NLP PROJECT - Research Paper Recommendation and Subject Area Prediction

In [ ]:
```
from datasets import load_dataset

ds = load_dataset("gfissore/arxiv-abstracts-2021")
```

In [2]:
```
import pandas as pd
import numpy as np
from sklearn.feature_extraction.text import TfidfVectorizer
from nltk.tokenize import word_tokenize
from nltk.corpus import stopwords
from nltk.stem import WordNetLemmatizer
import re
import nltk
import torch
```

In [3]:
```
# Download necessary NLTK data
nltk.download('punkt')
nltk.download('stopwords')
nltk.download('wordnet')
```

```
[nltk_data] Downloading package punkt to
[nltk_data]     C:\Users\hashw\AppData\Roaming\nltk_data...
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\hashw\AppData\Roaming\nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package wordnet to
[nltk_data]     C:\Users\hashw\AppData\Roaming\nltk_data...
[nltk_data]   Package wordnet is already up-to-date!
```

Out[3]:
```
True
```

In [4]:
```
print(ds)
```

```
DatasetDict({
    train: Dataset({
        features: ['id', 'submitter', 'authors', 'title', 'comments', 'journal-ref', 'doi', 'abstract', 'report
-no', 'categories', 'versions'],
        num_rows: 1999486
    })
})
```

Converting dataset into a dataframe

In [5]:
```
# Convert to DataFrame
df_main = ds['train'].to_pandas()
```

In [6]:
```
df_main.shape
```

Out[6]:
```
(1999486, 11)
```

In [7]:
```
df_main.head(10)
```

Out[7]:

	id	submitter	authors	title	comments	journal-ref	doi	abstrac
0	0704.0001	Pavel Nadolsky	C. Bal\'azs, E. L. Berger, P. M. Nadolsky, C.-...	Calculation of prompt diphoton production cros...	37 pages, 15 figures; published version	Phys.Rev.D76:013009,2007	10.1103/PhysRevD.76.013009	A full differentia calculation i perturba..
1	0704.0002	Louis Theran	Ileana Streinu and Louis Theran	Sparsity-certifying Graph Decompositions	To appear in Graphs and Combinatorics	None	None	We describe a new algorithm the (k,ℓ)-..
2	0704.0003	Hongjun Pan	Hongjun Pan	The evolution of the Earth-Moon system based o...	23 pages, 3 figures	None	None	The evolution c Earth-Moor system i descri..
3	0704.0004	David Callan	David Callan	A determinant of Stirling cycle numbers counts...	11 pages	None	None	We show that a determinant c Stirling cycle..
4	0704.0005	Alberto Torchinsky	Wael Abu-Shammala and Alberto Torchinsky	From dyadic Λ_{α} to $\Lambda_{\a...	None	Illinois J. Math. 52 (2008) no.2, 681-689	None	In this paper we show how t compute the $\L..
5	0704.0006	Yue Hin Pong	Y. H. Pong and C. K. Law	Bosonic characters of atomic Cooper pairs acro...	6 pages, 4 figures, accepted by PRA	None	10.1103/PhysRevA.75.043613	We study the two-particle wave functior of p..
6	0704.0007	Alejandro Corichi	Alejandro Corichi, Tatjana Vukasinac and Jose ...	Polymer Quantum Mechanics and its Continuum Limit	16 pages, no figures. Typos corrected to match...	Phys.Rev.D76:044016,2007	10.1103/PhysRevD.76.044016	A rather non standard quantum representation..
7	0704.0008	Damian Swift	Damian C. Swift	Numerical solution of shock and ramp compressi...	Minor corrections	Journal of Applied Physics, vol 104, 073536 (2...	10.1063/1.2975338	A genera formulation was developed t repre..
8	0704.0009	Paul Harvey	Paul Harvey, Bruno Merin, Tracy L. Huard, Luis...	The Spitzer c2d Survey of Large, Nearby, Inste...	None	Astrophys.J.663:1149-1173,2007	10.1086/518646	We discuss the results from the combined IRA..
9	0704.0010	Sergei Ovchinnikov	Sergei Ovchinnikov	Partial cubes: structures, characterizations, ...	36 pages, 17 figures	None	None	Partial cubes are isometri subgraphs c hyp..

