Sentiment Analysis

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- What is sentiment analysis?
- Why is it important?
- Project objectives

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Data Acquisition

- Data source: Twitter API
- About our data
- Data preprocessing

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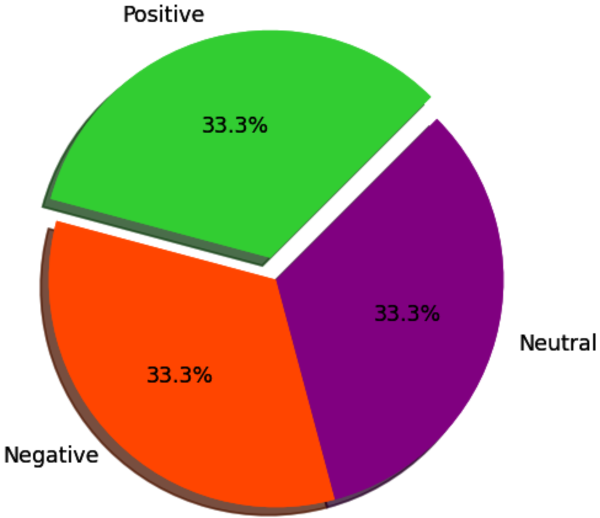
category

Describes the Actual Sentiment of the Respective Tweet Ranging from -1 to 1

Valid	163k	100%
Mismatched	0	0%
Missing	10	0%
Mean	0.23	
Std. Deviation	0.78	
Quantiles	-1	Min
	0	25%
	0	50%
	1	75%
	1	Max


Positive
33.3%
33.3%
Neutral
33.3%
Negative

Model Selection

Approaches

- Linear Regression
- SVM
- KNN
- Naive-Bayes
- Decison Tree

- Popular machine learning algorithm widely used for classification tasks
- How: learns a linear relationship between **features** (TF-IDF vectors from text data) and a **target variable** (the sentiment)
- Training: the model estimates coefficients for each feature that influence the probability of a data point belonging to a specific class
- Sentiment Analysis: the model predicts the most likely sentiment (positive, negative, neutral) for a new unseen text sample based on the learned coefficients and the features extracted from the text

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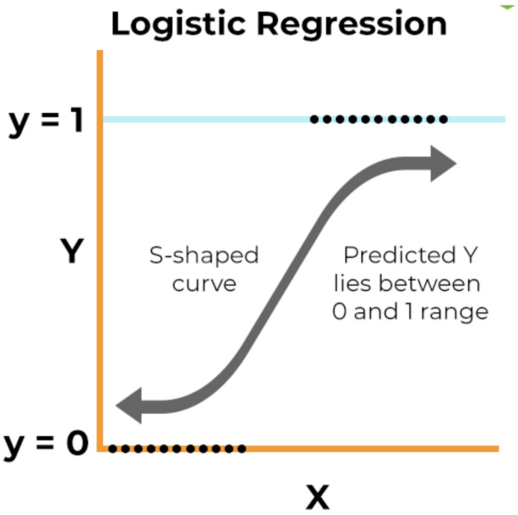
Logistic Regression



Advantages

- **Interpretability**: we can understand which features contribute most to predicting positive, neutral or negative sentiment
- **Simplicity**: it is a relatively simple algorithm
- **Efficiency**: computationally efficient to train and can handle large datasets effectively

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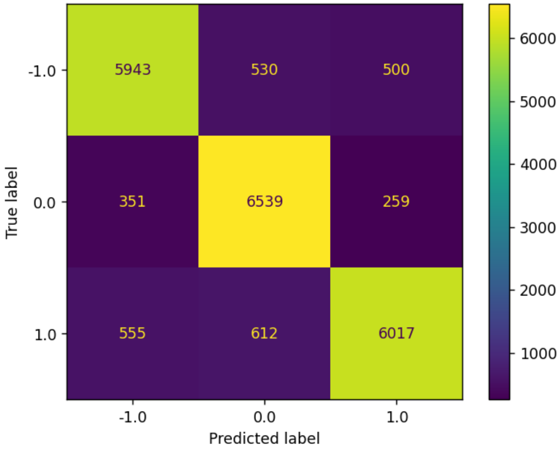
Performance



