



# **Sentiment Analysis of popular Sequels based on Reddit Comments:**

Attempting to understand the performance of sequels over time

**Group A**

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## Research Question

How have **sentiments** towards the Pirates of the Caribbean and Twilight movies **changed overtime** and does it have any **correlation with box office** overall ratings?

## Research Rationale

We focused on Pirates of the Caribbean and Twilight due to their five movies each and **popularity, ensuring sufficient data**.



## Research Goal

Our goal was to understand how **sequels are viewed** today and if there's a clear **change in sentiments over time**.

# Related Works

Sentiment analysis can be approached in two main ways: **lexicon-based tools** or **machine learning models**.

## Tonia & Rasha (2020) Ricardo et al. (2024)

We decided to use **VADER** as our lexicon-based baseline model, based on existing research and examples and due to its **consistency** in "microlog-like contexts" like Reddit comments.

## Hossen & Dev (2021)

Highlighted that traditional lexicon-based tools, while simple, lack nuance and context, **recommending more advanced models**.

## Chang et al. (2018)

Pre-trained BERT models can be fine-tuned with only an additional output layer. **Advancements in transformer-based pre-trained models show that they have received better results in text classification tasks**

## Chedia Dhaoui et al. (2017)

Found no **significant difference in accuracy** between lexicon-based and machine learning approaches, suggesting a **hybrid approach**.

## J. Sai Teja (2018)

Studies on movie reviews using Twitter's API showed **varied effectiveness for machine learning models**, with **SVM** and **Logistic Regression** being identified as effective in different contexts

# Data Description

## Data Collection



**Reddit comments for each movie** in the chosen sequels using **Reddit API**, focusing on **precise subreddits**.



**Box office gross revenues for each movie in the sequels.** Required for correlation analysis



**Rotten Tomatoes' film ratings** for subsequent analysis

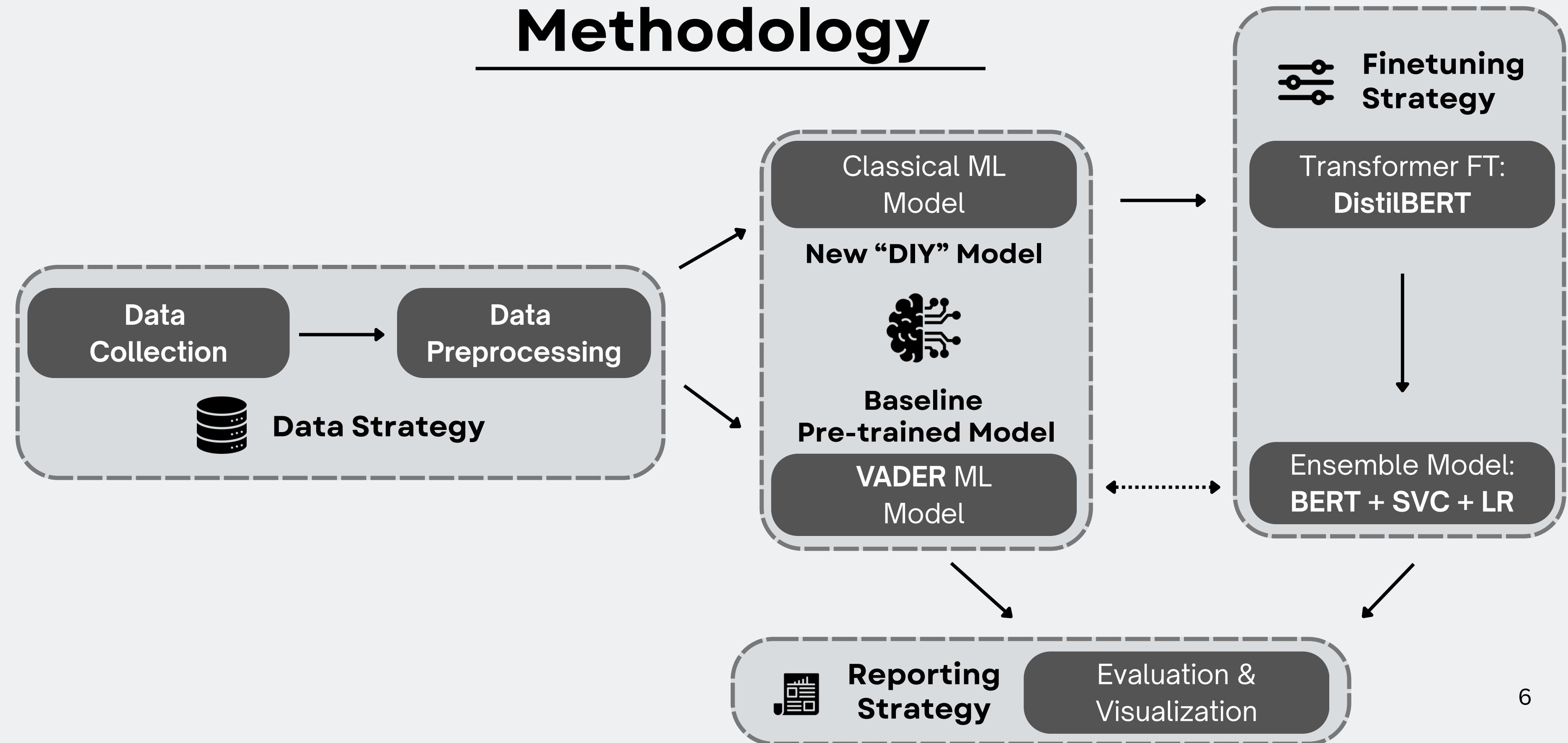
## Data Preprocessing



- **Remove URL links, symbols, stop words or common words, translate text into English language**
- **Split dataset** into train set and test set, including **oversampling** in order to **address imbalance**
- Text comments are **tokenized, trained, and tuned** in order to fit the classic model training process.

