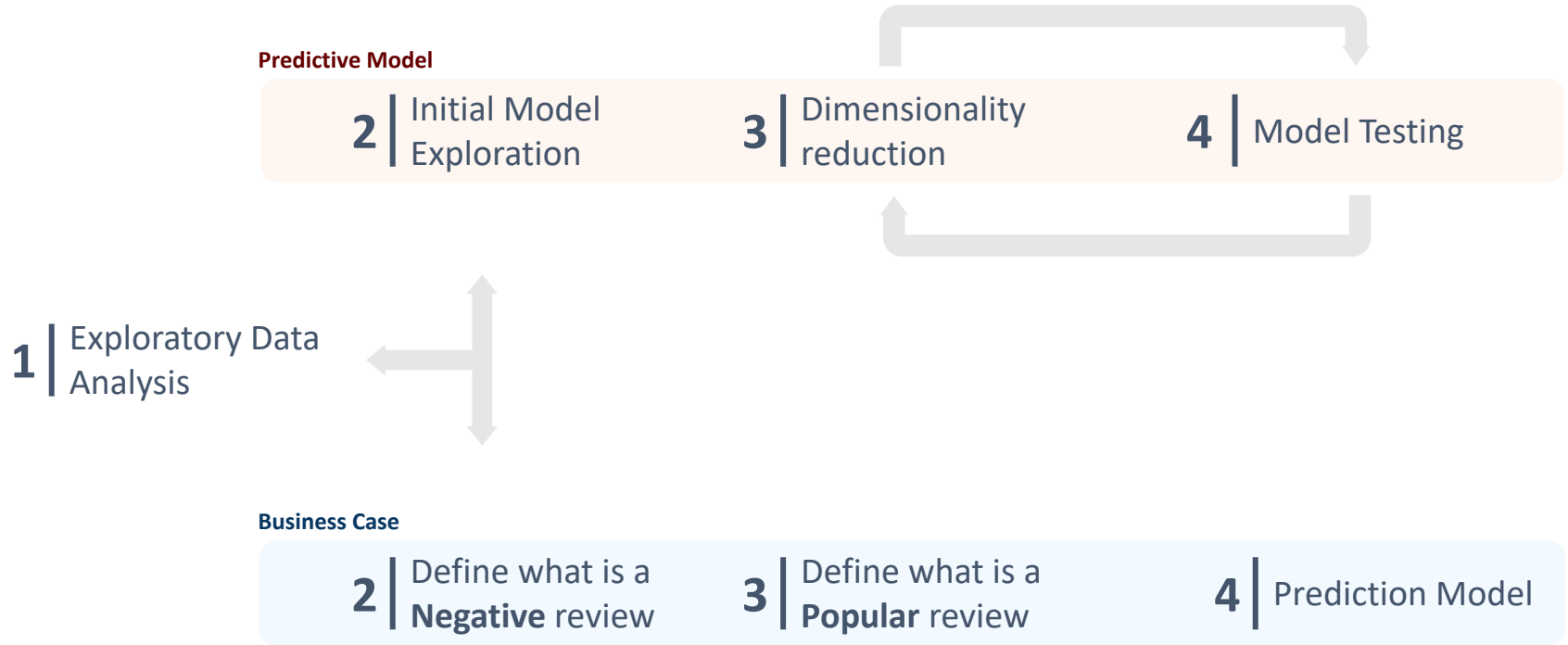


# Leveraging Machine Learning for Predicting Customer Satisfaction

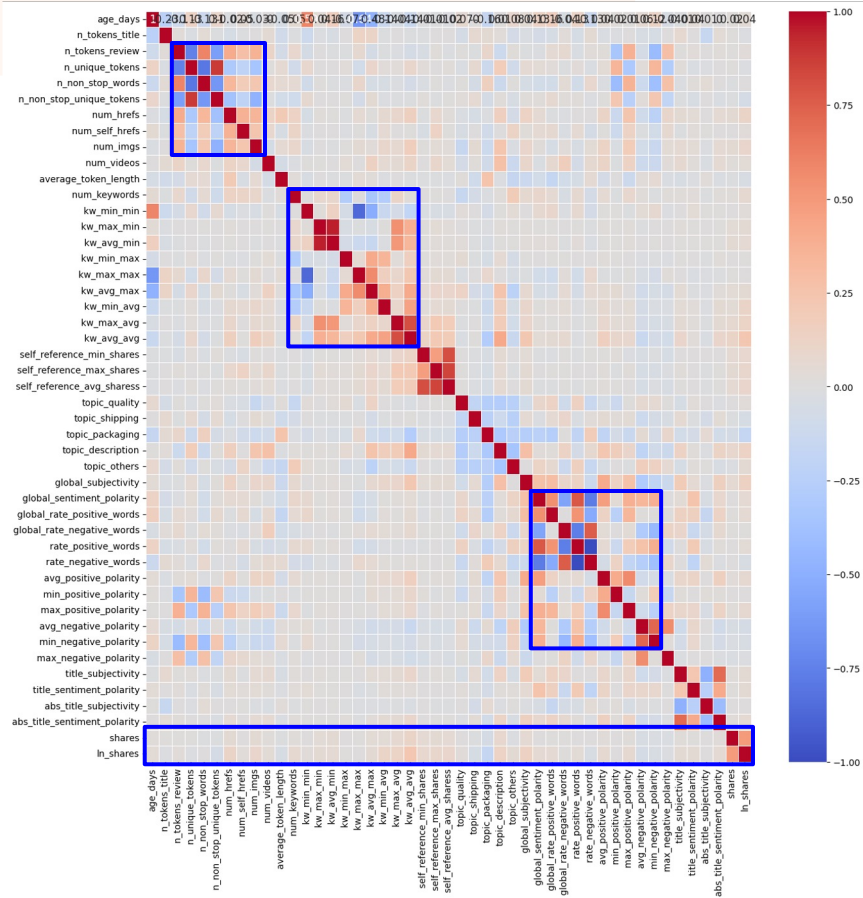