Keeping only the Columns required for our Task

In [8]:

```python
# Keep only the required columns
df = df_main[['title', 'abstract', 'categories']]
```

Convert 'categories' column from list/array to a string and extract only the primary category

In [9]:

```python
# Convert 'categories' column from list/array to a string with values separated by whitespace
df['categories'] = df['categories'].apply(lambda x: ' '.join(x) if isinstance(x, (list, np.ndarray)) else x)

# Extract the primary category (first category) and update the 'categories' column
df['categories'] = df['categories'].apply(lambda x: x.split()[0] if isinstance(x, str) and len(x.split()) > 0 e

# Print unique values in the 'categories' column after modification
unique_categories = df['categories'].unique()

# Print the unique values
print("Unique primary categories:")
print(unique_categories)

# Print the total number of unique primary categories
print("\nTotal number of unique primary categories:", len(unique_categories))
```

```
C:\Users\hashw\AppData\Local\Temp\ipykernel_1952\2545365738.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#ret
urning-a-view-versus-a-copy
  df['categories'] = df['categories'].apply(lambda x: ' '.join(x) if isinstance(x, (list, np.ndarray)) else x)
```

```
Unique primary categories:
['hep-ph' 'math.CO' 'physics.gen-ph' 'math.CA' 'cond-mat.mes-hall' 'gr-qc'
 'cond-mat.mtrl-sci' 'astro-ph' 'math.NT' 'hep-th' 'math.PR' 'hep-ex'
 'nlin.PS' 'math.NA' 'cond-mat.str-el' 'math.RA' 'physics.optics'
 'q-bio.PE' 'q-bio.QM' 'math.OA' 'math.QA' 'cond-mat.stat-mech' 'quant-ph'
 'cs.NE' 'physics.ed-ph' 'math.DG' 'cond-mat.soft' 'physics.pop-ph'
 'nucl-th' 'math.FA' 'cs.DS' 'math.AG' 'math.DS' 'physics.soc-ph'
 'math-ph' 'cond-mat.other' 'physics.data-an' 'cs.CE' 'math.GR' 'hep-lat'
 'cond-mat.supr-con' 'nlin.SI' 'cs.IT' 'math.AC' 'math.SG' 'cs.CC'
 'math.GT' 'nlin.CD' 'math.CV' 'math.AP' 'math.RT' 'q-bio.OT'
 'physics.plasm-ph' 'physics.bio-ph' 'nlin.CG' 'cs.DM' 'nucl-ex'
 'physics.flu-dyn' 'physics.comp-ph' 'math.MG' 'physics.atom-ph' 'math.ST'
 'physics.chem-ph' 'math.AT' 'physics.geo-ph' 'q-bio.NC' 'q-fin.RM'
 'cond-mat.dis-nn' 'q-bio.SC' 'q-bio.BM' 'math.OC' 'cs.CR' 'math.LO'
 'cs.NI' 'q-fin.PR' 'physics.class-ph' 'q-fin.GN' 'q-fin.ST' 'cs.PF'
 'stat.ME' 'q-fin.CP' 'math.GM' 'math.KT' 'physics.atm-clus'
 'physics.acc-ph' 'math.SP' 'physics.hist-ph' 'cs.LG' 'cs.CY' 'q-bio.GN'
 'cs.CG' 'cs.CV' 'math.HO' 'cs.SE' 'physics.ins-det' 'cs.OH' 'cs.PL'
 'q-bio.CB' 'cs.AI' 'physics.space-ph' 'nlin.AO' 'q-bio.MN' 'cs.IR'
 'cs.GT' 'cs.LO' 'stat.AP' 'cs.SC' 'cs.DC' 'cs.CL' 'math.CT' 'q-fin.PM'
 'physics.med-ph' 'cs.HC' 'physics.ao-ph' 'cs.AR' 'cs.DL' 'cs.MS' 'cs.RO'
 'cs.DB' 'math.GN' 'q-bio.TO' 'cs.GL' 'cs.MA' 'cs.MM' 'stat.ML' 'cs.OS'
 'q-fin.TR' 'cs.NA' 'cs.SD' 'stat.CO' 'cs.GR' 'cs.FL' 'cond-mat.quant-gas'
 'astro-ph.HE' 'astro-ph.SR' 'astro-ph.GA' 'astro-ph.CO' 'astro-ph.IM'
 'astro-ph.EP' 'cs.SI' 'stat.OT' 'cs.SY' 'eess.SY' 'cs.ET' 'eess.SP'
 'q-fin.EC' 'q-fin.MF' 'physics.app-ph' 'econ.GN' 'eess.AS' 'econ.TH'
 'eess.IV' 'econ.EM' 'acc-phys' 'adap-org' 'alg-geom' 'ao-sci' 'atom-ph'
 'bayes-an' 'chao-dyn' 'chem-ph' 'cmp-lg' 'comp-gas' 'cond-mat' 'dg-ga'
 'funct-an' 'mtrl-th' 'patt-sol' 'plasm-ph' 'q-alg' 'solv-int' 'supr-con']

Total number of unique primary categories: 172
```

```
C:\Users\hashw\AppData\Local\Temp\ipykernel_1952\2545365738.py:5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#ret
urning-a-view-versus-a-copy
  df['categories'] = df['categories'].apply(lambda x: x.split()[0] if isinstance(x, str) and len(x.split()) > 0
else None)
```