## Method

# Methodology



# Demonstration

The screenshot shows a GitHub repository interface for 'MovieSentimentAnalysis'. On the left, the repository structure is visible with files like .gitignore, Basic\_ML.py, BoxOfficeAndBudget.ipynb, FineTunedDistilBERT.py, ML\_transformers.py, Pirates 1.numbers, Pirates 2.csv, Project\_BasicMLipynb, Twilight.csv, breaking dawn part 1.csv, breaking dawn part 2.csv, distilBERTwithPreProcessing, eclipse 1.csv, and eclipse 2.csv. The main.py file is selected, showing its code. In the center, a GitHub commit by '00sora' titled 'Update main.py' is displayed, with a timestamp of '824906e · last week' and a link to 'History'. Below the commit, a 'Windows PowerShell' window is open, showing the command 'sentiment-env\Scripts\activate' followed by 'python ./success\_prediction.py --data historical\_sentiments.csv --new\_pirates 1.2 2000000 7.5 --new\_twilight 1.2 200000 7.5'. The output of the command is shown, including R<sup>2</sup> scores and predicted box office values for new Pirates and Twilight movies. The PowerShell window also shows the message 'Mean CV R<sup>2</sup>: -114.208' and '=> The new Pirates movie is predicted to be more successful.'

```
import argparse
import pandas as pd
import numpy as np
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
from sklearn.model_selection import StratifiedKFold
from sentiment_utils import (
    load_labeled_data, split_and_oversample,
    train_transformer, tune_negative_threshold,
    train_linear_svc, train_logistic_regression,
    ensemble_predict, clean_text
)
if __name__ == '__main__':
    parser = argparse.ArgumentParser()
    parser.add_argument('--movies', nargs='+', required=True, help='movie IDs e.g.')
    parser.add_argument('--folds', type=int, default=3, help='CV folds (reduce for')
    args = parser.parse_args()
    selected = [m for m in args.movies if m.isdigit()]
    labeled_map = {m: f'{m}_labeled.xlsx' for m in selected}
    all_map = {m: f'{m}_all.csv' for m in selected}
```

```
Windows PowerShell
Copyright (C) Microsoft Corporation. Alle Rechte vorbehalten.

Installieren Sie die neueste PowerShell für neue Funktionen und Verbesserungen! https://aka.ms/PSWindows

PS C:\Users\soras\OneDrive - Technische Universität Berlin\DALMwP\Project> sentiment-env\Scripts\activate
(sentiment-env) PS C:\Users\soras\OneDrive - Technische Universität Berlin\DALMwP\Project> python ./success_prediction.py --data hist
orical_sentiments.csv --new_pirates 1.2 2000000 7.5 --new_twilight 1.2 200000 7.5
Cross-validated R2 scores: [ 6.35557839e-02 -1.42737397e+01 -1.39873399e+00 -5.53332087e+02
-2.09845537e+00]
Mean CV R2: -114.208
Predicted box office for new Pirates movie: $943,393,525.08 USD
Predicted box office for new Twilight movie: $920,185,819.70 USD
=> The new Pirates movie is predicted to be more successful.
(sentiment-env) PS C:\Users\soras\OneDrive - Technische Universität Berlin\DALMwP\Project> |
```

# Results:

# Model Performance Summary

## Custom Ensemble Model

	Pred: Negative	Pred: Neutral	Pred: Positive
Actual Neg	72	42	27
Actual Neu	38	108	36
Actual Pos	46	43	99



Best overall performance on neutral sentiment

Class	Precision	Recall	F1-score	Support
Negative	0.46	0.51	0.48	141
Neutral	0.56	0.59	0.58	182
Positive	0.61	0.53	0.57	188



Overall Accuracy: 54.6% ★

Precision is highest in predicting positive and lowest precision in negative

## VADER Baseline Model

	Pred: Positive	Pred: Neutral	Pred: Negative
Actual Pos	778	89	197
Actual Neu	456	339	248
Actual Neg	354	73	341



Bias toward predicting positive sentiment

Class	Precision	Recall	F1-Score	Support
Negative	0.43	0.44	0.44	768
Neutral	0.68	0.33	0.44	1043
Positive	0.49	0.73	0.59	1064



