SOCIAL MEDIA DATA MINING TO GAUGE POSITIVE OR NEGATIVE RESPONSES TOWARDS A COMPANY

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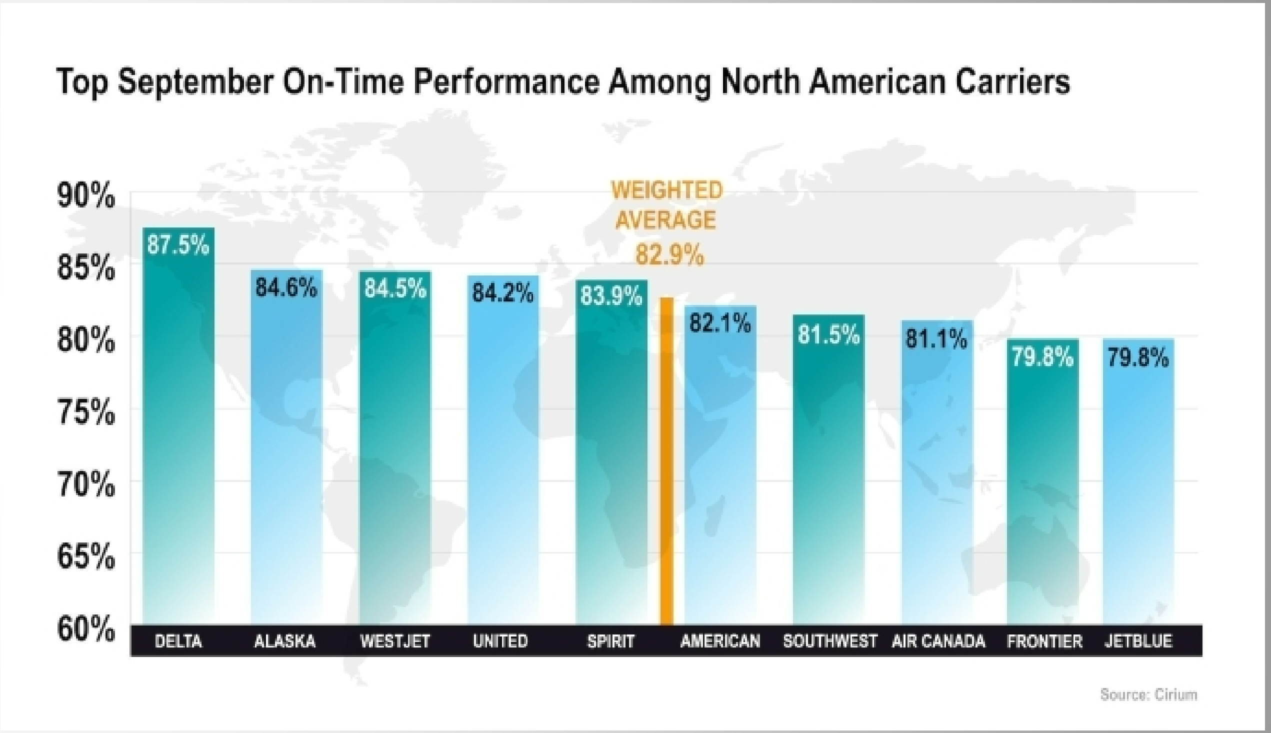
PROBLEM OVERVIEW

- Airline passengers post thousands of tweets daily
- Tweets contain real customer experiences
- Unstructured text is hard to analyze manually
- Need automated sentiment classification (Positive / Neutral / Negative)

WHY THIS MATTERS

- Airlines need to understand customer satisfaction trends
- Social media feedback reveals real-time issues
- Data mining helps extract sentiment patterns at scale
- Prior research shows ML and NLP methods perform well on tweet data



DATASET SUMMARY

- Airline-related tweets with sentiment labels
- Three sentiment classes: Negative, Neutral, Positive
- Key fields used: tweet text, airline, sentiment label, negative reason
- Dataset is imbalanced majority negative
- Provides real-world complexity for model evaluation