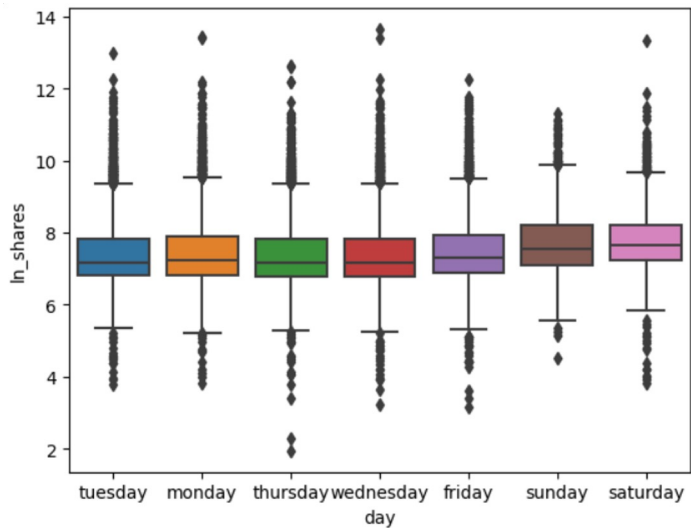
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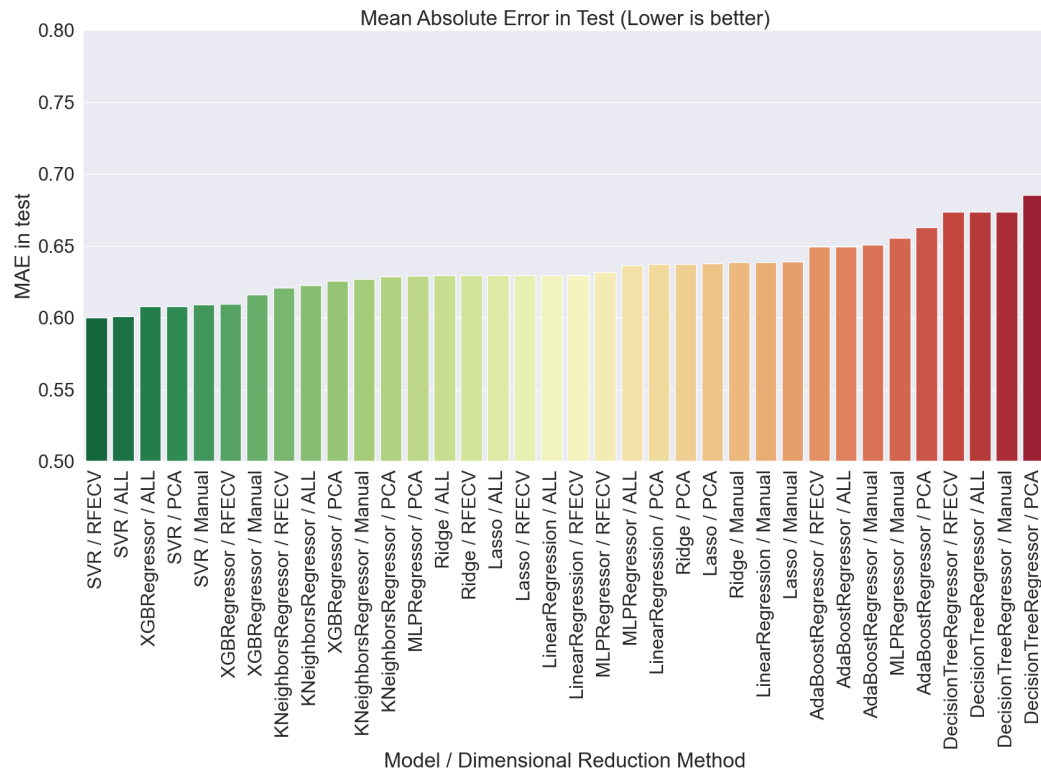
# Methodology