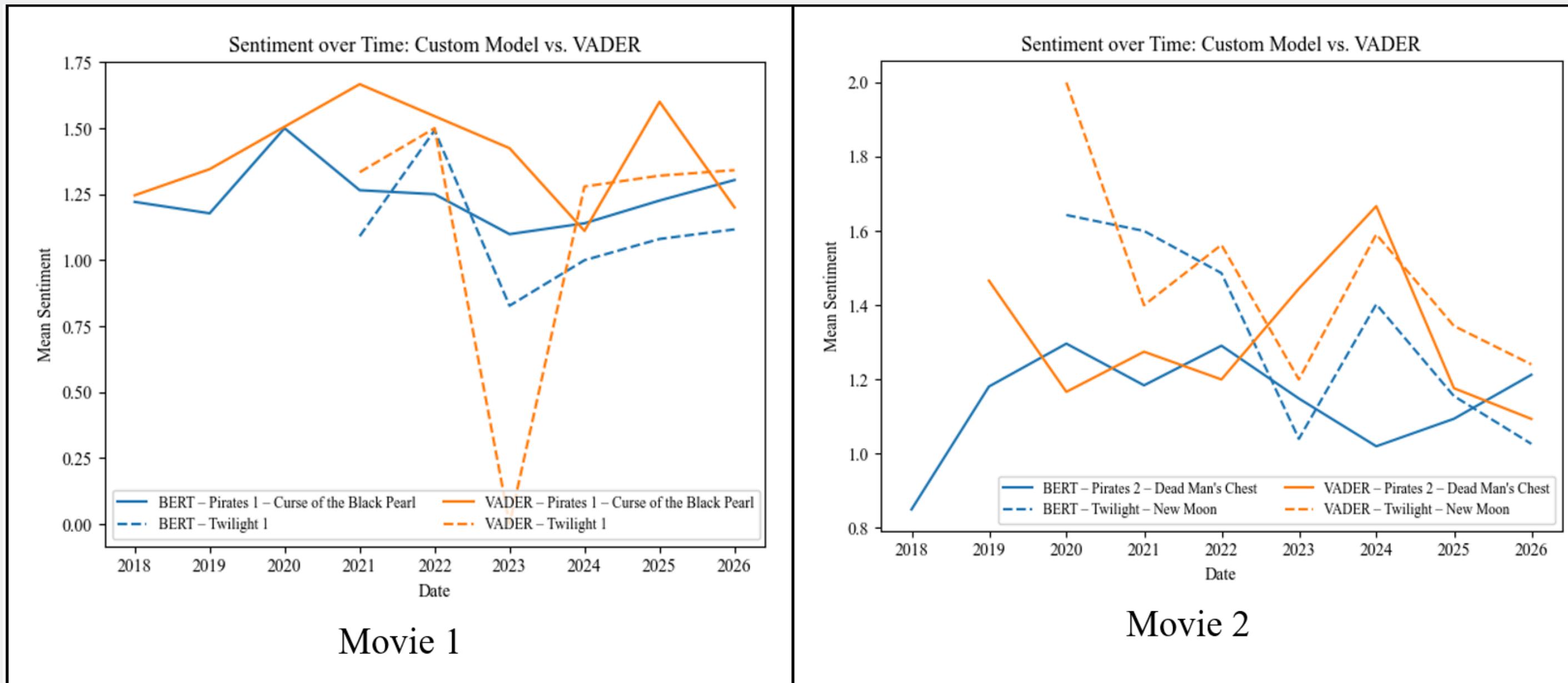
Overall Accuracy: 50.7%

Precision is highest for predicting neutral

# Results:

# Sentiment Over Time (1/3)

Comparison of Sentiment for each Franchise's Corresponding Movie Releases Over Time