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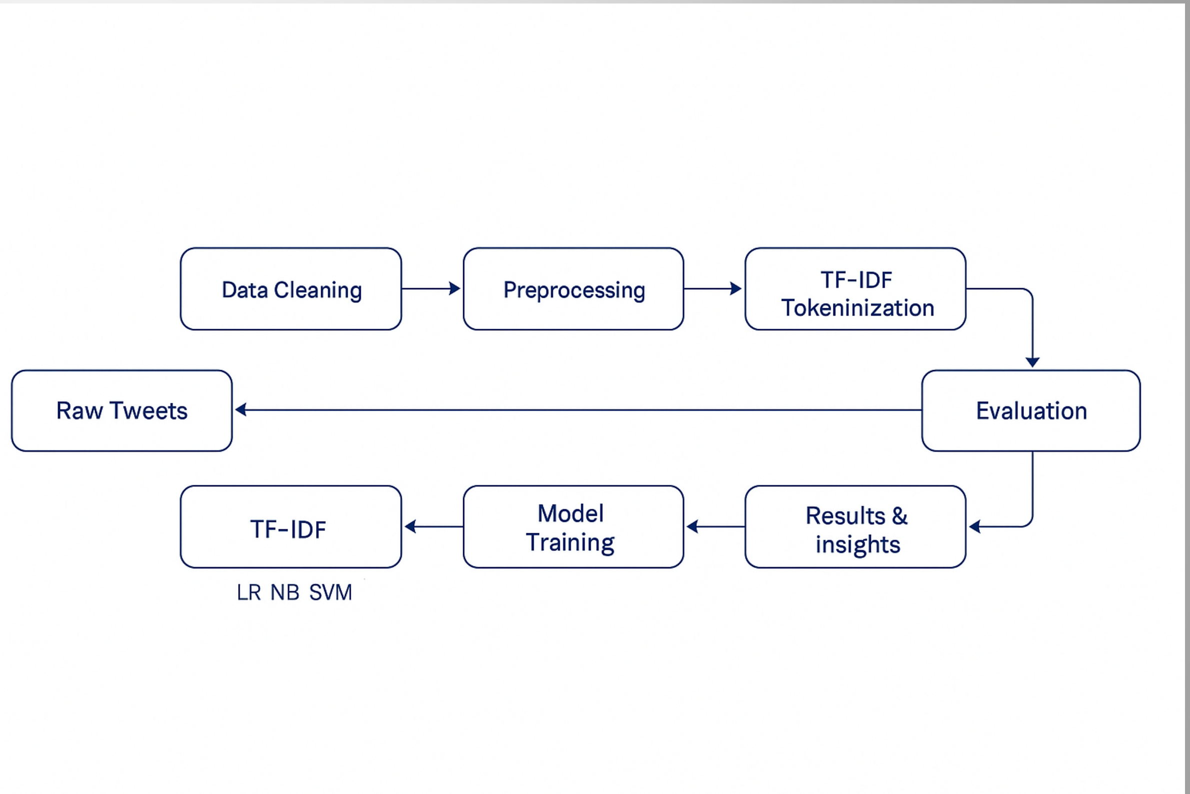
Virgin America		TenantsUpstairs		0	@VirginAr	[33.945404	########	Brooklyn	Atlantic Time (Can
Virgin America		jordanpichler		0	@VirginAmerica hi I		########		Vienna

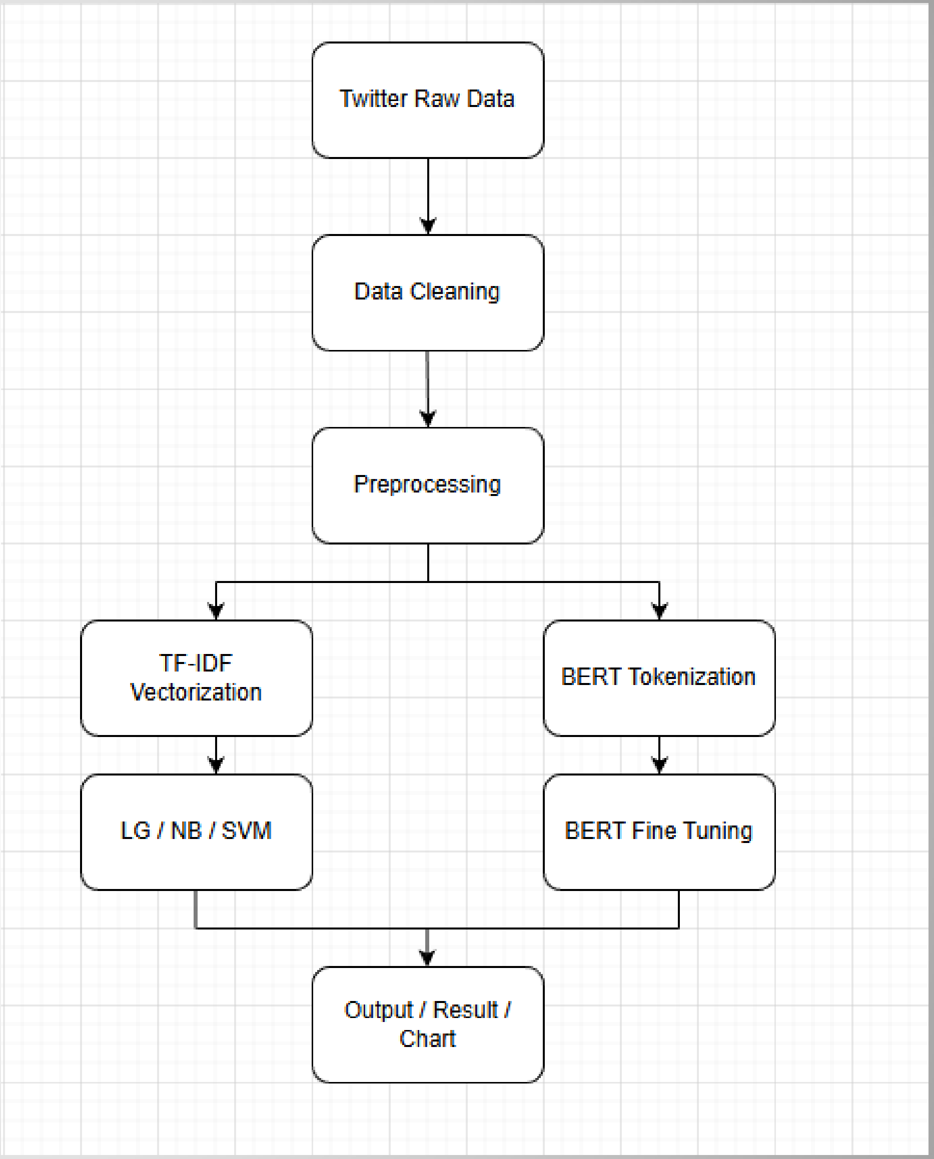
DATA PREPARATION

- Social media text contains noise and inconsistencies
- Cleaning ensures high-quality input for models
- Preprocessing improves model accuracy and stability
- Supports both classical ML and BERT pipelines