# EDA



# Model Testing



**MAE TEST:**

**Best:**

SVR/RFECV  
0.59(2272)

**Worst:**

Decision Tree/PCA  
0.68(2412)

# Final Model

- XGBoost ( Gradient Boosting)
- All predictors (45 numerical, 14 categorical dummies)



- MAE in tests 0.607 (2293)
- R2 in test 0.184

# Business Case

## Objective

Identify potentially popular negative reviews to prevent negative feedback

## How

1 | Define what is a  
**Negative** review

2 | Define what is a  
**Popular** review

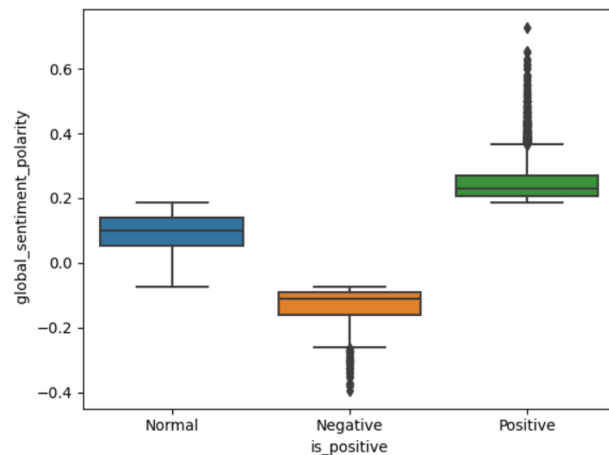
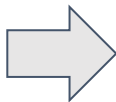
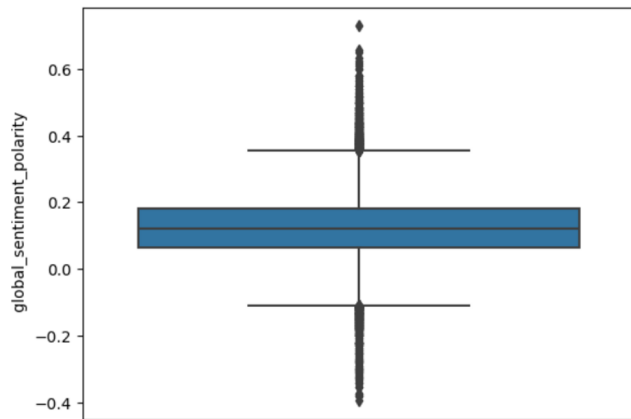
3 | Prediction Model

# Business Case

## 1 | Define what is a **Negative** review

### Rule

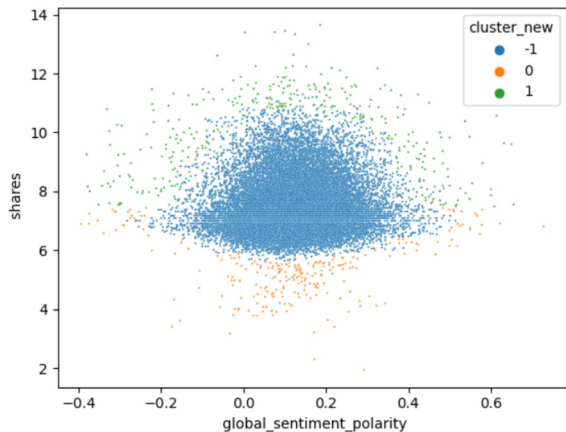
- Global sentiment polarity > mean + std -> Positive
- Global sentiment polarity < mean - std -> Negative



# Business Case

## 2 | Define what is a Popular review

**Hypothesis:** Popularity hinges on sentiment polarity, with extreme values garnering less attention than moderate ones. Outliers indicate what's trending.



**Cluster 1 - Interesting:** Comments with a larger number of shares than usual for a given sentiment polarity

**Cluster 0 - Not Interesting:** Comments with a low amount of shares

**Cluster -1 - Normal behaviour**



# Business Case

## 3 | Prediction Model

**Classification Tree:** Classify new comments to assign a level of urgency to be reviewed based on Clusters and Polarity

	Negative	Normal	Positive
Cluster 1			
Cluster -1			
Cluster 0			

\*\*98% accuracy

- Critical: Negative comment with potential to become popular
- High: Average negative comment
- Moderate: Neutral comment with potential to become popular
- Low: Average Neutral comment