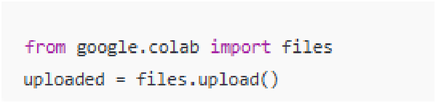
LDA Topic Modeling Workflow

This document provides a detailed overview of the Latent Dirichlet Allocation (LDA) topic modeling process we conducted as part of our project repository. The goal was to analyze patent abstracts related to cyberbullying and cyber safety in order to uncover latent thematic structures in the data.

Step 1: Data Upload

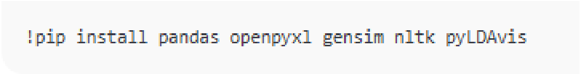
We used Google Colab to upload the Excel dataset containing patent abstracts. The abstracts served as the input corpus for topic modeling.



```python
from google.colab import files
uploaded = files.upload()
```

Step 2: Install Dependencies

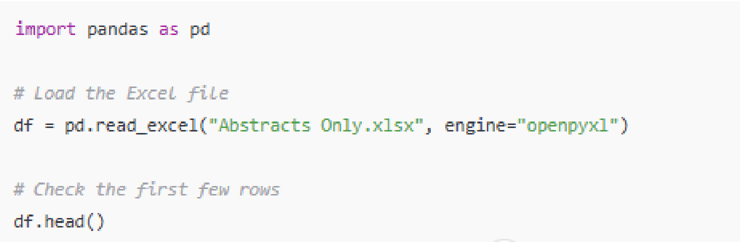
The following Python libraries were installed and used: pandas (data handling), openpyxl (Excel support), gensim (LDA modeling), nltk (text preprocessing), and pyLDAvis (visualization).



```
!pip install pandas openpyxl gensim nltk pyLDAvis
```

Step 3: Data Loading

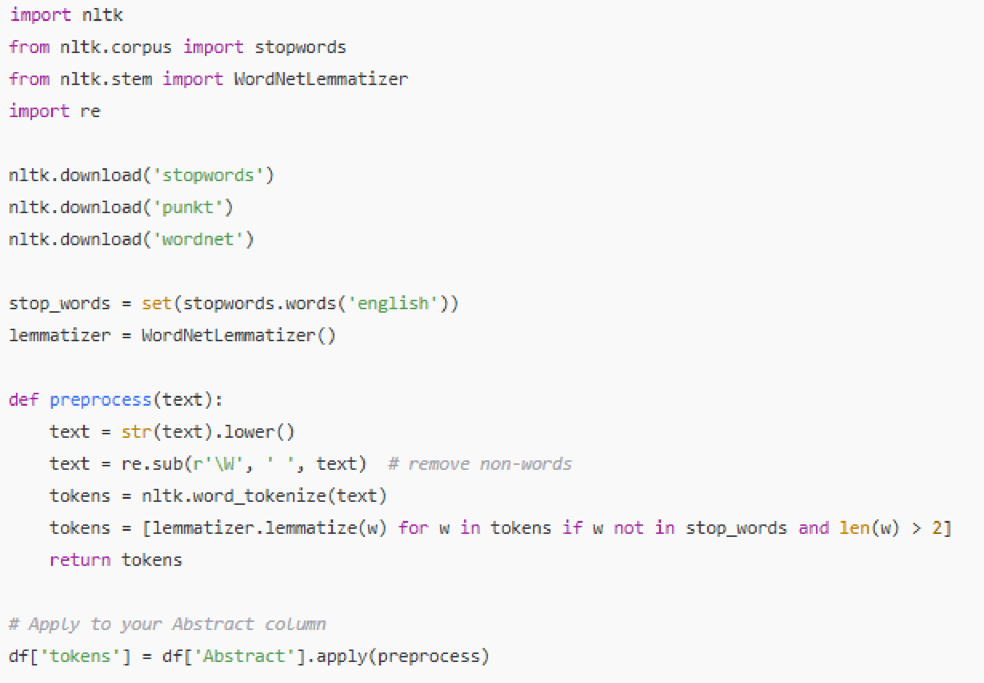
The Excel dataset was loaded into a pandas DataFrame, focusing specifically on the 'Abstract' column for further processing.



```python
import pandas as pd

# Load the Excel file
df = pd.read_excel("Abstracts Only.xlsx", engine="openpyxl")

# Check the first few rows
df.head()
```