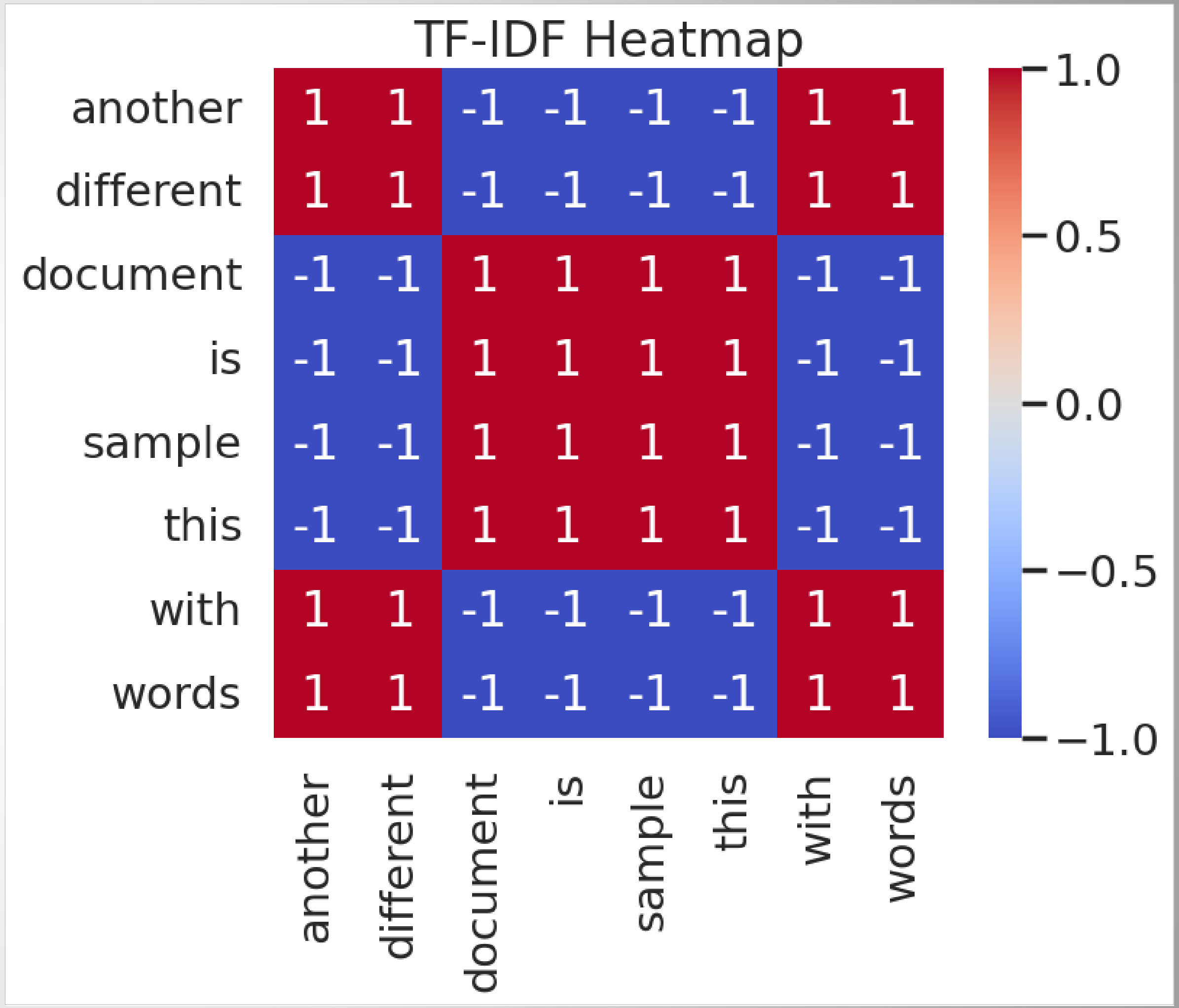
DATA FLOW DIAGRAM

- Both ML and BERT follow shared preprocessing
- TF-IDF powers LR, NB, SVM
- Tokenization powers BERT fine-tuning
- All models evaluated on the same test split