Legend

BERT  
Pirates

BERT  
Twilight

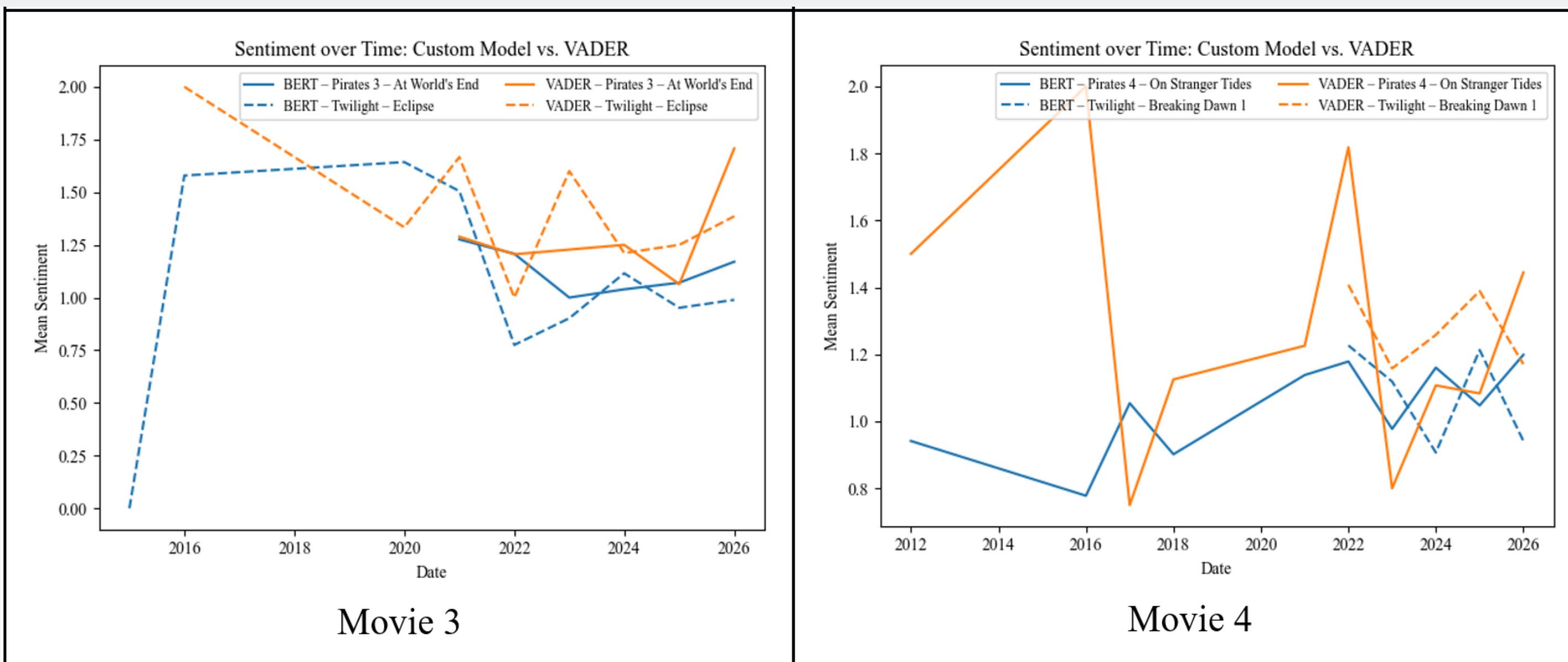
VADER  
Pirates

VADER  
Twilight

# Results:

# Sentiment Over Time (2/3)

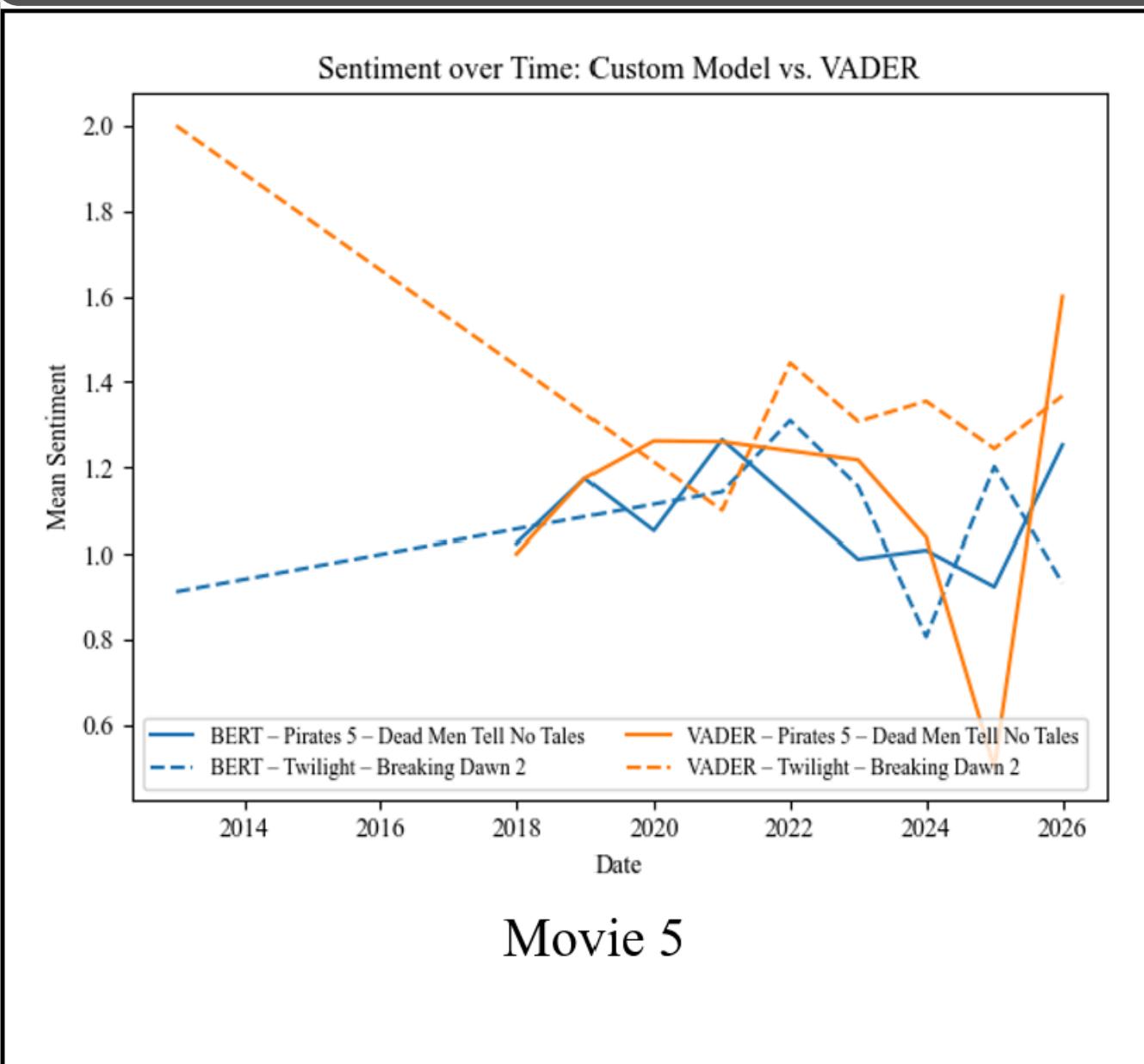
## Comparison of Sentiment for each Franchise's Corresponding Movie Releases Over Time

**Legend****BERT  
Pirates****BERT  
Twilight****VADER  
Pirates****VADER  
Twilight**

# Results:

# Sentiment Over Time (3/3)

Comparison of Sentiment for each Franchise's Corresponding Movie Releases Over Time



## Summary

- Twilight:  
BERT and VADER show **similar sentiment trends** across movies
- Pirates:  
**Greater difference** between BERT and VADER predictions
  - Suggests **Pirates comments are more complex** and nuanced, harder for VADER to analyze
  - Twilight comments are more direct and **emotionally charged**, making VADER and **BERT align more closely**



## Legend

BERT  
Pirates

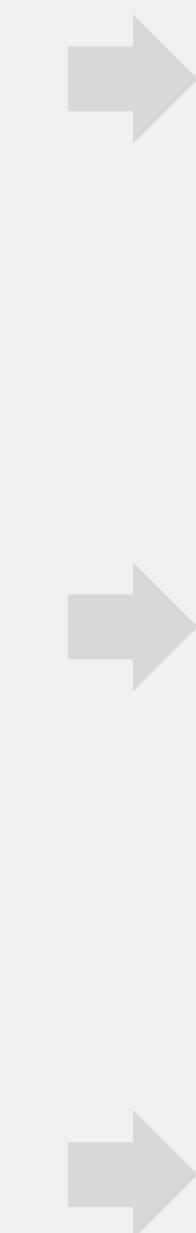
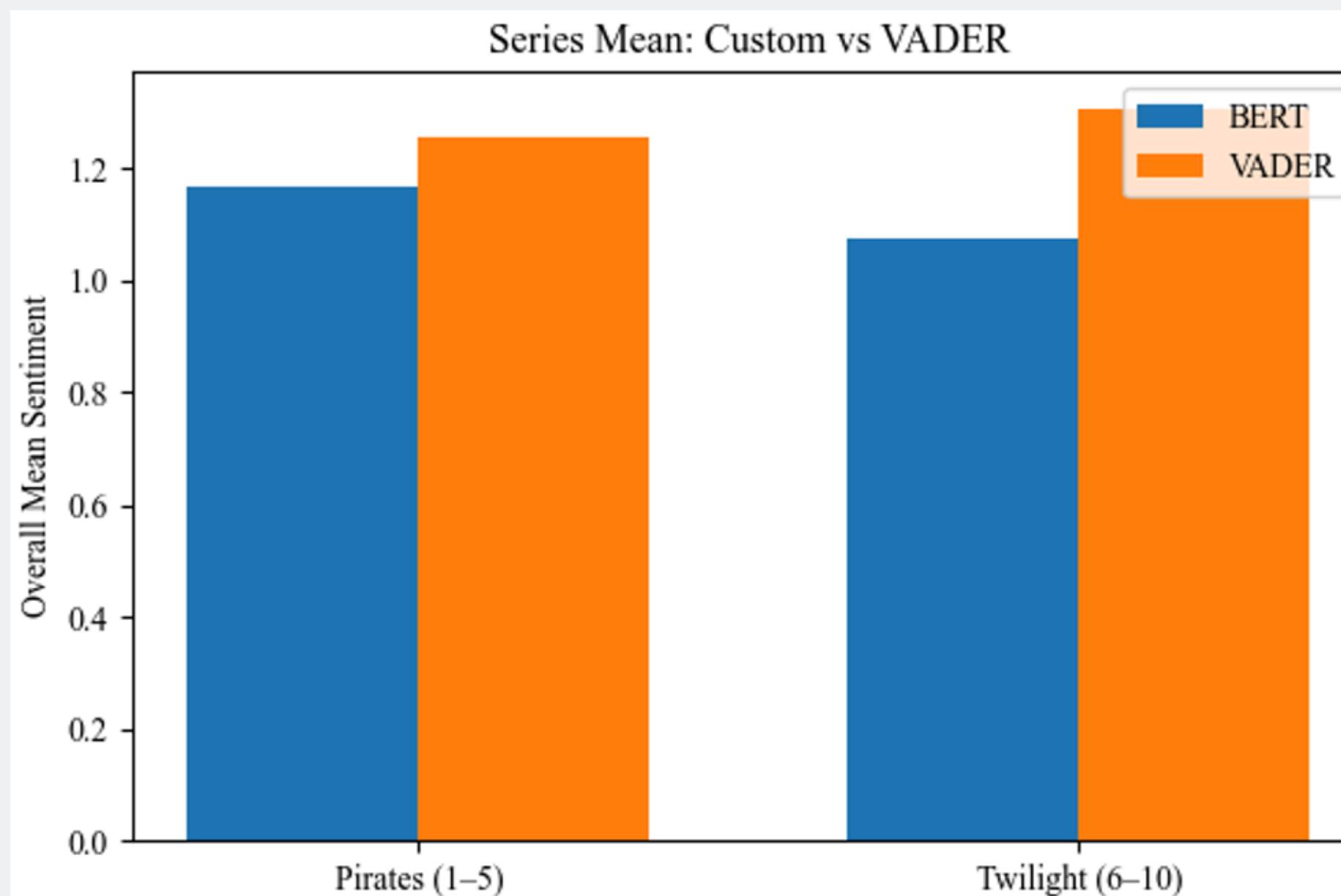
BERT  
Twilight

