linear_model import LinearRegression
from sklearn.neural_network import MLPRegressor
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
from sklearn.decomposition import PCA
from datetime import datetime

# Load the merged dataset
df = pd.read_csv('merged_steam_data.csv', encoding='latin-1')

# Define game types (now as numerical features)
game_types = ['1980s', '1990s', '2.5d', '2d', '2d_fighter', '360_video', '3d', '3d_platformer',
              '3d_vision', '4_player_local', '4x', '6dof', 'atv', 'abstract', 'action', 'action_rpg',
              'action_adventure', 'addictive', 'adventure', 'agriculture', 'aliens', 'alternate_history',
              'america', 'animation_&_modeling', 'anime', 'arcade', 'arena_shooter', 'artificial_intelligence',
              'assassin', 'asynchronous_multiplayer', 'atmospheric', 'audio_production', 'bmx', 'base_building',
              'baseball', 'based_on_a_novel', 'basketball', 'batman', 'battle_royale', 'beat_em_up',
              'beautiful', 'benchmark', 'bikes', 'blood', 'board_game', 'bowling', 'building', 'bullet_hell',
              'bullet_time', 'crpg', 'capitalism', 'card_game', 'cartoon', 'cartoony', 'casual', 'cats',
              'character_action_game', 'character_customization', 'chess', 'choices_matter',
              'choose_your_own_adventure', 'cinematic', 'city_builder', 'class_based', 'classic', 'clicker',
              'co_op', 'co_op_campaign', 'cold_war', 'colorful', 'comedy', 'comic_book', 'competitive',
              'conspiracy', 'controller', 'conversation', 'crafting', 'crime', 'crowdfunded', 'cult_classic',
              'cute', 'cyberpunk', 'cycling', 'dark', 'dark_comedy', 'dark_fantasy', 'dark_humor',
              'dating_sim', 'demons', 'design_&_illustration', 'destruction', 'detective', 'difficult',
              'dinosaurs', 'diplomacy', 'documentary', 'dog', 'dragons', 'drama', 'driving',
              'dungeon_crawler', 'dungeons_&_dragons', 'dynamic_narration', 'dystopian_', 'early_access',
              'economy', 'education', 'emotional', 'epic', 'episodic', 'experience', 'experimental',
              'exploration', 'fmv', 'fps', 'faith', 'family_friendly', 'fantasy', 'fast_paced',
              'feature_film', 'female_protagonist', 'fighting', 'first_person', 'fishing', 'flight',
              'football', 'foreign', 'free_to_play', 'funny', 'futuristic', 'gambling', 'game_development',
              'gamemaker', 'games_workshop', 'gaming', 'god_game', 'golf', 'gore', 'gothic',
              'grand_strategy', 'great_soundtrack', 'grid_based_movement', 'gun_customization',
```

```
            'hack_and_slash', 'hacking', 'hand_drawn', 'hardware', 'heist', 'hex_grid', 'hidden_object',
            'historical', 'hockey', 'horror', 'horses', 'hunting', 'illuminati', 'indie',
            'intentionally_awkward_controls', 'interactive_fiction', 'inventory_management',
            'investigation', 'isometric', 'jrpg', 'jet', 'kickstarter', 'lego', 'lara_croft',
            'lemmings', 'level_editor', 'linear', 'local_co_op', 'local_multiplayer', 'logic', 'loot',
            'lore_rich', 'lovecraftian', 'mmorpg', 'moba', 'magic', 'management', 'mars', 'martial_arts',
            'massively_multiplayer', 'masterpiece', 'match_3', 'mature', 'mechs', 'medieval', 'memes',
            'metroidvania', 'military', 'mini_golf', 'minigames', 'minimalist', 'mining', 'mod',
            'moddable', 'modern', 'motocross', 'motorbike', 'mouse_only', 'movie', 'multiplayer',
            'multiple_endings', 'music', 'music_based_procedural_generation', 'mystery', 'mystery_dungeon',
            'mythology', 'nsfw', 'narration', 'naval', 'ninja', 'noir', 'nonlinear', 'nudity',
            'offroad', 'old_school', 'on_rails_shooter', 'online_co_op', 'open_world', 'otome',
            'parkour', 'parody_', 'party_based_rpg', 'perma_death', 'philisophical', 'photo_editing',
            'physics', 'pinball', 'pirates', 'pixel_graphics', 'platformer', 'point_&_click',
            'political', 'politics', 'pool', 'post_apocalyptic', 'procedural_generation', 'programming',
            'psychedelic', 'psychological', 'psychological_horror', 'puzzle', 'puzzle_platformer',
            'pve', 'pvp', 'quick_time_events', 'rpg', 'rpgmaker', 'rts', 'racing', 'real_time_tactics',
            'real_time', 'real_time_with_pause', 'realistic', 'relaxing', 'remake', 'replay_value',
            'resource_management', 'retro', 'rhythm', 'robots', 'rogue_like', 'rogue_lite', 'romance',
            'rome', 'runner', 'sailing', 'sandbox', 'satire', 'sci_fi', 'science', 'score_attack',
            'sequel', 'sexual_content', 'shoot_em_up', 'shooter', 'short', 'side_scroller',
            'silent_protagonist', 'simulation', 'singleplayer', 'skateboarding', 'skating', 'skiing',
            'sniper', 'snow', 'snowboarding', 'soccer', 'software', 'software_training', 'sokoban',
            'souls_like', 'soundtrack', 'space', 'space_sim', 'spectacle_fighter', 'spelling',
            'split_screen', 'sports', 'star_wars', 'stealth', 'steam_machine', 'steampunk',
            'story_rich', 'strategy', 'strategy_rpg', 'stylized', 'submarine', 'superhero',
            'supernatural', 'surreal', 'survival', 'survival_horror', 'swordplay', 'tactical',
            'tactical_rpg', 'tanks', 'team_based', 'tennis', 'text_based', 'third_person',
            'third_person_shooter', 'thriller', 'time_attack', 'time_management', 'time_manipulation',
            'time_travel', 'top_down', 'top_down_shooter', 'touch_friendly', 'tower_defense',
            'trackir', 'trading', 'trading_card_game', 'trains', 'transhumanism', 'turn_based',
            'turn_based_combat', 'turn_based_strategy', 'turn_based_tactics', 'tutorial',
            'twin_stick_shooter', 'typing', 'underground', 'underwater', 'unforgiving', 'utilities',
            'vr', 'vr_only', 'vampire', 'video_production', 'villain_protagonist', 'violent',
            'visual_novel', 'voice_control', 'voxel', 'walking_simulator', 'war', 'wargame',
            'warhammer_40k', 'web_publishing', 'werewolves', 'western', 'word_game', 'world_war_i',
            'world_war_ii', 'wrestling', 'zombies', 'e_sports']
def prepare_features(df, use_pca=False, n_components=50):
    """
    Prepare features with option for PCA transformation
    """
    # Convert release_date to datetime features
    df['release_date'] = pd.to_datetime(df['release_date'])
    df['release_year'] = df['release_date'].dt.year
    df['release_month'] = df['release_date'].dt.month