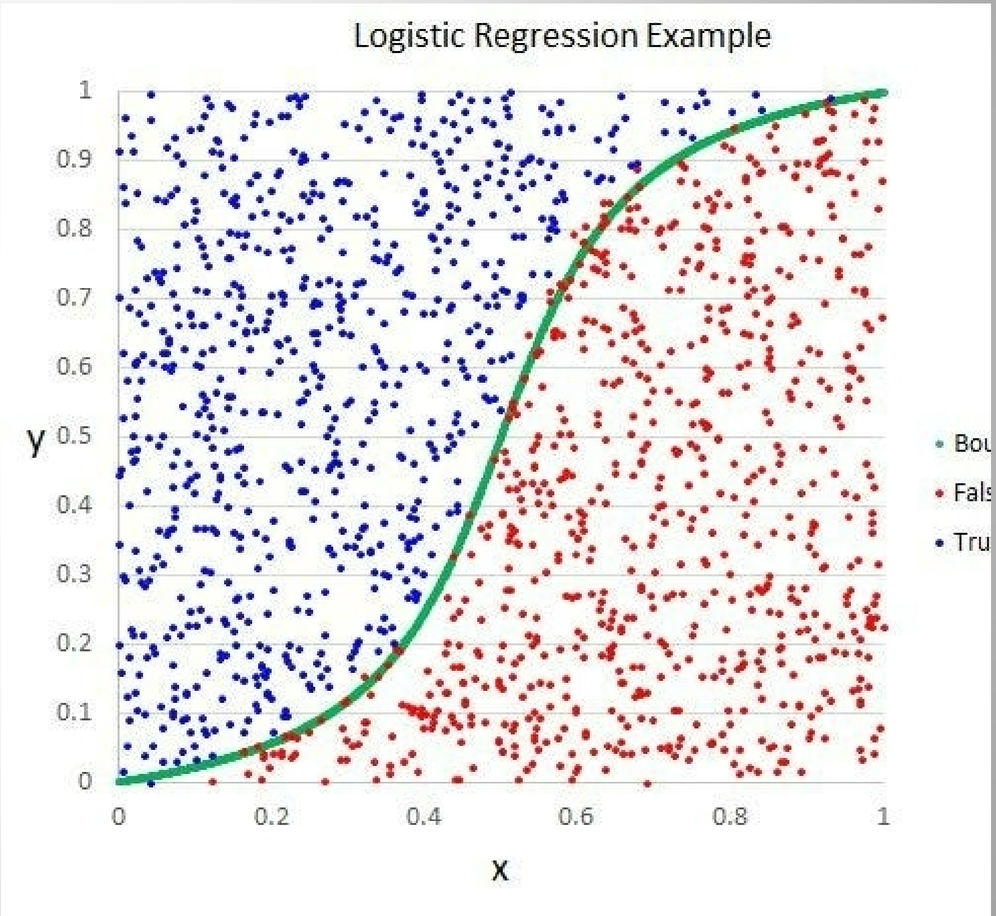
FEATURE EXTRACTION (TF-IDF)

- Converts text into numerical vectors
- Captures important words across tweets
- Works extremely well for classical ML models
- Uses unigrams and bigrams for richer representation



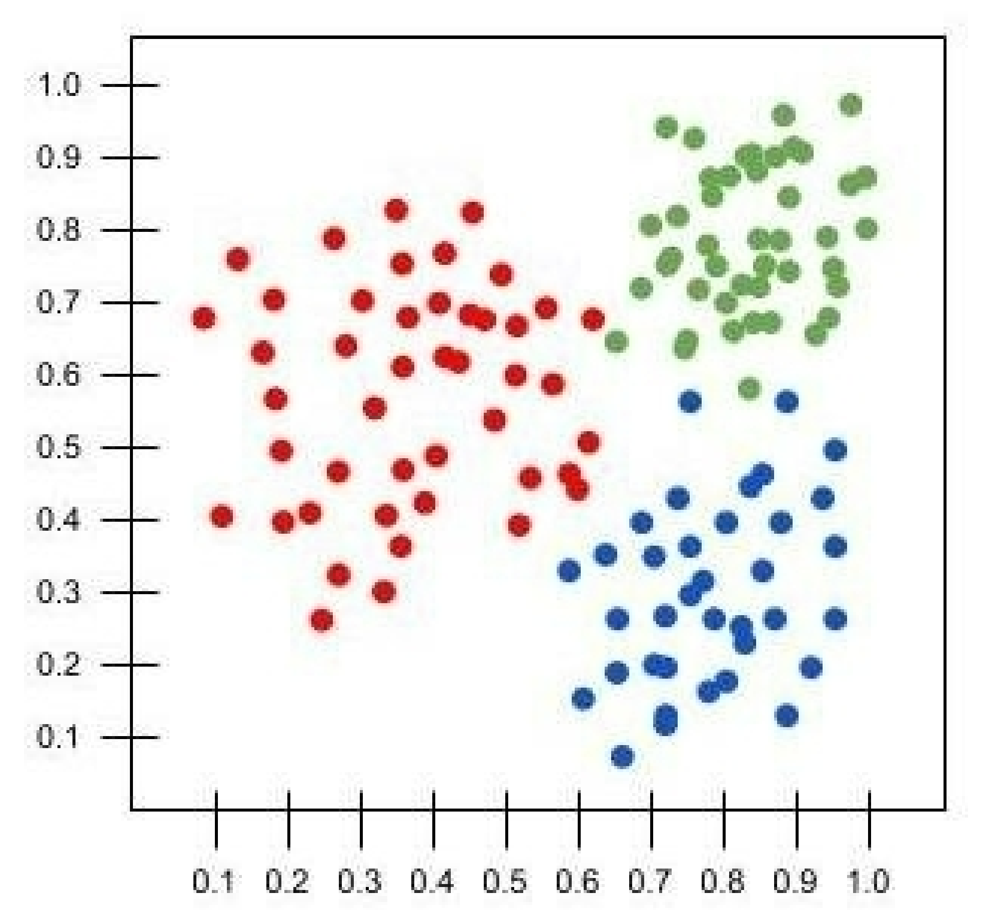
MODELS USED
LOGISTIC REGRESSION

- Works well with high-dimensional sparse text data
- Interpretable weight coefficients show which words influence sentiment
- Fast training + strong baseline performance
- Handles linearly separable classes effectively