VADER  
Pirates

VADER  
Twilight

# Results:

## Series Mean Values



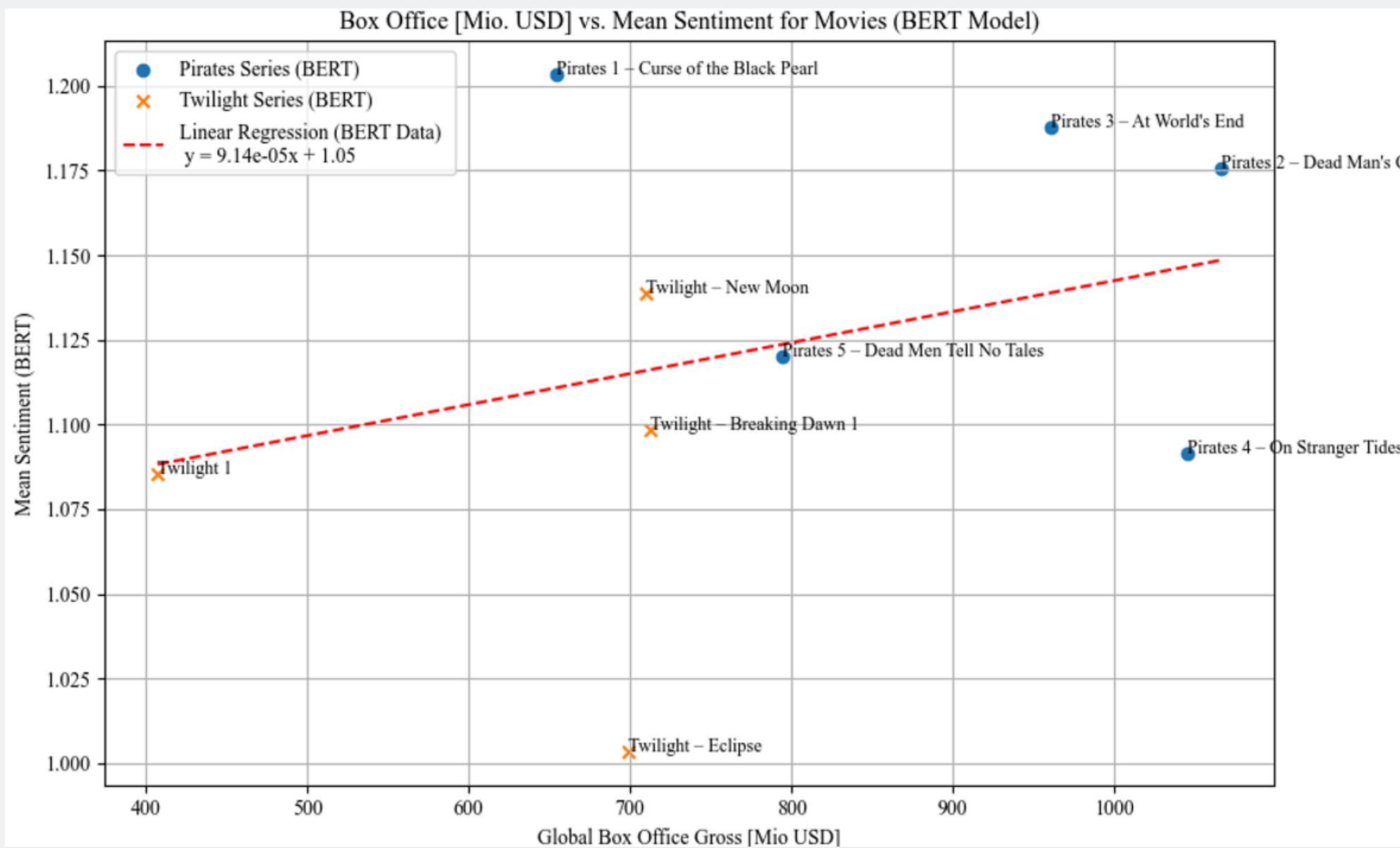
### Key Take-aways

- VADER produces higher overall sentiment scores than BERT for both franchises
- BERT shows Pirates sequels with slightly higher sentiment than Twilight
- VADER suggests the opposite, Twilight shows slightly higher sentiment
- Indicates that VADER may be biased toward overly positive interpretations