- While Logistic Regression learns a linear decision boundary, SVMs aim to find a hyperplane in the feature space that **maximizes** the margin between the data points (the support vectors) belonging to different classes
- The margin = **confidence** of classification
- In Sentiment Analysis: SVMs learn a hyperplane that effectively separates positive, neutral and negative sentiment data points based on extracted features (TF-IDF vectors)
- New text data is then classified based on which side of the hyperplane it falls on

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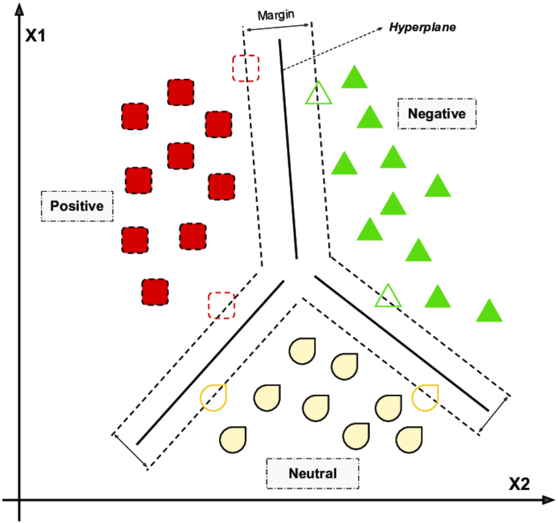
SVM



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- **High Accuracy**: SVMs are known for achieving
- **Effective with high-dimension data**: SVMs perform well, even in high-dimensional feature spaces (commonly encountered in NLP)
- **Robust to noise**: SVMs are relatively insensitive to irrelevant data points (that might impact other algorithms)

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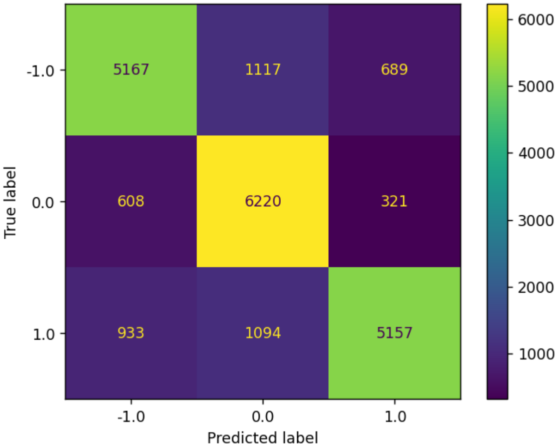

- Classifies based on nearest neighbors in training data (similar features).
- Training: Stores the entire training dataset. It doesn't learn a model by fitting coefficients, but rather memorizes the data points and their corresponding sentiment labels. This essentially creates a reference set for comparison during prediction.
- Sentiment Analysis: New text assigned sentiment based on majority vote of its k nearest neighbors.

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- **Simple and intuitive**: KNN is a very easy algorithm to understand and implement. The core idea of finding similar neighbors is easy and doesn't involve complex mathematical models.
- **Effective with high-dimensional data**: KNN can handle high-dimensional data without significant performance degradation.
- **No assumptions about data distribution**: Unlike some algorithms that require specific assumptions about the underlying data distribution, KNN makes no such assumptions.

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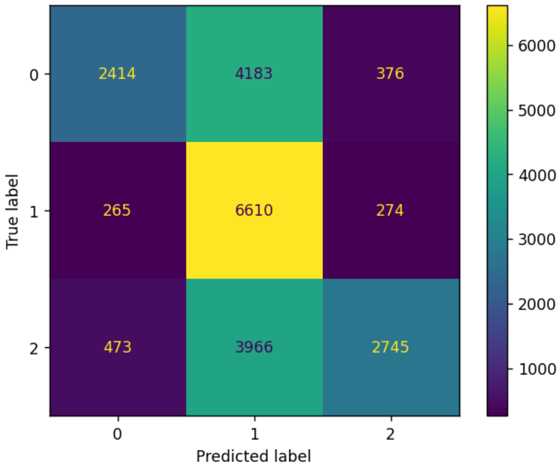

Naive-Bayes

- Popular probabilistic classifier
- It assumes independence between features when predicting the class of a new data point
- The class with the highest probability is assigned to the document