Step 4: Text Preprocessing

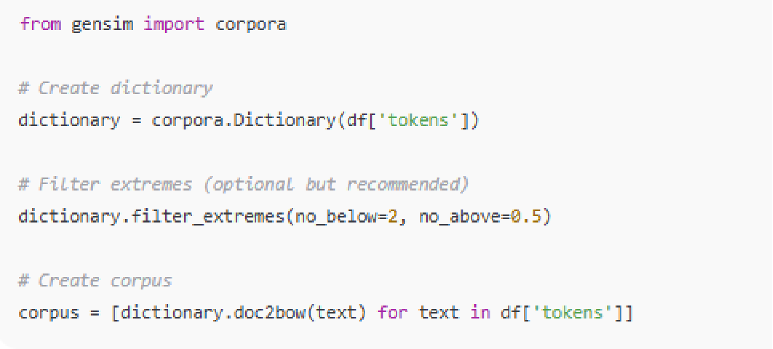
We applied a standard text preprocessing pipeline: lowercasing, removal of punctuation and non-words, tokenization, stopword removal, and lemmatization. This ensured consistent and meaningful tokens for topic modeling.



```python
import nltk
from nltk.corpus import stopwords
from nltk.stem import WordNetLemmatizer
import re

nltk.download('stopwords')
nltk.download('punkt')
nltk.download('wordnet')

stop_words = set(stopwords.words('english'))
lemmatizer = WordNetLemmatizer()

def preprocess(text):
    text = str(text).lower()
    text = re.sub(r'\W', ' ', text)  # remove non-words
    tokens = nltk.word_tokenize(text)
    tokens = [lemmatizer.lemmatize(w) for w in tokens if w not in stop_words and len(w) > 2]
    return tokens

# Apply to your Abstract column
df['tokens'] = df['Abstract'].apply(preprocess)
```

Step 5: Dictionary and Corpus Creation

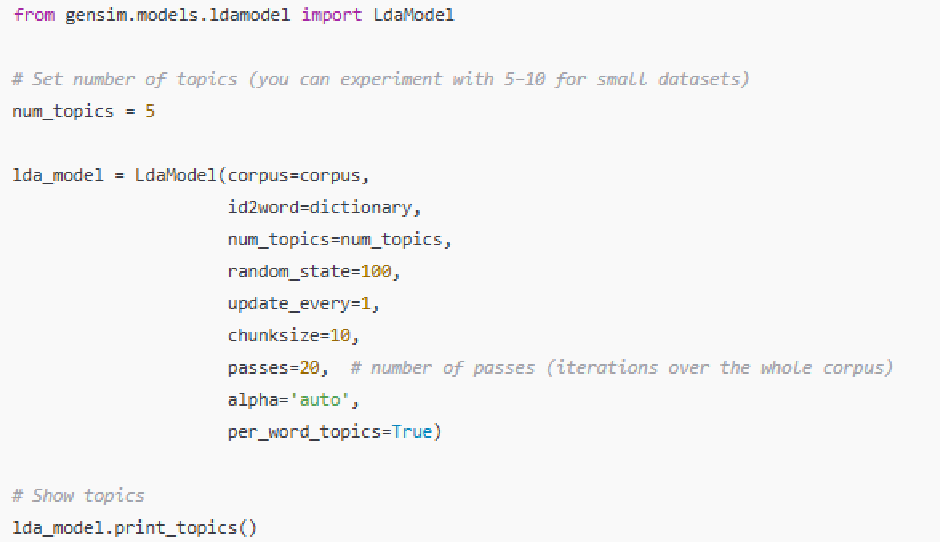
Using Gensim, we created a dictionary mapping each token to an ID. We applied filtering (no_below=2, no_above=0.5) to remove rare and overly frequent terms. The corpus was then converted into a bag-of-words representation suitable for LDA.



```python
from gensim import corpora

# Create dictionary
dictionary = corpora.Dictionary(df['tokens'])

# Filter extremes (optional but recommended)
dictionary.filter_extremes(no_below=2, no_above=0.5)

# Create corpus
corpus = [dictionary.doc2bow(text) for text in df['tokens']]
```