In [10]:

```python
category_counts = df['categories'].value_counts()
print(category_counts)
```

```
categories
hep-ph               119400
hep-th                95479
astro-ph              94246
quant-ph              87454
cond-mat.mes-hall     54691
                      ...
atom-ph                  68
acc-phys                 46
plasm-ph                 28
ao-sci                   13
bayes-an                 11
Name: count, Length: 172, dtype: int64
```

Set a general category named 'Other' if the count of records is less than 1000

In [11]:

```python
# Set a threshold for "Other"
threshold = 1000

# Assign "Other" to categories with fewer papers than the threshold
df['categories'] = df['categories'].apply(lambda x: x if category_counts[x] >= threshold else 'Other')

# Verify the new distribution
category_counts = df['categories'].value_counts()
print(category_counts)
```

```
categories
hep-ph               119400
hep-th                95479
astro-ph              94246
quant-ph              87454
cond-mat.mes-hall     54691
                      ...
q-fin.MF               1128
physics.atm-clus       1113
cs.NA                  1083
q-fin.PR               1064
cs.SC                  1008
Name: count, Length: 142, dtype: int64
```

```
C:\Users\hashw\AppData\Local\Temp\ipykernel_1952\3258524472.py:5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#ret

urning-a-view-versus-a-copy
  df['categories'] = df['categories'].apply(lambda x: x if category_counts[x] >= threshold else 'Other')
```