# Results:

# Correlation Analysis

## BoxOffice's Gross and Sentiment Score



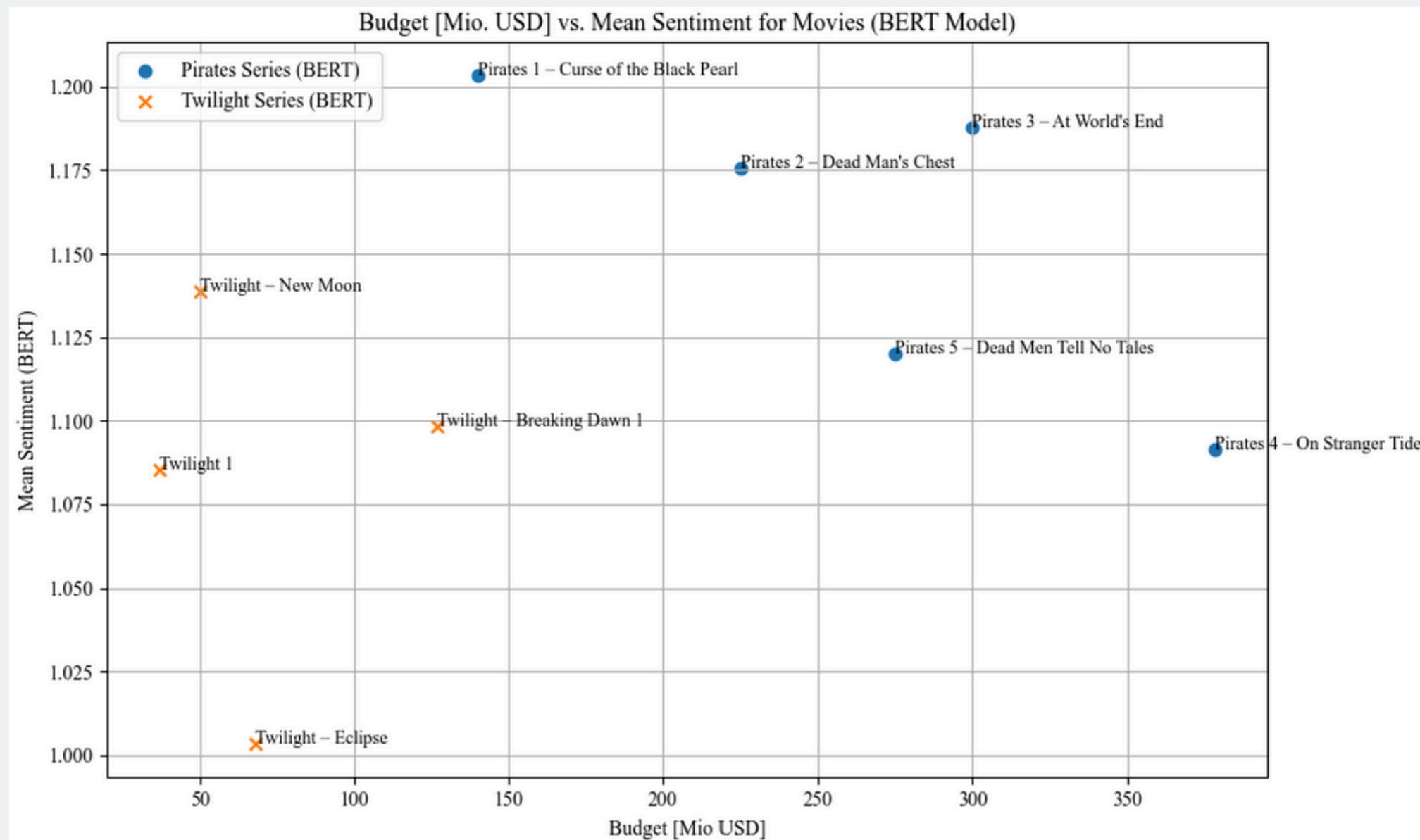
## Key Take-aways

- Scatterplot shows **positive correlation** between sentiment and box office gross
- Movies with **higher sentiment scores tend to earn more globally**
- Suggests **positive audience engagement reflects in commercial success**