Step 6: LDA Model Training

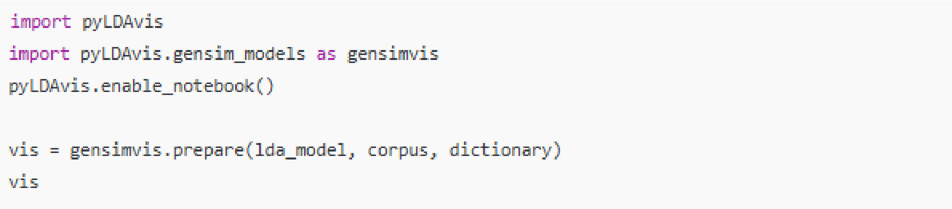
We trained LDA models with varying numbers of topics (k=4 to k=10). Model parameters included passes=20, chunksize=10, and alpha='auto'. The optimal number of topics was chosen based on coherence scores.



```python
from gensim.models.ldamodel import LdaModel

# Set number of topics (you can experiment with 5-10 for small datasets)
num_topics = 5

lda_model = LdaModel(corpus=corpus,
                     id2word=dictionary,
                     num_topics=num_topics,
                     random_state=100,
                     update_every=1,
                     chunksize=10,
                     passes=20,  # number of passes (iterations over the whole corpus)
                     alpha='auto',
                     per_word_topics=True)

# Show topics
lda_model.print_topics()
```

Step 7: Visualization

pyLDAvis was used to generate interactive visualizations. These allowed exploration of topic distributions, keyword importance, and topic overlap.



```python
import pyLDAvis
import pyLDAvis.gensim_models as gensimvis
pyLDAvis.enable_notebook()

vis = gensimvis.prepare(lda_model, corpus, dictionary)
vis
```

Step 8: Model Evaluation

Topic coherence was assessed using Gensim's CoherenceModel with c_v metric. Scores ranged from ~0.31 to ~0.39, with k=9 yielding the highest coherence (~0.39). Although modest, these results are expected in short-text corpora such as patent abstracts.

Insights Summary

Our topic analysis revealed a mix of highly relevant, moderately relevant, and outlier themes:
A score of ~0.39 (k=9) is **modest but acceptable** in short-text corpora like patent abstracts. Patent language is often technical and vague, which can limit coherence scores. A value above 0.35 is considered informative, especially if topics make semantic sense.

Topic by topic Analysis

Topic	Top Keywords	Interpretation	Relevance
0	application, access, web, information, request, dashboard	**Web-based software applications** managing user access or content — could include dashboards for moderation or parental controls	Possibly relevant to managing user interfaces or access for vulnerable groups
1	abuse, service, image, medium, processing, social	**Abuse detection in media/social services** — analyzing images or multimedia on platforms like social media	Highly relevant for cyberbullying, especially visual abuse
2	detection, video, network, control, url	**Network-based abuse/video content detection**, likely involving deep packet inspection or streaming video moderation	Relevant for online video/chat safety
3	content, input, module, message, virtual	**Content moderation systems**, modules processing virtual inputs (like messages or chats)	Important for chat and messaging safety, especially for kids
4	data, digital, event, threat, machine	**Cybersecurity / digital threat detection**, using AI to detect malicious activity in online events	Foundational to cyber safety infrastructure
5	device, user, response, call, communication	**Mobile or communication device protection**, maybe anti-phishing or spam control	Possibly relevant, depending on application context
6	model, vehicle, apparatus, motor, signal	**Autonomous or physical systems**, less aligned with cyber safety (likely about cars or IoT)	Not directly relevant
7	wearable, air, child, internet, designed	**IoT/wearable devices for children**, possibly air quality monitors or parental monitoring	Great connection to safety for children
8	server, security, unit, managing, database	**Back-end security infrastructure**, managing user data securely	Infrastructure-level safety, could support cyber safety systems