    # Basic numerical features
    basic_numeric_features = [
        'price', 'release_year', 'release_month', 'required_age',
        'achievements', 'average_playtime', 'median_playtime'
    ]

    # Categorical features
    categorical_features = ['developer', 'publisher']

    if use_pca:
        # Get game type columns
        game_type_data = df[game_types]

        # Standardize game type data
        scaler = StandardScaler()
        game_type_scaled = scaler.fit_transform(game_type_data)

        # Apply PCA
        pca = PCA(n_components=n_components)
        game_type_pca = pca.fit_transform(game_type_scaled)

        # Create DataFrame with PCA components
        pca_cols = [f'game_type_pc_{i+1}' for i in range(n_components)]
        game_type_pca_df = pd.DataFrame(game_type_pca, columns=pca_cols)

        # Print PCA analysis
        cumulative_variance_ratio = np.cumsum(pca.explained_variance_ratio_)
        print("\nPCA Analysis:")
        print(f"Explained variance ratio by {n_components} components: {cumulative_variance_ratio[-1]:.4f}")

        # Save PCA component analysis
```

```
        component_correlations = pd.DataFrame()
        for i in range(5):
            correlations = pd.Series(pca.components_[i], index=game_types)
            top_correlations = correlations.abs().sort_values(ascending=False).head(10)
            component_correlations[f'PC{i+1}_features'] = [f"{game}: {correlations[game]:.3f}"
                                                         for game in top_correlations.index]
        component_correlations.to_csv('pca_component_analysis.csv', index=False)

        # Combine features
        base_features = df[basic_numeric_features + categorical_features]
        final_df = pd.concat([base_features, game_type_pca_df], axis=1)
        return final_df, pca, scaler

    else:
        # Use original game type features
        game_type_columns = [col for col in df.columns if col in game_types]
        all_features = basic_numeric_features + categorical_features + game_type_columns
        return df[all_features], None, None


def evaluate_model(model, X, y, cv=3, sample_size=1000):
    """
    Evaluate model with cross-validation and optional sampling
    """
    if len(X) > sample_size:
        sample_idx = np.random.choice(len(X), sample_size, replace=False)
        X_sample = X.iloc[sample_idx]
        y_sample = y.iloc[sample_idx]
    else:
        X_sample = X
        y_sample = y

    cv_scores = cross_val_score(model, X_sample, y_sample, cv=cv, scoring='r2')
    return {
        'mean_cv_r2': cv_scores.mean(),
        'std_cv_r2': cv_scores.std()
    }



def create_models(use_pca=False):
    """
    Create model pipelines with appropriate parameters
    """
    return {
        'Random Forest': Pipeline([
            ('preprocessor', preprocessor),
            ('regressor', RandomForestRegressor(
                n_estimators=50,
                max_depth=10 if use_pca else 15,
                min_samples_split=10,
                n_jobs=-1,
                random_state=42
            ))
        ]),
        'Linear Regression': Pipeline([
            ('preprocessor', preprocessor),
            ('regressor', LinearRegression())
        ]),
        'Neural Network': Pipeline([
            ('preprocessor', preprocessor),
            ('regressor', MLPRegressor(
                hidden_layer_sizes=(64, 32),
                max_iter=500,                 # Increased from 200
                learning_rate_init=0.001,     # Added explicit learning rate
                alpha=0.0001,                 # L2 regularization term
                early_stopping=True,
                validation_fraction=0.1,
                n_iter_no_change=20,          # Increased patience
                random_state=42
            ))
        ])
    }

def train_and_evaluate(models, X_train, X_test, y_train, y_test, X_full, y_full):
    """
    Train and evaluate models, returning results
    """
```

```
    results = {}
    for name, model in models.items():
        print(f"\nTraining {name}...")

        # Cross-validation
        cv_results = evaluate_model(model, X_full, y_full)

        # Train and evaluate
        model.fit(X_train, y_train)
        y_pred = model.predict(X_test)

        results[name] = {
            'r2': r2_score(y_test, y_pred),
            'rmse': np.sqrt(mean_squared_error(y_test, y_pred)),
            'mae': mean_absolute_error(y_test, y_pred),
            'cv_r2_mean': cv_results['mean_cv_r2'],
            'cv_r2_std': cv_results['std_cv_r2'],
            'predictions': y_pred
        }

    return results
```

Model Traning

For this project, we attempt to use

- Multi-linear regression
- Random Forest Model
- Neural Networks

for model fitting to predict positive ratings for new games, and then assesses how well the model performed using R^2 and RMSE.

```
y = df['positive_ratings']


X_original, _, _ = prepare_features(df, use_pca=False)
X_train_orig, X_test_orig, y_train, y_test = train_test_split(X_original, y, test_size=0.2, random_state=42)

# PCA
X_pca, pca, scaler = prepare_features(df, use_pca=True, n_components=50)
X_train_pca, X_test_pca, y_train_pca, y_test_pca = train_test_split(X_pca, y, test_size=0.2, random_state=42)

# Create preprocessing pipelines for both approaches
numeric_features_orig = X_original.select_dtypes(include=['int64', 'float64']).columns
categorical_features_orig = X_original.select_dtypes(include=['object']).columns

numeric_features_pca = X_pca.select_dtypes(include=['int64', 'float64']).columns
categorical_features_pca = X_pca.select_dtypes(include=['object']).columns

# Train and evaluate models for both approaches
print("\nTraining models with original features...")
preprocessor = ColumnTransformer(
    transformers=[
        ('num', StandardScaler(), numeric_features_orig),
        ('cat', OneHotEncoder(handle_unknown='ignore'), categorical_features_orig)
    ])
original_models = create_models(use_pca=False)
original_results = train_and_evaluate(original_models, X_train_orig, X_test_orig,
                                      y_train, y_test, X_original, y)

print("\nTraining models with PCA features...")
preprocessor = ColumnTransformer(
    transformers=[
        ('num', StandardScaler(), numeric_features_pca),
        ('cat', OneHotEncoder(handle_unknown='ignore'), categorical_features_pca)
    ])
pca_models = create_models(use_pca=True)
pca_results = train_and_evaluate(pca_models, X_train_pca, X_test_pca,
                                 y_train_pca, y_test_pca, X_pca, y)
```

```
Training Linear Regression...

Training Neural Network...

Training models with PCA features...

Training Random Forest...

Training Linear Regression...

Training Neural Network...

