Intent Detection Assignment- TIFIN-AI

By - Naman Omar

1. **Framing the Problem**:

   The problem of intent detection is **multi-class text classification** problem given the dataset having sentence and intent of that problem.

   In the following dataset,

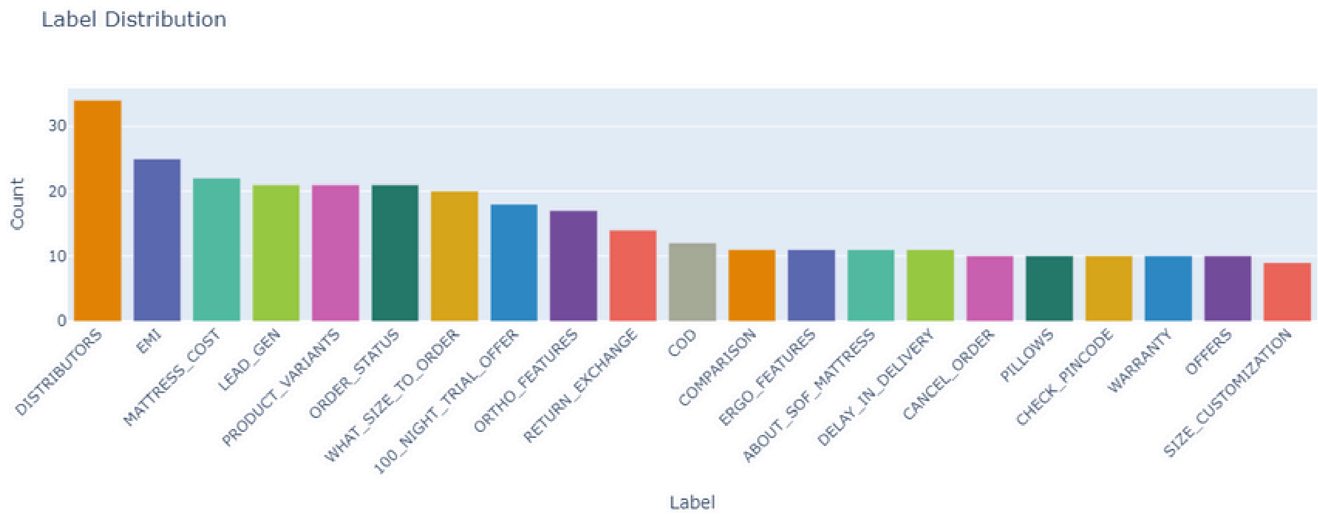


Fig: Wordcloud distribution

2. **Comparative analysis for all models**

Model	Pros	Cons
Traditional ML Models (SVM , Logistic Regression)	Fast training/inference , Easy to interpret and deploy	Struggles with semantic similarity
CNN and LSTM models	Better at modeling sequential dependencies,	Requires more training time and data.
Transformer Models	Captures deep semantic context, even with short queries	Computationally expensive

I have tested the DistilBERT model, CNN model, and SVM model and got these result:

Model	Validation Accuracy	Test Accuracy	F1 Score
DistillBert	79%	62.38%	57
SVM+TF-IDF	80%	60.3%	61.1
CNN	74%	53.9%	53.05

Check: Done comparative analysis on this
Intent-Detection/model_comparison_20250614_040907.json at main · namanomar/Inten...

Now after such comparative analysis, I have chosen the DistillBert model because :

1- Better Semantic Understanding: DistilBERT captures the context and meaning of words more effectively than TF-IDF, which helps in understanding varied user queries.