# Results:

# Scatterplot Analysis

## Scatterplot of Budget and Mean Sentiment Score of Both Sequels



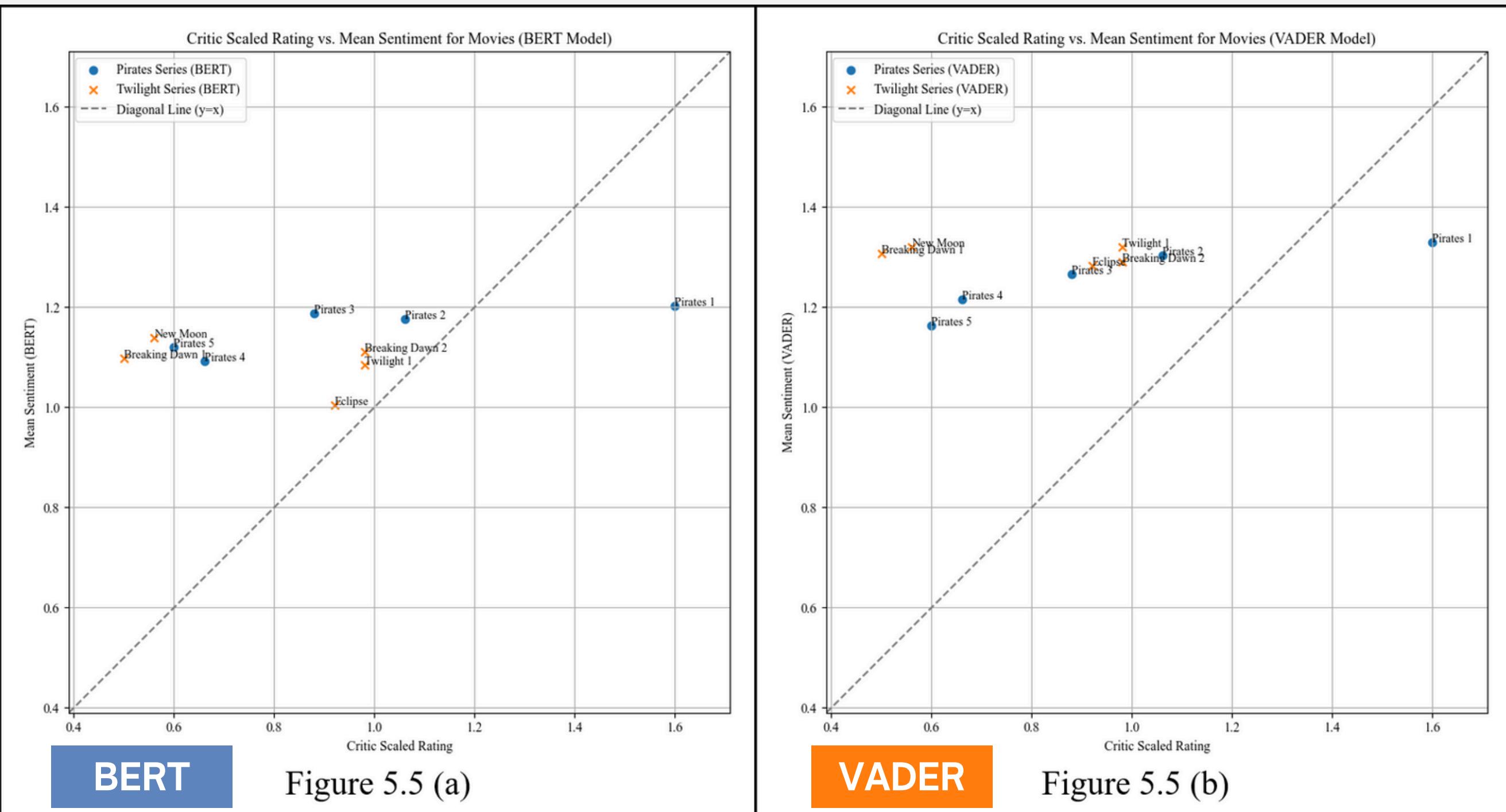
## Key Take-aways

- Pirates had much **higher budgets** than Twilight
- Later Pirates movies had **lower sentiment despite higher spending**
- **Budget doesn't guarantee audience approval**