Original Features Results:
--------------------------------------------------

Random Forest:
Test R² Score: 0.8260
Cross-val R² Score: 0.5656 (±0.1757)
RMSE: 4310.62
MAE: 429.84

Linear Regression:
Test R² Score: 0.4133
Cross-val R² Score: -0.8359 (±1.4647)
RMSE: 7916.27
MAE: 1320.87

Neural Network:
Test R² Score: 0.4456
Cross-val R² Score: 0.1032 (±0.1938)
RMSE: 7695.40
MAE: 864.79

PCA Features Results:
--------------------------------------------------

Random Forest:
Test R² Score: -0.3729
Cross-val R² Score: 0.5105 (±0.0307)
RMSE: 12109.59
MAE: 704.14

Linear Regression:
Test R² Score: 0.5273
Cross-val R² Score: -0.6606 (±1.0588)
RMSE: 7105.39
MAE: 1246.31

Neural Network:
Test R² Score: 0.6803
Cross-val R² Score: 0.4108 (±0.0867)
RMSE: 5843.18
MAE: 710.01
```

Comparison

Compare the efficiency of multiple linear regression, neural networks, and random forest regression models.

For evaluation, we are using appropriate metrics (like Mean Absolute Error, Mean Squared Error, R-squared) to compare their performance.

```
def print_results(results, approach_name):
    print(f"\n{approach_name} Results:")
    print("-" * 50)
    for name, result in results.items():
        print(f"\n{name}:")
        print(f"Test R² Score: {result['r2']:.4f}")
        print(f"Cross-val R² Score: {result['cv_r2_mean']:.4f} (±{result['cv_r2_std']:.4f})")
        print(f"RMSE: {result['rmse']:.2f}")
        print(f"MAE: {result['mae']:.2f}")

print_results(original_results, "Original Features")
print_results(pca_results, "PCA Features")
```

```
Original Features Results:
--------------------------------------------------

Random Forest:
Test R² Score: 0.8260
Cross-val R² Score: 0.5656 (±0.1757)
```

```
RMSE: 4310.62
MAE: 429.84

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Test R² Score: 0.4133
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--------------------------------------------------

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RMSE: 5843.18
MAE: 710.01
```
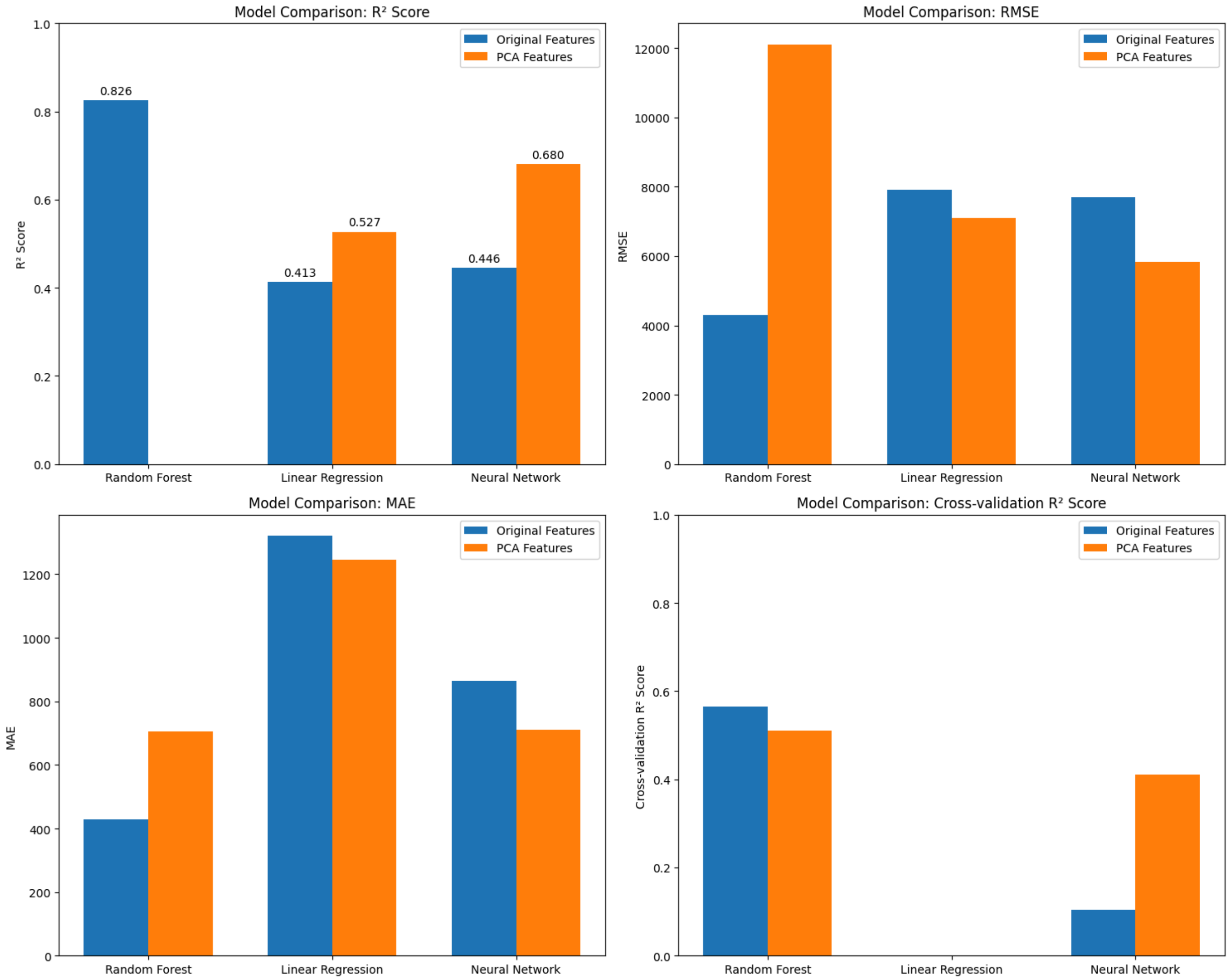
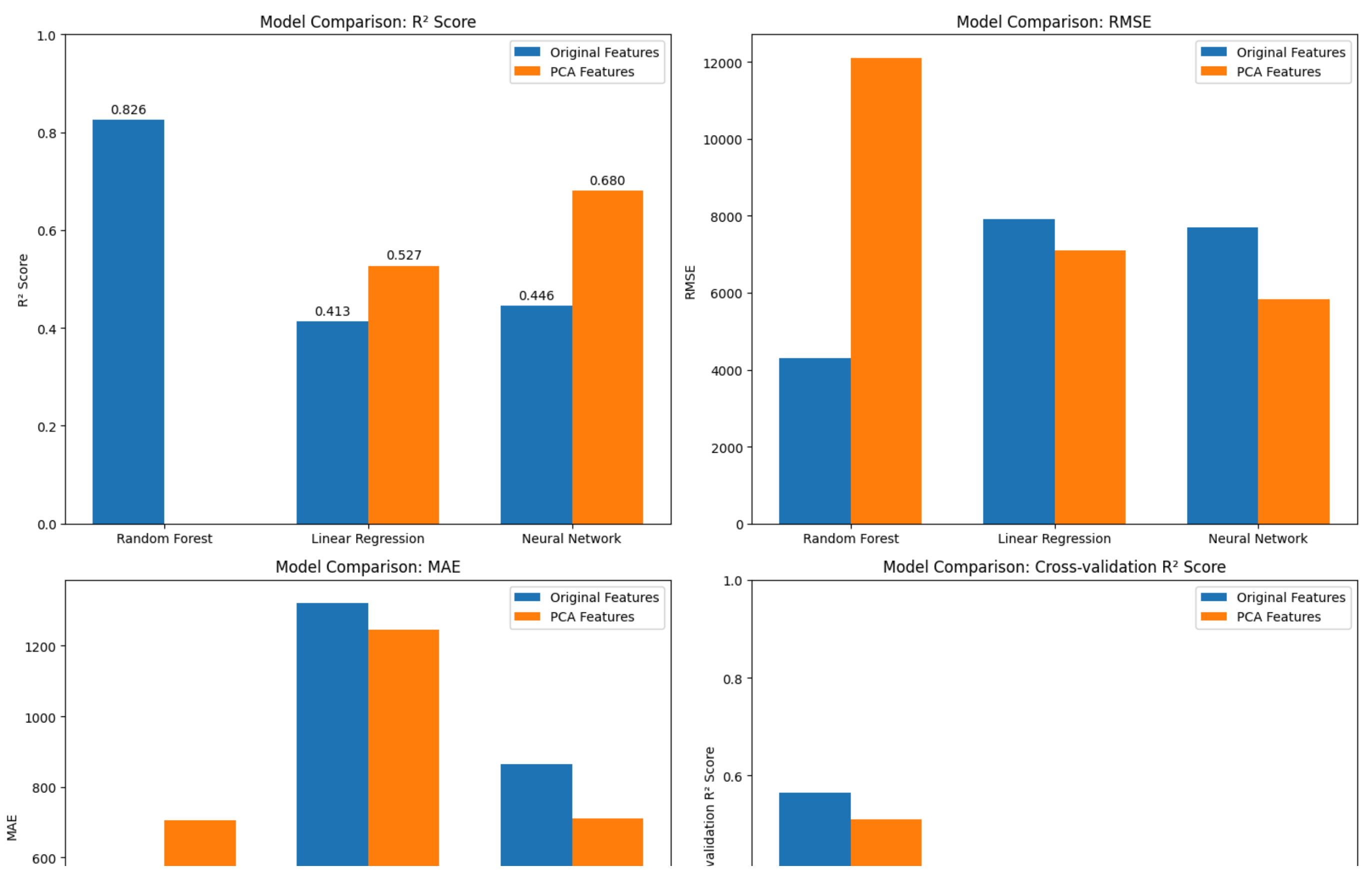
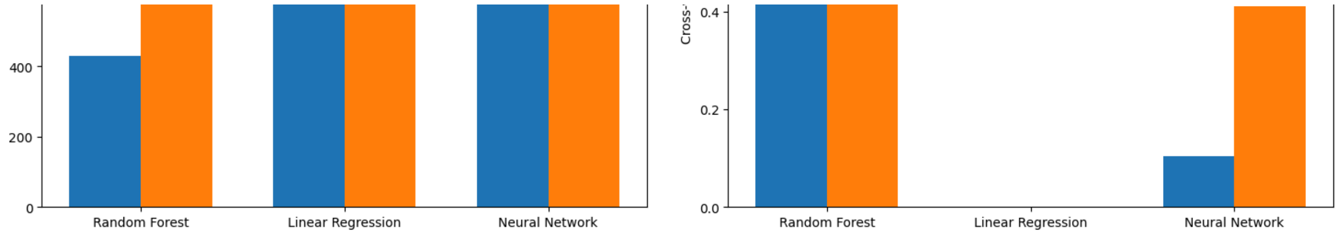