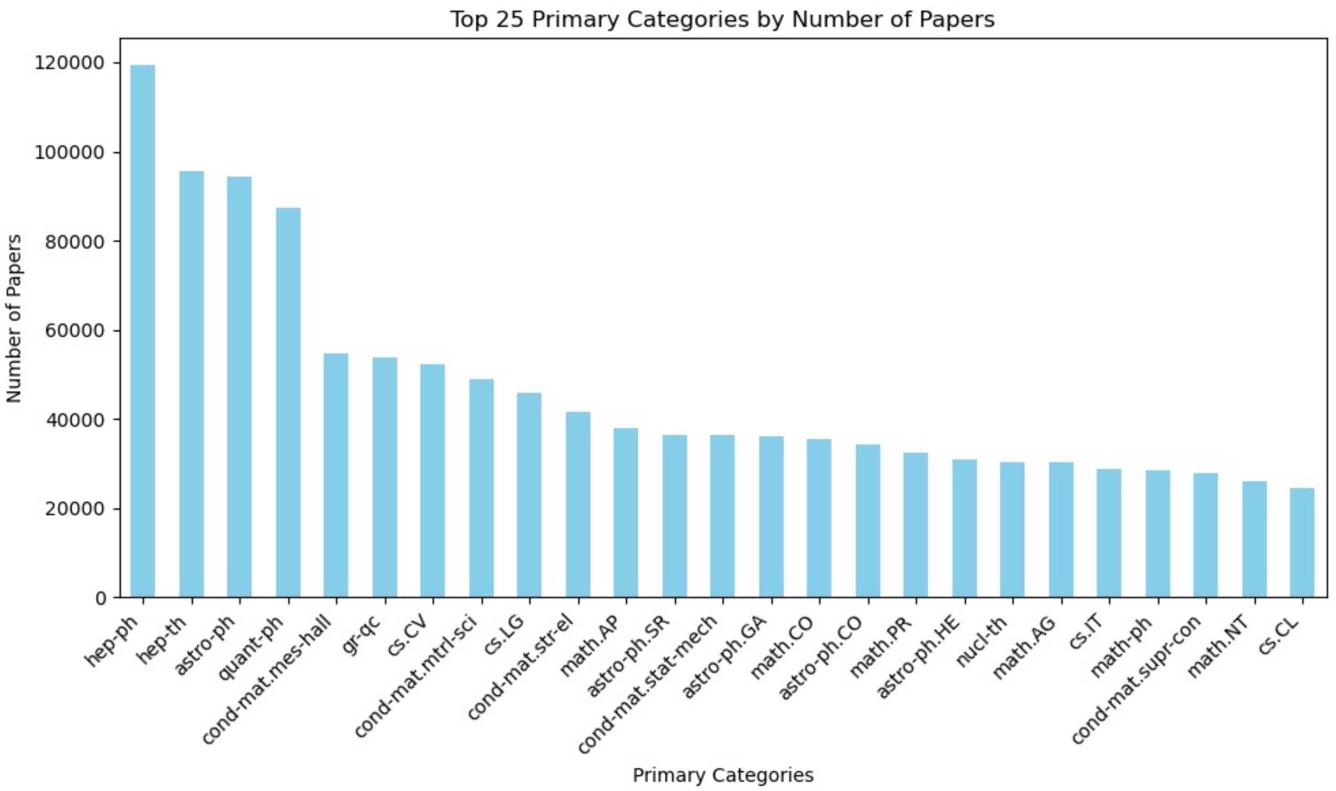
In [12]:

```
unique_primary_categories = df['categories'].unique()

# Print the unique primary categories and their count
print("Unique primary categories:")
print(unique_primary_categories)
print("\nTotal number of unique primary categories:", len(unique_primary_categories))
```

```
Unique primary categories:
['hep-ph' 'math.CO' 'physics.gen-ph' 'math.CA' 'cond-mat.mes-hall' 'gr-qc'
 'cond-mat.mtrl-sci' 'astro-ph' 'math.NT' 'hep-th' 'math.PR' 'hep-ex'
 'nlin.PS' 'math.NA' 'cond-mat.str-el' 'math.RA' 'physics.optics'
 'q-bio.PE' 'q-bio.QM' 'math.OA' 'math.QA' 'cond-mat.stat-mech' 'quant-ph'
 'cs.NE' 'physics.ed-ph' 'math.DG' 'cond-mat.soft' 'physics.pop-ph'
 'nucl-th' 'math.FA' 'cs.DS' 'math.AG' 'math.DS' 'physics.soc-ph'
 'math-ph' 'cond-mat.other' 'physics.data-an' 'cs.CE' 'math.GR' 'hep-lat'
 'cond-mat.supr-con' 'nlin.SI' 'cs.IT' 'math.AC' 'math.SG' 'cs.CC'
 'math.GT' 'nlin.CD' 'math.CV' 'math.AP' 'math.RT' 'Other'
 'physics.plasm-ph' 'physics.bio-ph' 'cs.DM' 'nucl-ex' 'physics.flu-dyn'
 'physics.comp-ph' 'math.MG' 'physics.atom-ph' 'math.ST' 'physics.chem-ph'
 'math.AT' 'physics.geo-ph' 'q-bio.NC' 'cond-mat.dis-nn' 'q-bio.BM'
 'math.OC' 'cs.CR' 'math.LO' 'cs.NI' 'q-fin.PR' 'physics.class-ph'
 'q-fin.GN' 'q-fin.ST' 'stat.ME' 'math.GM' 'math.KT' 'physics.atm-clus'
 'physics.acc-ph' 'math.SP' 'physics.hist-ph' 'cs.LG' 'cs.CY' 'q-bio.GN'
 'cs.CG' 'cs.CV' 'math.HO' 'cs.SE' 'physics.ins-det' 'cs.OH' 'cs.PL'
 'cs.AI' 'physics.space-ph' 'nlin.AO' 'q-bio.MN' 'cs.IR' 'cs.GT' 'cs.LO'
 'stat.AP' 'cs.SC' 'cs.DC' 'cs.CL' 'math.CT' 'physics.med-ph' 'cs.HC'
 'physics.ao-ph' 'cs.AR' 'cs.DL' 'cs.RO' 'cs.DB' 'math.GN' 'cs.MA' 'cs.MM'
 'stat.ML' 'cs.NA' 'cs.SD' 'stat.CO' 'cs.GR' 'cs.FL' 'cond-mat.quant-gas'
 'astro-ph.HE' 'astro-ph.SR' 'astro-ph.GA' 'astro-ph.CO' 'astro-ph.IM'
 'astro-ph.EP' 'cs.SI' 'cs.SY' 'eess.SY' 'cs.ET' 'eess.SP' 'q-fin.MF'
 'physics.app-ph' 'econ.GN' 'eess.AS' 'eess.IV' 'econ.EM' 'alg-geom'
 'chao-dyn' 'cond-mat' 'q-alg']

Total number of unique primary categories: 142
```