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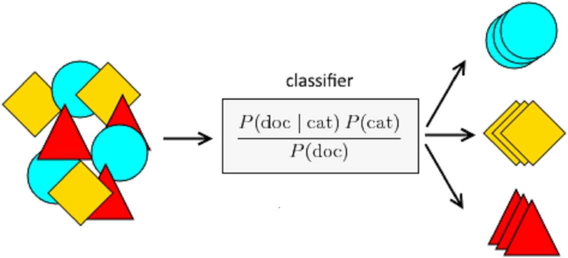
classifier
$\frac{P(\mathrm{doc} \mid \mathrm{cat})\, P(\mathrm{cat})}{P(\mathrm{doc})}$

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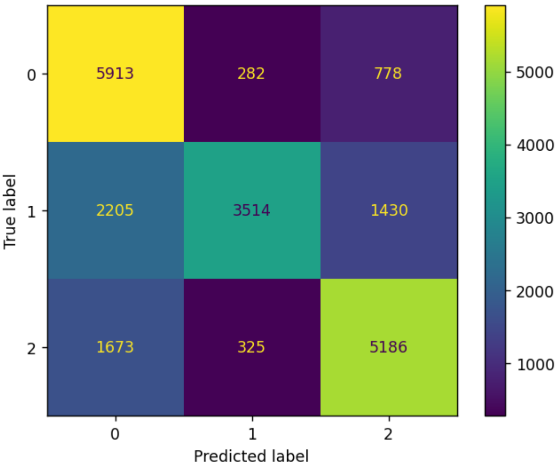
- **Handling high-dimensional data**: can effectively handle high-dimensional feature spaces common in NLP tasks (due to its focus on individual feature probabilities)

Performance



- Fundamental machine learning algorithm
- How: build a tree-like structure where internal **nodes** represent features and **branches** represent decision rules based on those features
- During training, the model iteratively splits the data based on the feature that best separates the data points belonging to different classes
- The process continues until a stopping criterion is met $\longrightarrow$ tree structure where leaf nodes represent the predicted sentiment class
- In Sentiment Analysis: the model analyzes the text and traverses the decision tree based on word presence or absence, ultimately reaching a leaf node that represents the predicted sentiment (positive, negative, or neutral)

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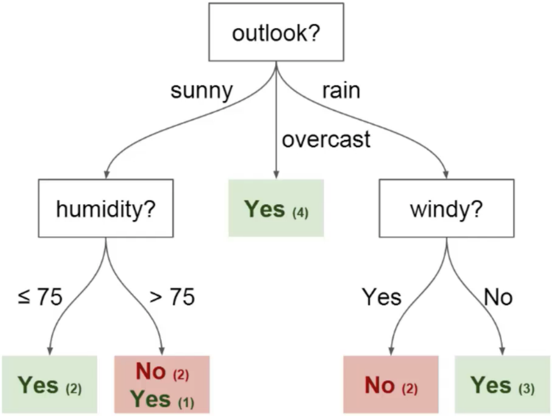
Decision Tree



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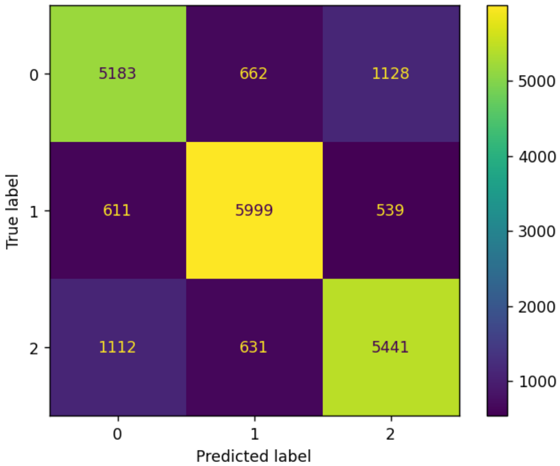
- **Handles missing data**: can effectively handle missing data points by incorporating them into the decision-making process during tree construction
- **Fast training and prediction**: they are known for their computational efficiency; this can be advantageous for real-time sentiment analysis applications

Performance



Conclusion

Model used	Accuracy
Logistic Regression	86.83%
SVM	77.65%
KNN	55.24%
Naive Bayes	68.59%
Decision Tree	78.02%