# Results:

# Scaled Rating Analysis (1/2)

## Comparison between Rating Scores and Predicted Sentiment Score by Two Models



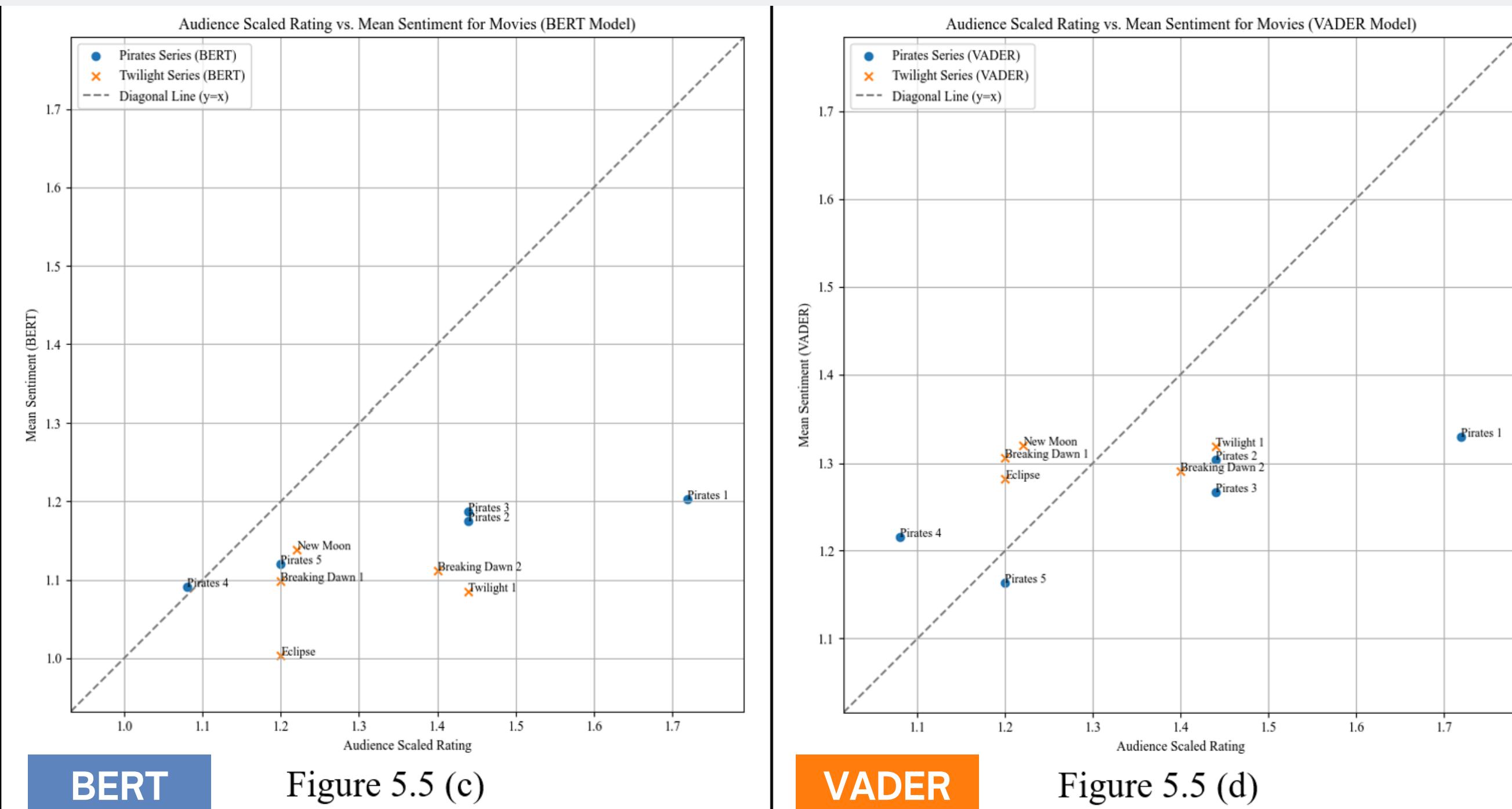
## Key Take-aways

- BERT aligns better with critic ratings than VADER
- Audience ratings are often higher than predicted sentiment
- Shows that **BERT is better for modeling nuanced reactions**

# Results:

# Scaled Rating Analysis (2/2)

## Comparison between Audience Scaled Ratings and Predicted Sentiment Score by Two Models



## Key Take-aways

- In the BERT model, most movies have **lower sentiment scores** than their audience ratings.
- Pirates 4** is the only case where sentiment prediction matches audience rating.
- In the VADER model, Twilight movies show **higher sentiment scores** than their audience ratings.
- Pirates movies generally receive **higher audience scores** than what VADER predicts.

# Conclusion and Future Work

1

VADER often overestimates positivity and struggles with context and sarcasm.

2

BERT performs better with nuanced Reddit comments but still limited.

3

Pirates had higher early sentiment, but later films dropped despite big budgets

4

Sentiment ≠ guaranteed box office success --> Factors like timing and fan loyalty matter

5

Labeling was hard: Reddit comments often mixed or off-topic.

6

Accuracy stayed modest, even after using advanced models.

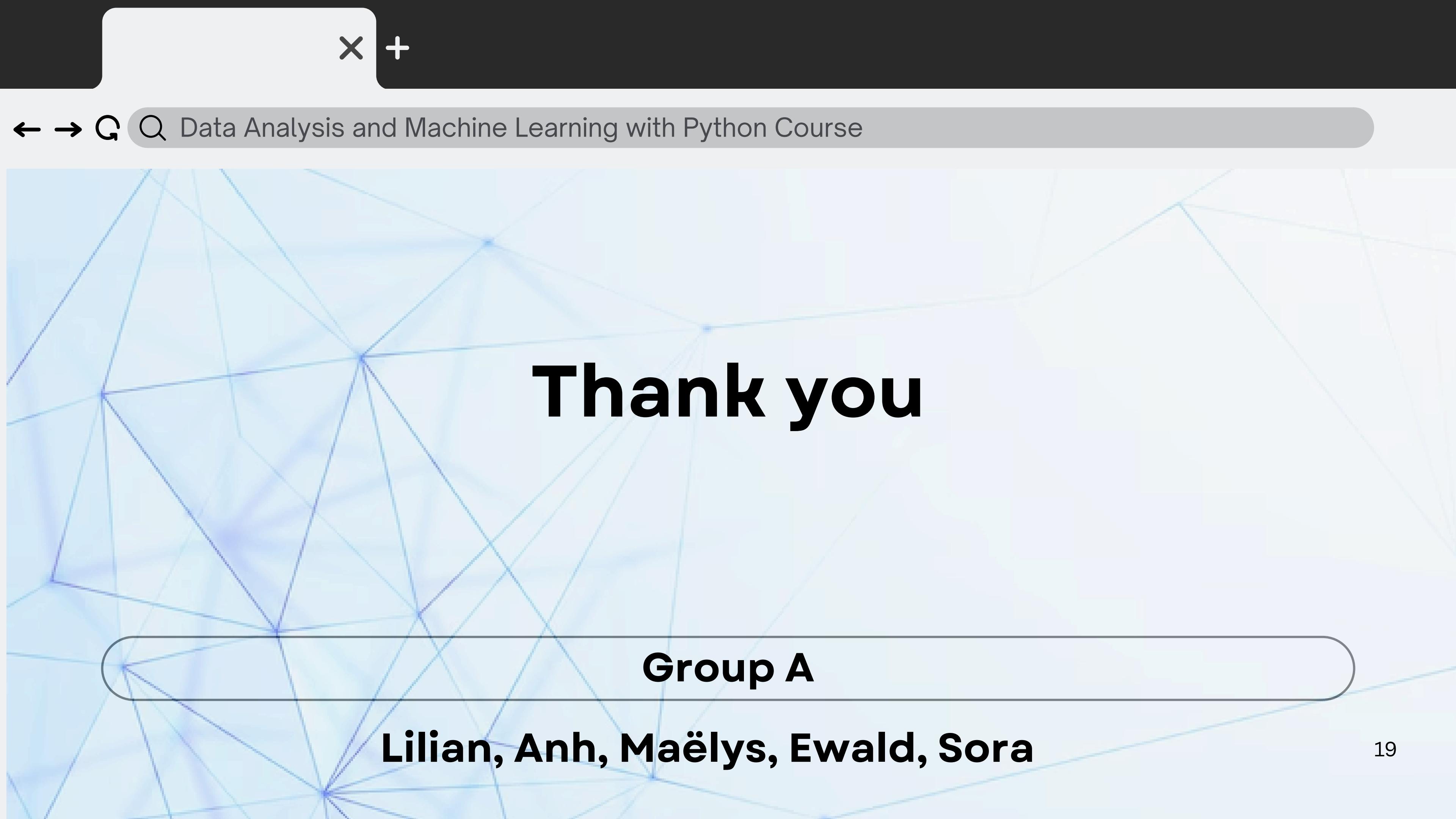
7

Reddit may not reflect the broader public, limiting generalizability.

8

Future models should include more data and context (e.g., release dates, trailers).





# Thank you

Group A

**Lilian, Anh, Maëlys, Ewald, Sora**



← → Q References used for the final group project



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