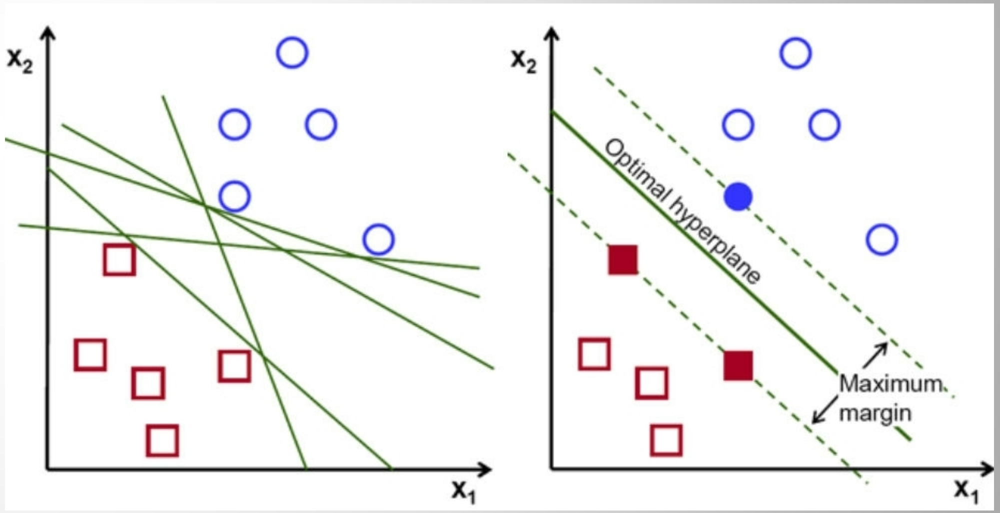
NAIVE BAYES

- Based on probability of words given each sentiment class
- Very fast and efficient for large text datasets
- Performs well when word distributions differ strongly across classes
- Assumes independence between words (can be a limitation)



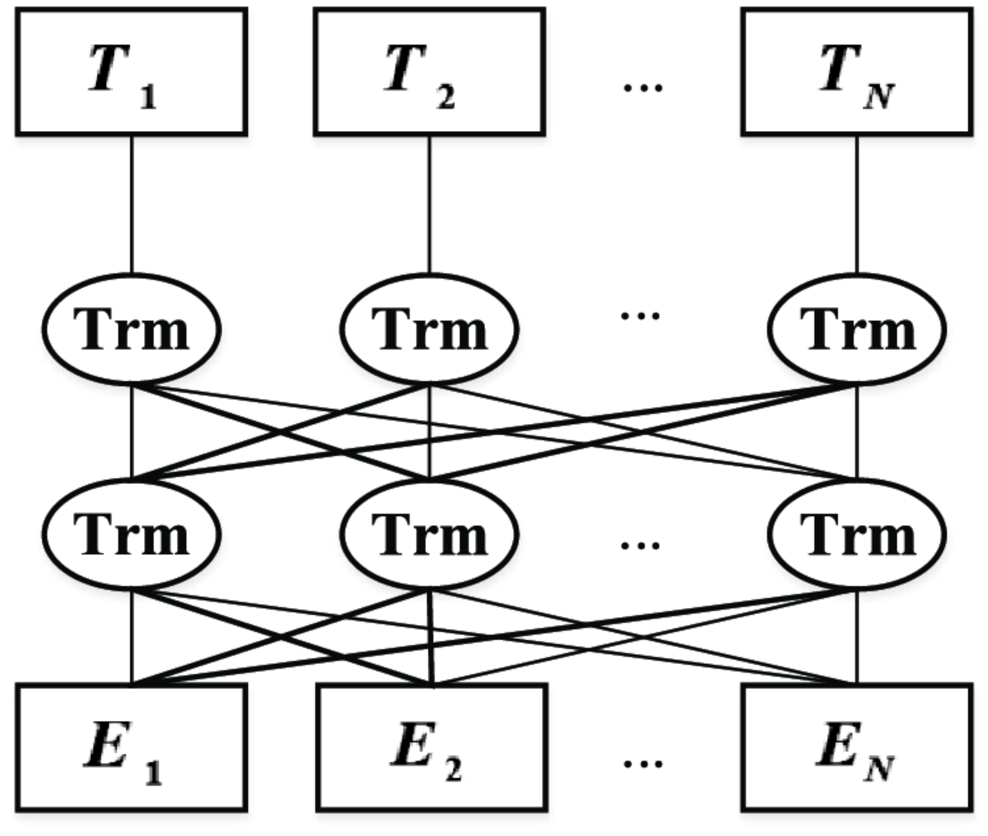
SUPPORT VECTOR MACHINE (SVM)

- Maximizes the margin between sentiment classes
- Very effective with TF-IDF vectors
- Handles high-dimensional text data better than many models
- Typically produces the highest accuracy in classical text classification tasks



BERT (BIDIRECTIONAL ENCODER REPRESENTATIONS FROM TRANSFORMERS)

- Reads entire sentence context (before + after each word)
- Generates powerful contextual embeddings for each token
- Pretrained on massive corpus strong language understanding
- Fine-tuned on airline sentiment for better task-specific accuracy
- Handles sarcasm, negation, and nuanced tweet language better than TF-IDF models
- More computationally expensive (GPU recommended)