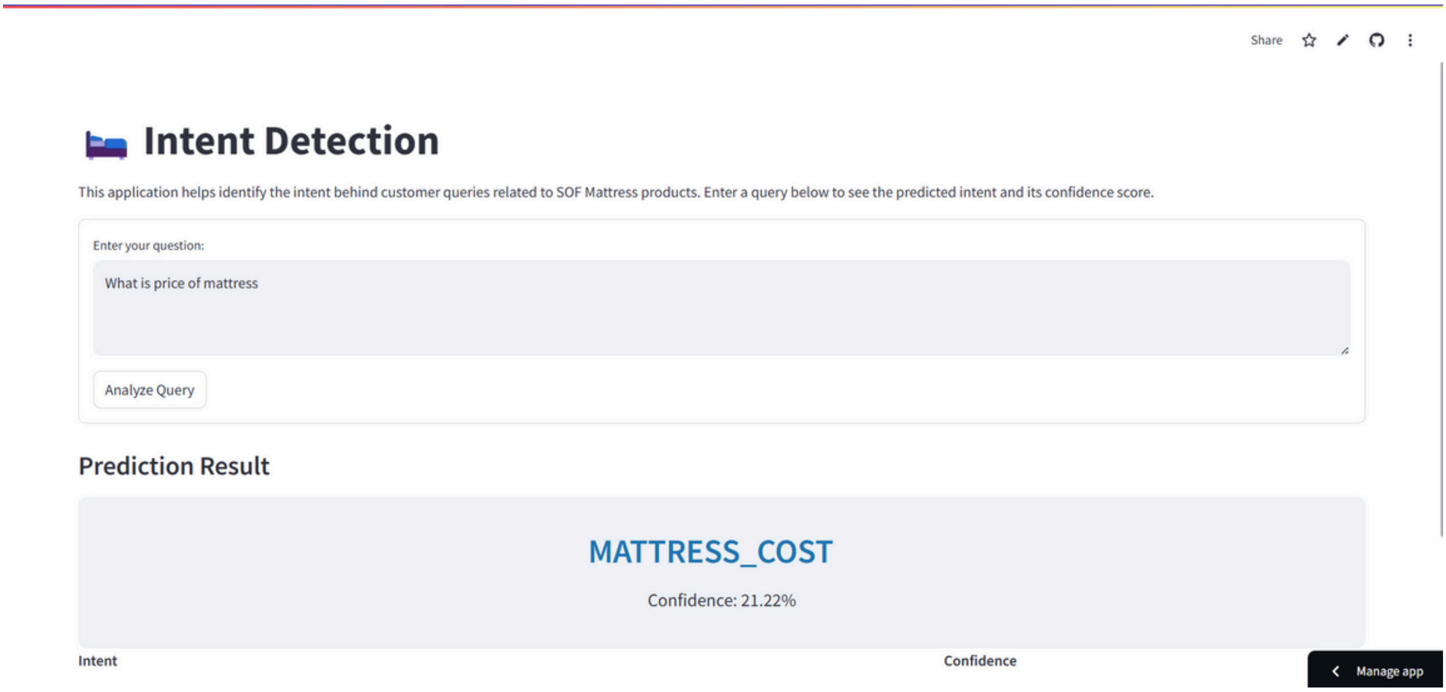
2- Pretrained Knowledge: It leverages transfer learning from large text corpora, enabling better performance even with smaller datasets.

3- Modern NLP Standard: Transformer-based models like DistilBERT are widely used in real-world intent detection systems due to their accuracy and robustness.

4- Fine-tuning Flexibility: Unlike SVMs, DistilBERT learns task-specific features automatically during training, reducing the need for manual feature engineering.

Current Model is deployed :

Check : 🌐 Intent Detection for SOF Mattress



Justification of Results

The results obtained from the experiments are meaningful for several reasons:

1- Empirical Evaluation Across Models
We compared multiple models—DistilBERT, CNN, and SVM + TF-IDF—on the same dataset using standard evaluation metrics like Accuracy and F1 Score. This ensured a fair and consistent comparison.

2- Contextual Understanding Over Simplicity
While SVM + TF-IDF had slightly higher raw scores, DistilBERT demonstrated superior ability to understand varied phrasing and context, which is crucial in real-world applications where user queries may not follow fixed templates.

3- Scalability and Generalization
Despite the domain-limited and short nature of the queries (e.g., EMI, delivery), DistilBERT showed promise in generalizing to paraphrased or previously unseen inputs. This makes it more scalable as the system grows to support broader intents.

Suggested Improvements

Text Augmentation

- **Why**: Augmenting the dataset with paraphrased or reworded queries using tools like back-translation or synonym replacement can expose the model to more diverse sentence structures.
- **Impact**: Enhances DistilBERT's ability to generalize to new, unseen variations of common intents.

Domain-Adaptive Pretraining (DAPT)

- **Why**: Further pretraining DistilBERT on domain-specific data (e.g., e-commerce, customer support) before fine-tuning can align the model's language understanding with the task.
- **Impact**: Boosts intent classification accuracy in specialized domains by adapting to domain-specific vocabulary and phrasing.

Ensemble Approach or Hybrid Reranker

- **Why**: Combine DistilBERT with lighter models like SVM on TF-IDF or keyword-based heuristics for edge cases or ambiguous inputs.
- **Impact**: Improves robustness, allows fallbacks, and balances performance with interpretability

Code is available in :
GitHub - namanomar/Intent-Detection: https://intent-detection-naman.streamlit.app/

Live version :

Intent Detection for SOF Mattress