```
import matplotlib.pyplot as plt


def plot_model_comparison(original_results, pca_results):

    # Create figure with subplots
    fig, ((ax1, ax2), (ax3, ax4)) = plt.subplots(2, 2, figsize=(15, 12))

    # Prepare data
    models = ['Random Forest', 'Linear Regression', 'Neural Network']
    x = np.arange(len(models))
    width = 0.35

    # Get metrics
    original_r2 = [original_results[m]['r2'] for m in models]
    pca_r2 = [pca_results[m]['r2'] for m in models]

    original_rmse = [original_results[m]['rmse'] for m in models]
    pca_rmse = [pca_results[m]['rmse'] for m in models]

    original_mae = [original_results[m]['mae'] for m in models]
    pca_mae = [pca_results[m]['mae'] for m in models]

    original_cv = [original_results[m]['cv_r2_mean'] for m in models]
    pca_cv = [pca_results[m]['cv_r2_mean'] for m in models]

    # Plot R² Scores
    rects1 = ax1.bar(x - width/2, original_r2, width, label='Original Features')
    rects2 = ax1.bar(x + width/2, pca_r2, width, label='PCA Features')

    ax1.set_ylabel('R² Score')
    ax1.set_title('Model Comparison: R² Score')
    ax1.set_xticks(x)
    ax1.set_xticklabels(models)
    ax1.legend()
    ax1.set_ylim(0, 1)

    # Add value labels
    def autolabel(rects, ax):
        for rect in rects:
            height = rect.get_height()
            ax.annotate(f'{height:.3f}',
                        xy=(rect.get_x() + rect.get_width() / 2, height),
```

```
                        xytext=(0, 3),
                        textcoords="offset points",
                        ha='center', va='bottom', rotation=0)

        autolabel(rects1, ax1)
        autolabel(rects2, ax1)

        # Plot RMSE
        ax2.bar(x - width/2, original_rmse, width, label='Original Features')
        ax2.bar(x + width/2, pca_rmse, width, label='PCA Features')

        ax2.set_ylabel('RMSE')
        ax2.set_title('Model Comparison: RMSE')
        ax2.set_xticks(x)
        ax2.set_xticklabels(models)
        ax2.legend()

        # Plot MAE
        ax3.bar(x - width/2, original_mae, width, label='Original Features')
        ax3.bar(x + width/2, pca_mae, width, label='PCA Features')

        ax3.set_ylabel('MAE')
        ax3.set_title('Model Comparison: MAE')
        ax3.set_xticks(x)
        ax3.set_xticklabels(models)
        ax3.legend()

        # Plot Cross-validation R² Scores
        ax4.bar(x - width/2, original_cv, width, label='Original Features')
        ax4.bar(x + width/2, pca_cv, width, label='PCA Features')

        ax4.set_ylabel('Cross-validation R² Score')
        ax4.set_title('Model Comparison: Cross-validation R² Score')
        ax4.set_xticks(x)
        ax4.set_xticklabels(models)
        ax4.legend()
        ax4.set_ylim(0, 1)

        plt.tight_layout()