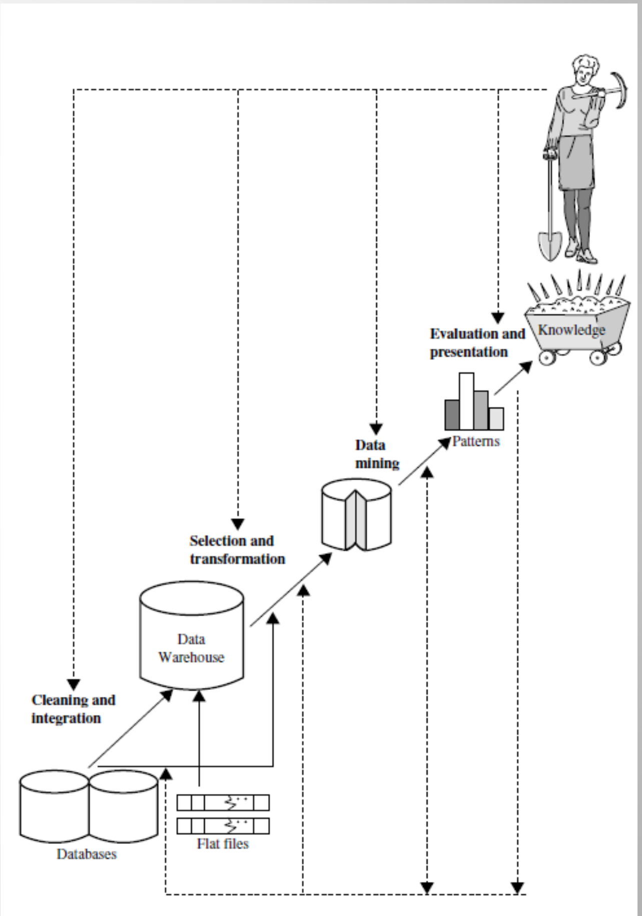
EXPERIMENTAL SETUP

- 80/20 train-test split
- TF-IDF features - LR, NB, SVM
- Token IDs + attention masks - BERT

Evaluation metrics:

- ➢ Accuracy
- ➢ Precision, Recall
- ➢ F1-Score
- ➢ Confusion Matrix

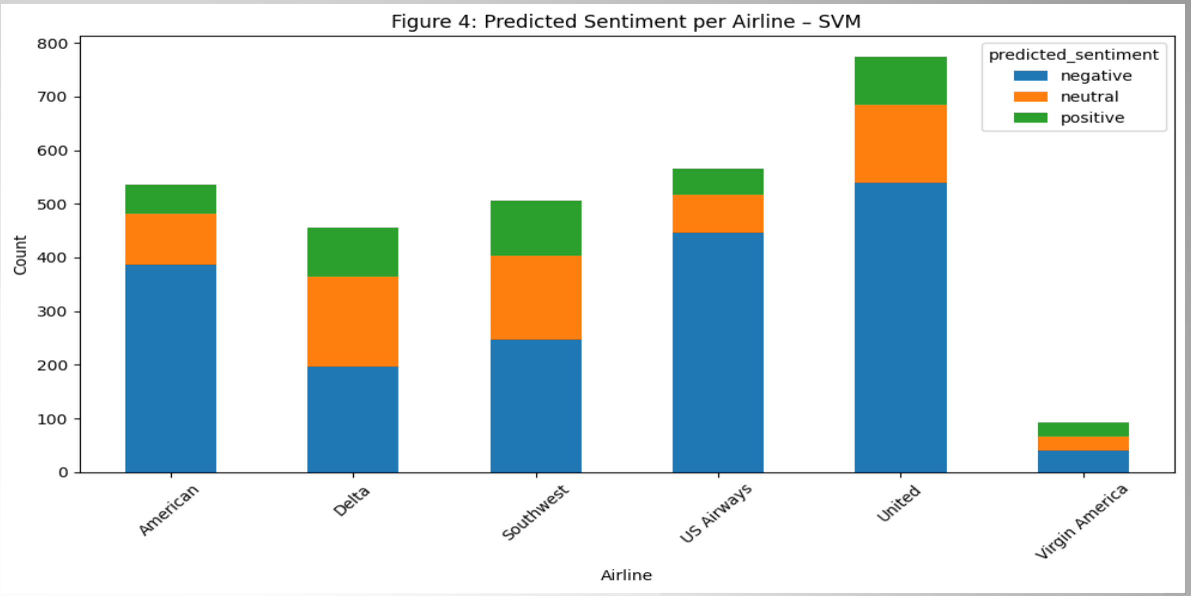
- Same test set for fair model comparison



RESULTS: CLASSICAL ML

SUPPORT VECTOR MACHINE (SVM)

- Best performance: 93% accuracy
- Strong at differentiating negative vs. neutral sentiment

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=== SVM Performance ===
Accuracy: 0.9279371584699454

              precision    recall  f1-score   support

    negative       0.99      1.00      0.99      1835
     neutral       0.82      0.87      0.84       620
    positive       0.84      0.72      0.77       473