Insights Summary

High-Relevance Topics

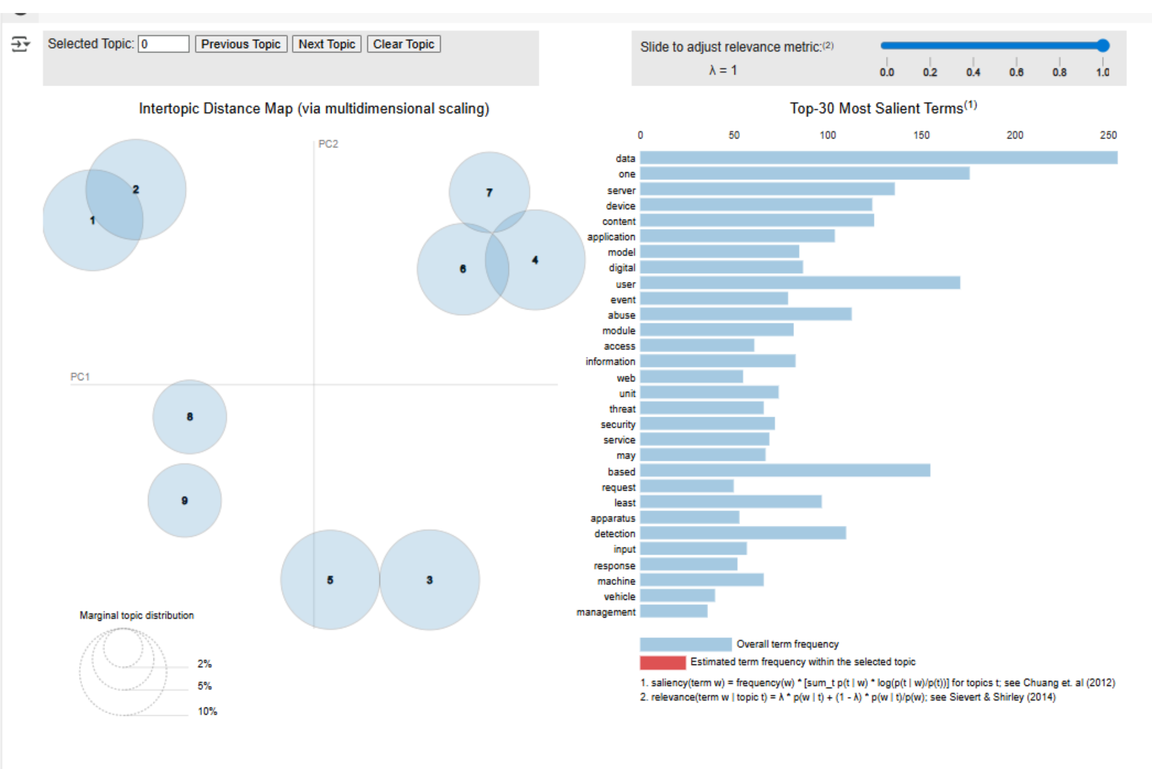
- **Topic 1**: Abuse in media and social systems
- **Topic 2**: Video/network-based content detection
- **Topic 3**: Chat/message filtering modules
- **Topic 4**: Digital threat & ML-based cybersecurity
- **Topic 7**: Wearables & IoT for kids

Medium-Relevance Topics

- **Topic 0**: Application/web dashboard design
- **Topic 5**: Mobile device abuse detection
- **Topic 8**: Secure server and backend management

Low-Relevance/Outlier

- **Topic 6**: Autonomous vehicles/sensors (likely out of scope)



1. saliency(term w) = frequency(w) * [sum_t p(t | w) * log(p(t | w)/p(t))] for topics t; see Chuang et. al (2012)

2. relevance(term w | topic t) = λ * p(w | t) + (1 - λ) * p(w | t)/p(w); see Sievert & Shirley (2014)