        # Save the plot
        plt.savefig('model_comparison.png', dpi=300, bbox_inches='tight')
        plt.show()

    # Call the plotting function
    plot_model_comparison(original_results, pca_results)

    # Create additional visualizations for feature importance (for Random Forest)
    def plot_feature_importance(rf_pipeline, feature_names, n_features=20):
        plt.figure(figsize=(12, 6))

        if hasattr(rf_pipeline.named_steps['regressor'], 'feature_importances_'):
            importances = rf_pipeline.named_steps['regressor'].feature_importances_

            # Create DataFrame and sort
            feat_imp = pd.DataFrame({
                'Feature': feature_names,
                'Importance': importances
            }).sort_values('Importance', ascending=True)

            # Plot top n features
            plt.barh(feat_imp['Feature'].tail(n_features), feat_imp['Importance'].tail(n_features), color='skyblue')
            plt.title(f'Top {n_features} Most Important Features (Random Forest)')
            plt.xlabel('Importance')

            plt.tight_layout()
            plt.savefig('feature_importance.png', dpi=300, bbox_inches='tight')
            plt.show()
    plot_model_comparison(original_results, pca_results)
```

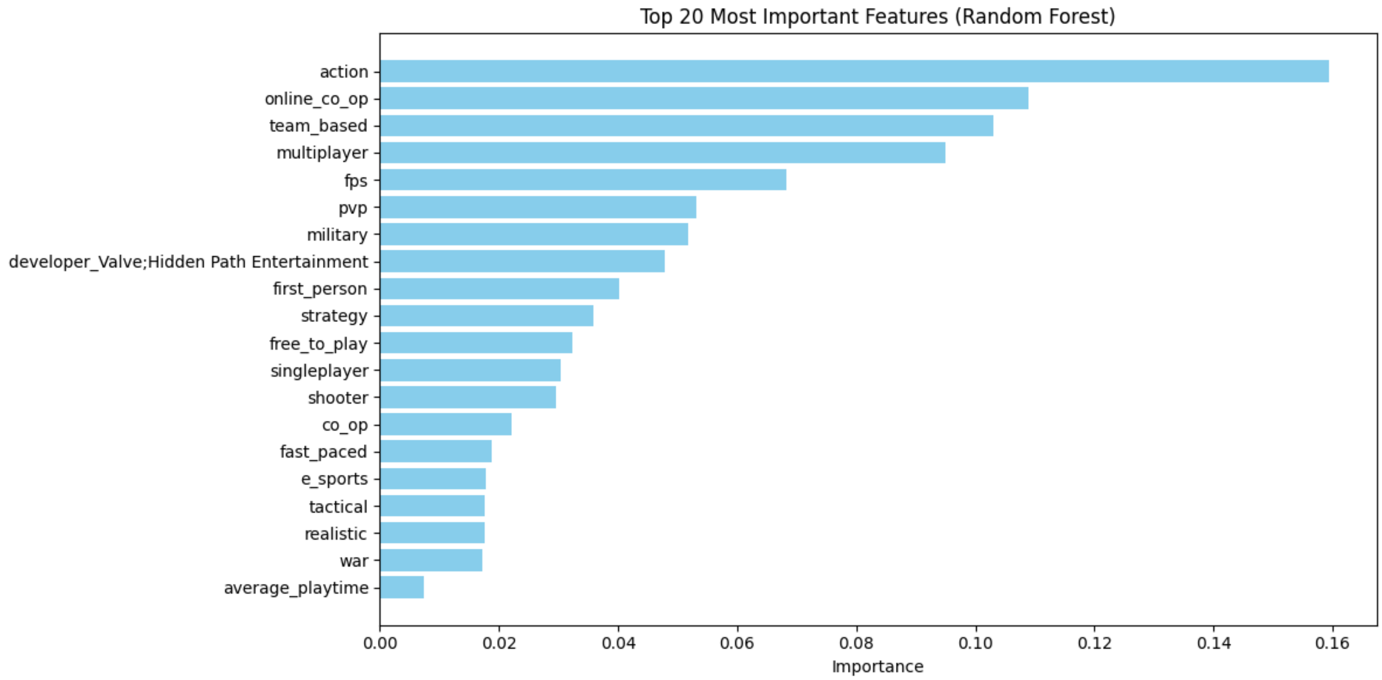

Model Comparison: R² Score
R² Score
Original Features
PCA Features
0.826
0.413
0.527
0.446
0.680
Random Forest
Linear Regression
Neural Network
Model Comparison: RMSE
RMSE
Model Comparison: MAE
MAE
Model Comparison: Cross-validation R² Score
Cross-validation R² Score


Model Comparison: R² Score
R² Score
Original Features
PCA Features
0.826
0.413
0.527
0.446
0.680
Random Forest
Linear Regression
Neural Network
Model Comparison: RMSE
RMSE
Model Comparison: MAE
MAE
Model Comparison: Cross-validation R² Score


400
200
0
Random Forest
Linear Regression
Neural Network
Cross-
0.4
0.2
0.0
Random Forest
Linear Regression
Neural Network

Then, let us look at the importance of different features based on the random forest to see what may be the main factors concerning the success of games.

```
# Feature importance for Random Forest
rf_pipeline = original_models['Random Forest']