    accuracy                           0.93      2928
   macro avg       0.88      0.86      0.87      2928
weighted avg       0.93      0.93      0.93      2928
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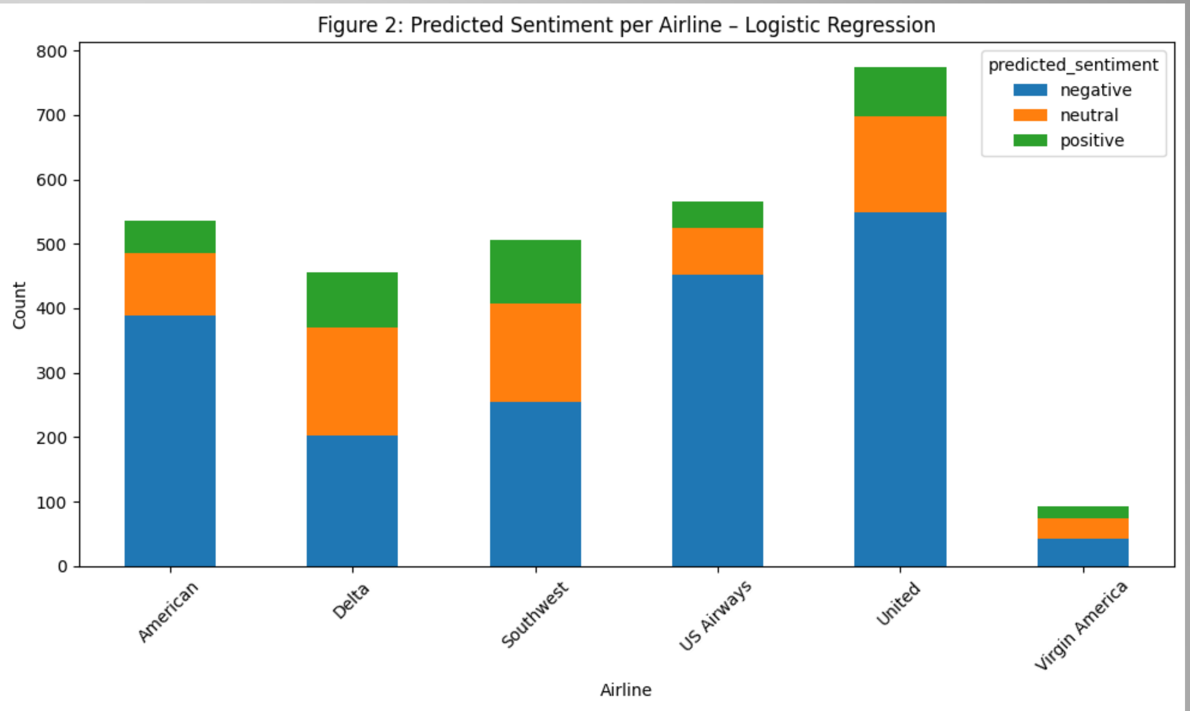
LOGISTIC REGRESSION

- Accuracy: 92%
- Stable and consistent across classes

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=== Logistic Regression Performance ===
Accuracy: 0.9183743169398907

              precision    recall  f1-score   support

    negative       0.97      1.00      0.99      1835
     neutral       0.80      0.87      0.83       620
    positive       0.86      0.67      0.75       473

    accuracy                           0.92      2928
   macro avg       0.88      0.85      0.86      2928
weighted avg       0.92      0.92      0.92      2928
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NAIVE BAYES

- Accuracy: 79%
- Struggles with overlapping sentiment vocabulary

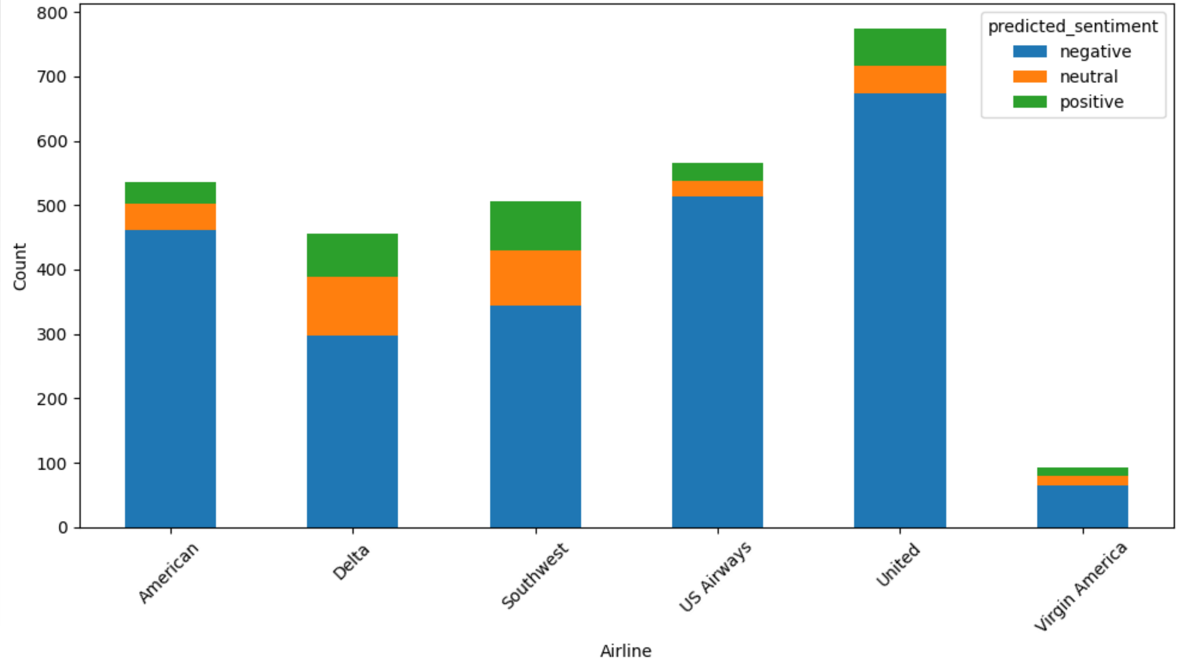

Figure 6: Predicted Sentiment per Airline – Naive Bayes

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=== Naive Bayes Performance ===
Accuracy: 0.7920081967213115