# Now plot feature importance
feature_names = (numeric_features_orig.tolist() +
                rf_pipeline.named_steps['preprocessor']
                .named_transformers_['cat']
                .get_feature_names_out(categorical_features_orig).tolist())
plot_feature_importance(rf_pipeline, feature_names)
```



Segmenting Analysis

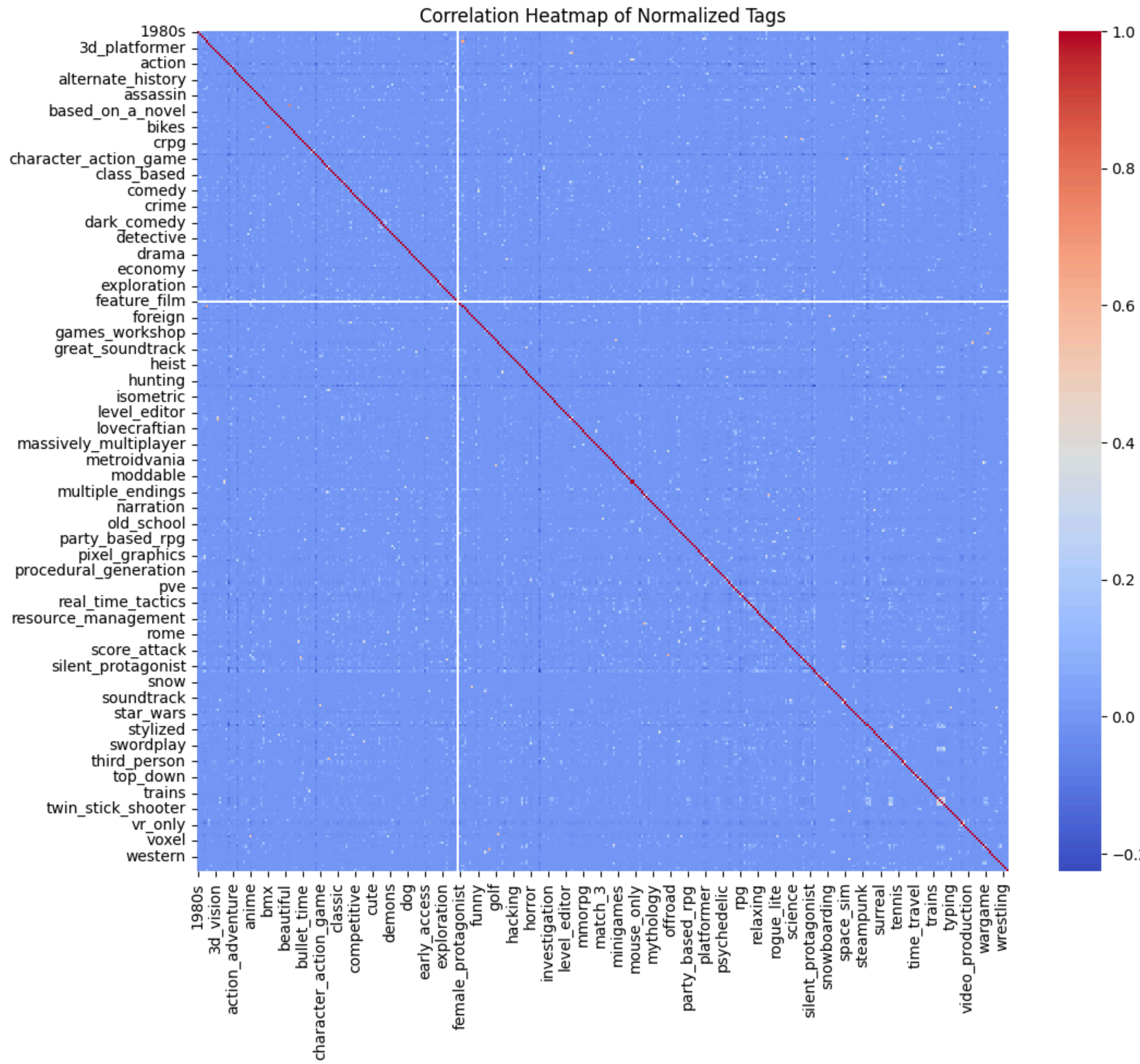
If we look closely to the Supplementary file of the dataset. It contains tags from SteamSpy and the number of votes for each tag for each game. Higher numbers can be considered more strongly associated with that tag.

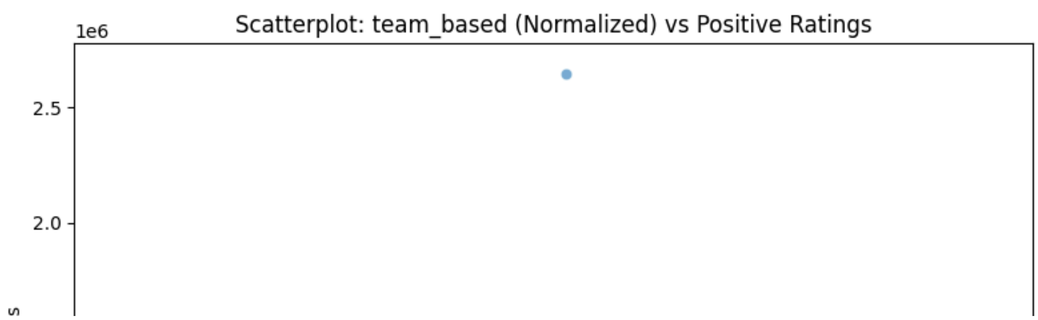
Tags & Genre-Specific Analysis: Certain genres may respond differently to various factors (e.g., narrative depth for RPGs versus multiplayer dynamics for shooters). Understanding these nuances can aid developers in creating genre-appropriate gameplay and marketing strategies.

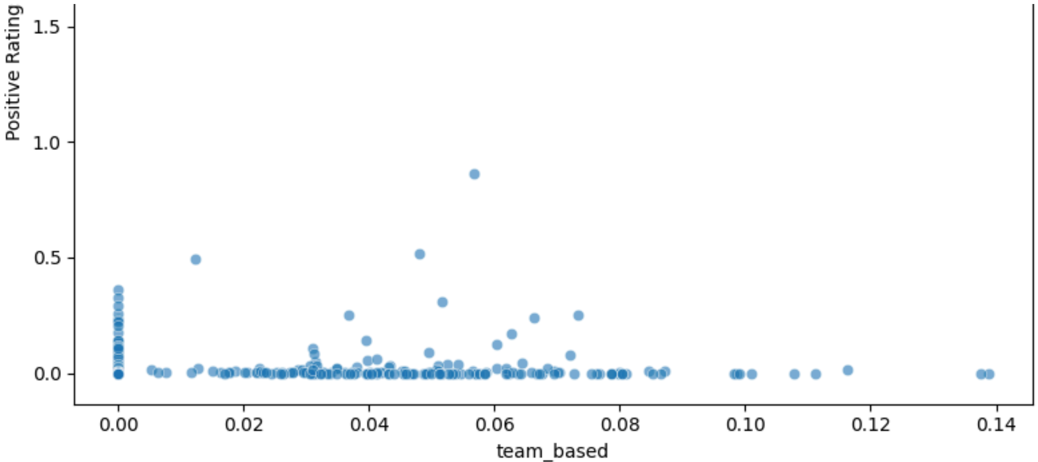
```
import seaborn as sns

tag_columns = [col for col in steamspy_tag_data.columns if col != 'appid']

# Normalize tag values by summing across all games
total_tag_votes = df[tag_columns].sum(axis=1)
normalized_tags = df[tag_columns].div(total_tag_votes, axis=0)

# Correlation between normalized tags and positive ratings
correlations = normalized_tags.corrwith(df['positive_ratings'])
correlations_sorted = correlations.sort_values(ascending=False)

# Display top 10 tags by correlation
print("Top 10 Tags by Correlation with Positive Ratings (Normalized):")
print(correlations_sorted.head(10))

# Visualization: Correlation heatmap of normalized tags
plt.figure(figsize=(12, 10))
```

```
sns.heatmap(normalized_tags.corr(), cmap='coolwarm', annot=False, cbar=True)
plt.title('Correlation Heatmap of Normalized Tags')
plt.show()

# Visualization: Top 10 normalized tags by correlation with scatterplots
for tag in correlations_sorted.head(10).index:
    plt.figure(figsize=(8, 6))
    sns.scatterplot(x=normalized_tags[tag], y=df['positive_ratings'], alpha=0.6)
    plt.title(f'Scatterplot: {tag} (Normalized) vs Positive Ratings')
    plt.xlabel(tag)
    plt.ylabel('Positive Ratings')
    plt.tight_layout()
    plt.show()

# Visualization: Top 10 tags by total normalized votes
normalized_tag_sums = normalized_tags.sum().sort_values(ascending=False)
plt.figure(figsize=(12, 6))
sns.barplot(x=normalized_tag_sums.head(10).index, y=normalized_tag_sums.head(10).values)
plt.title('Top 10 Tags by Total Normalized Votes')
plt.ylabel('Total Normalized Votes')
plt.xlabel('Tags')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

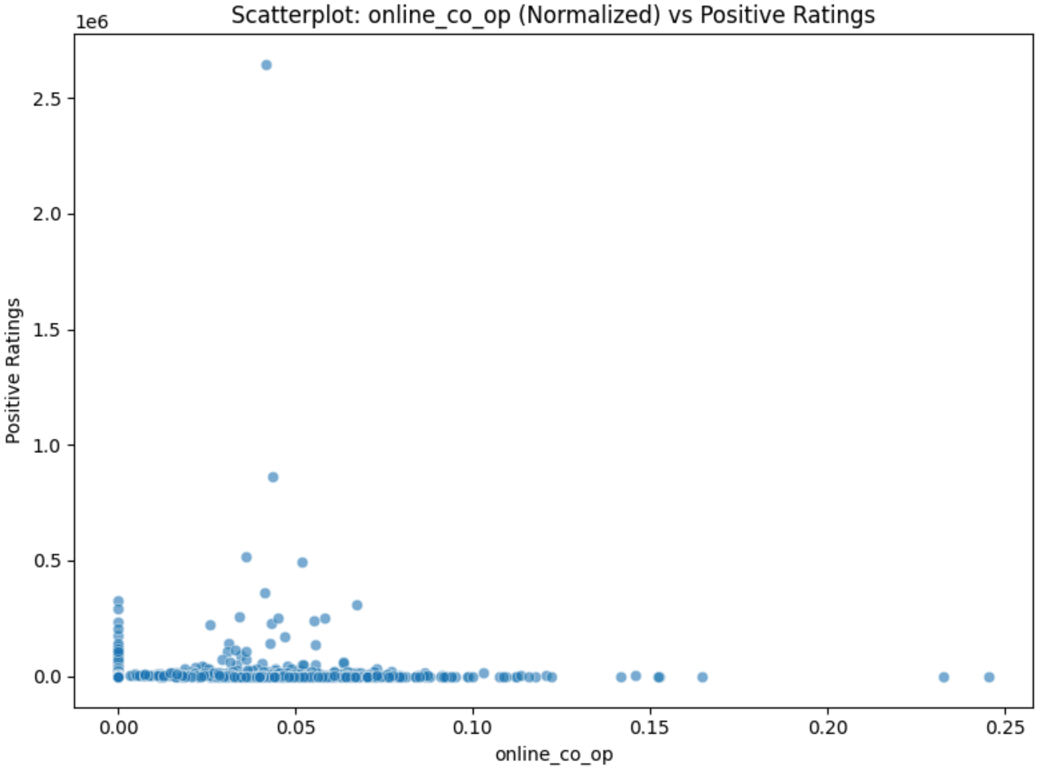
```
/usr/local/lib/python3.10/dist-packages/numpy/lib/function_base.py:2897: RuntimeWarning: invalid value encountered in divide
  c /= stddev[:, None]
/usr/local/lib/python3.10/dist-packages/numpy/lib/function_base.py:2898: RuntimeWarning: invalid value encountered in divide
  c /= stddev[None, :]
Top 10 Tags by Correlation with Positive Ratings (Normalized):
team_based      0.179139
online_co_op    0.110073
e_sports        0.104223
multiplayer     0.092134
moddable        0.085315
pvp             0.084765
co_op           0.080846
competitive     0.079527
shooter         0.072342
fps             0.071057
dtype: float64
```