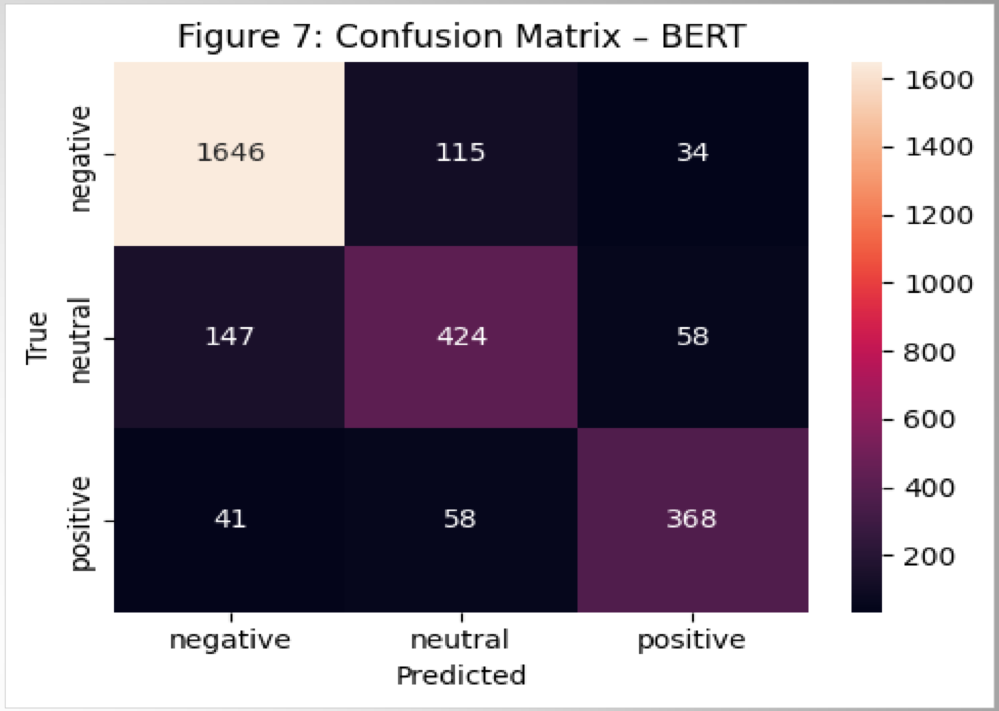
              precision    recall  f1-score   support

    negative       0.78      1.00      0.87      1835
     neutral       0.81      0.39      0.53       620
    positive       0.90      0.52      0.66       473

    accuracy                           0.79      2928
   macro avg       0.83      0.64      0.69      2928
weighted avg       0.80      0.79      0.77      2928
```

RESULTS: BERT

- Accuracy: 84%
- Better at capturing positive and nuanced sentiment
- Balanced confusion matrix
- Requires more computation + careful tuning




```
=== BERT Classification Report ===
              precision    recall  f1-score   support

    negative       0.90      0.92      0.91      1795
     neutral       0.71      0.67      0.69       629
    positive       0.80      0.79      0.79       467

    accuracy                           0.84      2891
   macro avg       0.80      0.79      0.80      2891
weighted avg       0.84      0.84      0.84      2891
```

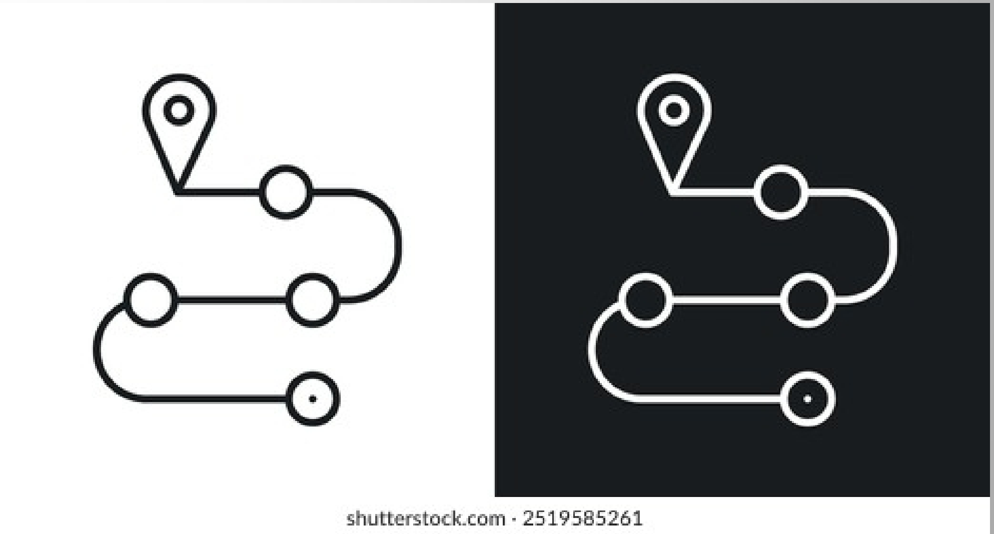
CONCLUSION & FUTURE WORK

Conclusion

- Classical ML models (especially SVM) perform extremely well with TF-IDF
- BERT provides deeper semantic understanding
- Best model depends on dataset size and complexity

Future Work

- Use larger and richer datasets
- Test more advanced transformers (RoBERTa, DistilBERT)
- Perform topic-specific sentiment analysis (delays, pricing, staff behavior)



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