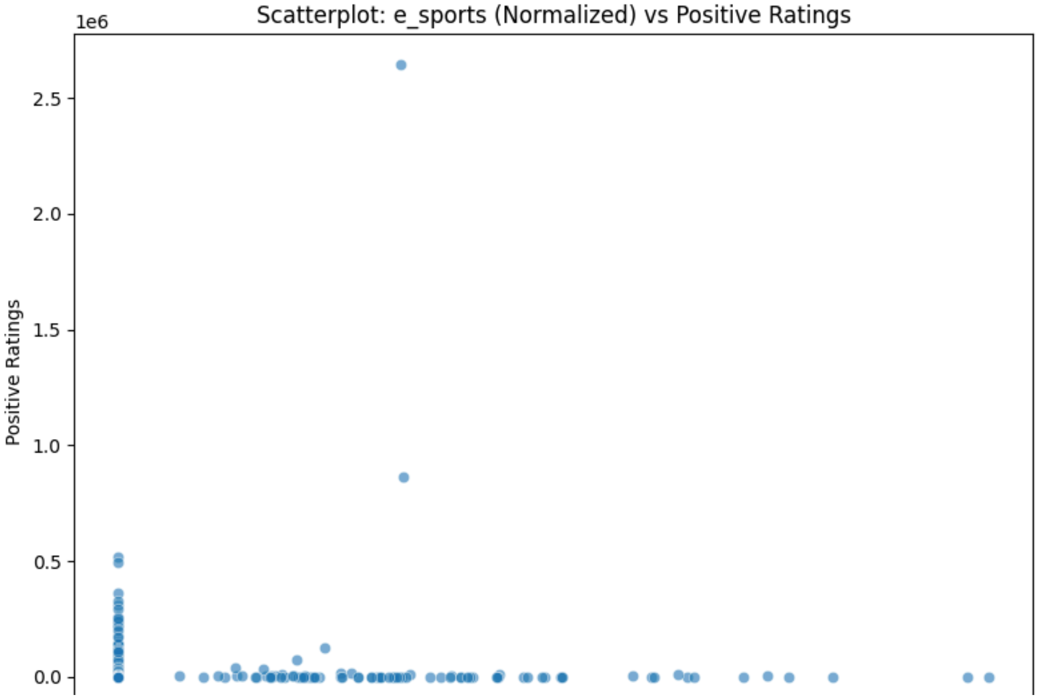


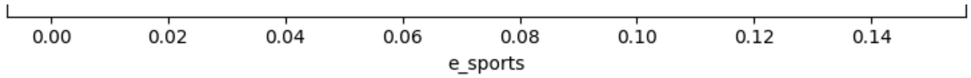


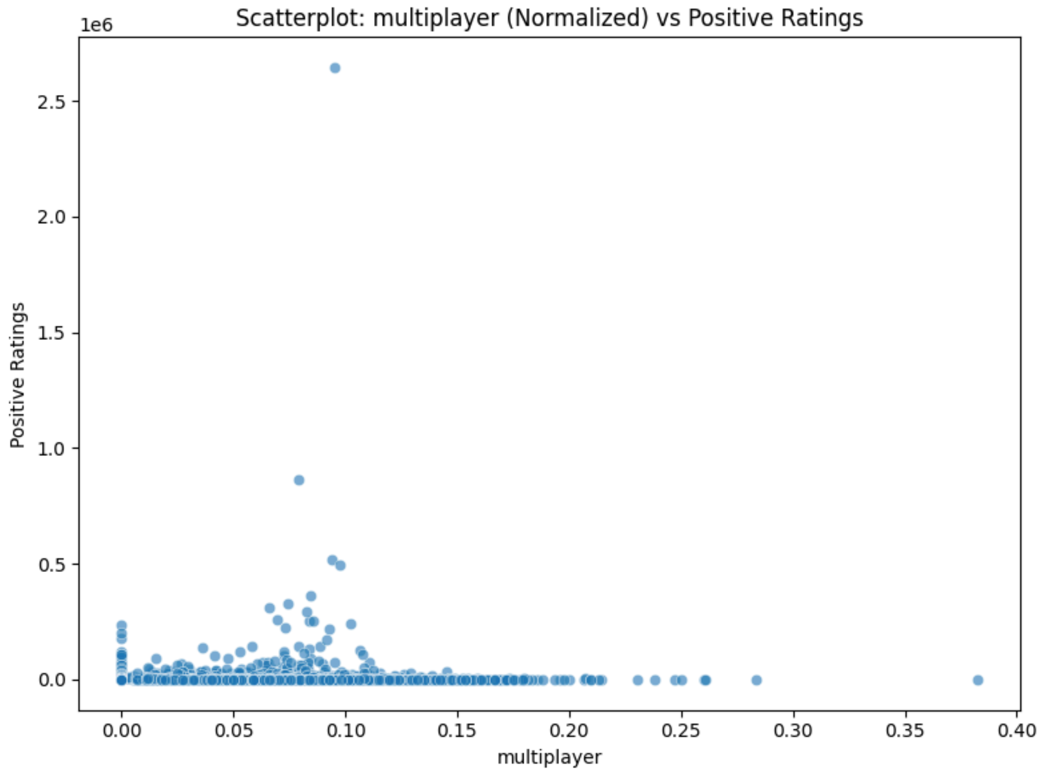
Scatterplot: online_co_op (Normalized) vs Positive Ratings

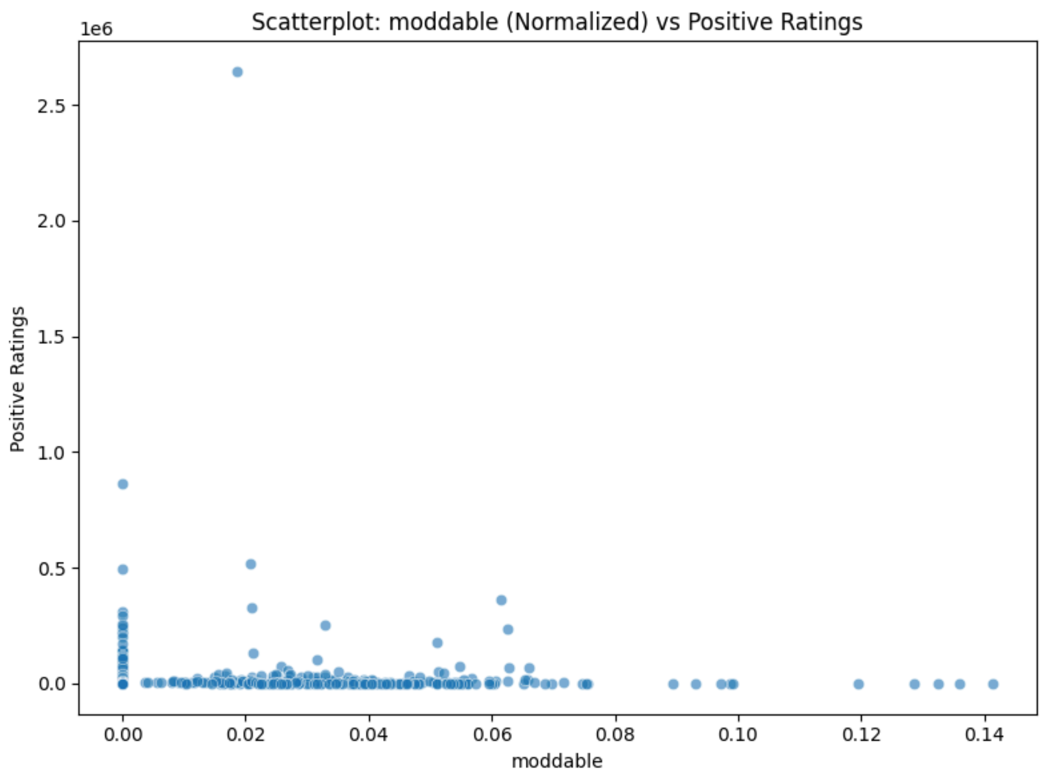


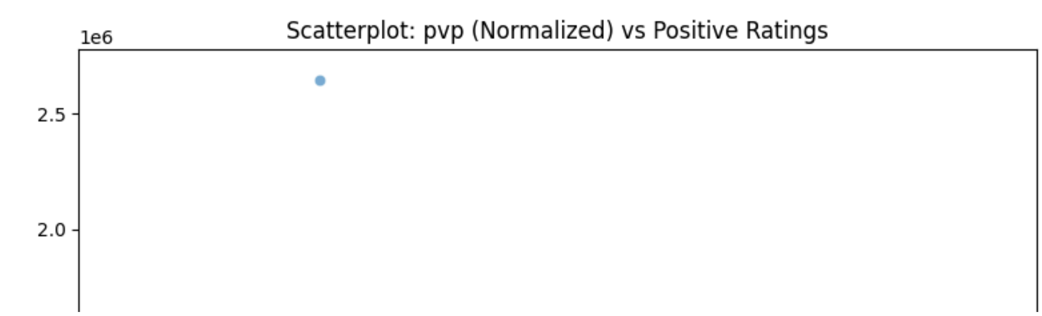
Scatterplot: e_sports (Normalized) vs Positive Ratings




0.00
0.02
0.04
0.06
0.08
0.10
0.12
0.14
e_sports


Scatterplot: multiplayer (Normalized) vs Positive Ratings
1e6
2.5
2.0
1.5
1.0
0.5
0.0
Positive Ratings
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0.35
0.40
multiplayer


Scatterplot: moddable (Normalized) vs Positive Ratings
1e6
2.5
2.0
1.5
1.0
0.5
0.0
Positive Ratings
0.00
0.02
0.04
0.06
0.08
0.10
0.12
0.14
moddable


Scatterplot: pvp (Normalized) vs Positive Ratings
1e6
2.5
2.0