In [13]:

```
import matplotlib.pyplot as plt

# Get the top N categories (e.g., top 10)
top_n = 25
top_categories = category_counts.head(top_n)

# Plot the top N categories
plt.figure(figsize=(10, 6))
top_categories.plot(kind='bar', color='skyblue')
plt.title(f'Top {top_n} Primary Categories by Number of Papers')
plt.xlabel('Primary Categories')
plt.ylabel('Number of Papers')
plt.xticks(rotation=45, ha='right')
plt.tight_layout()
plt.show()
```



In [14]:

```
# Get the top 25 categories by count
top_25_categories = category_counts.head(25)

# Print the top 25 categories and their counts
print("Top 25 categories and their counts:")
print(top_25_categories)
```

```
Top 25 categories and their counts:
categories
hep-ph                119400
hep-th                 95479
astro-ph               94246
quant-ph               87454
cond-mat.mes-hall      54691
gr-qc                  53919
cs.CV                  52308
cond-mat.mtrl-sci      49011
cs.LG                  45816
cond-mat.str-el        41671
math.AP                37938
astro-ph.SR            36377
cond-mat.stat-mech     36307
astro-ph.GA            35963
math.CO                35571
astro-ph.CO            34287
math.PR                32468
astro-ph.HE            31036
nucl-th                30368
math.AG                30204
cs.IT                  28752
math-ph                28544
cond-mat.supr-con      28015
math.NT                26163
cs.CL                  24667
Name: count, dtype: int64
```

Filter the dataframe to hold only top 25 category for our analysis

In [15]:

```
# Filter the DataFrame for top 25 categories
df = df[df['categories'].isin(top_25_categories.index)]

# Check the filtered DataFrame
print(top_25_categories.head())
```

```
categories
hep-ph               119400
hep-th                95479
astro-ph              94246
quant-ph              87454
cond-mat.mes-hall     54691
Name: count, dtype: int64
```

In [16]:

```
df.shape
```

Out[16]: (1170655, 3)

In [17]:
```
df['categories'].nunique()
```

Out[17]: 25

Downsampling the dataset

In [18]:
```
df= df.sample(frac=0.25, random_state=42)
```

In [19]:
```
df.shape
```

Out[19]: (292664, 3)

In [20]:
```
# Check GPU availability
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
print(f"Using device: {device}")
```

```
Using device: cuda
```

Data Cleaning and Pre-processing

In [21]:
```
# Shell 2: Data Cleaning and Preprocessing
import re
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from nltk.tokenize import word_tokenize
import nltk
nltk.download('stopwords')
nltk.download('punkt')

# Initialize stemmer and stop words
stemmer = PorterStemmer()
stop_words = set(stopwords.words('english'))

# Preprocessing function
def preprocess_text(text):
    # Lowercase
    text = text.lower()
    # Remove special characters
    text = re.sub(r'[^a-zA-Z\s]', '', text)
    # Tokenize
    tokens = word_tokenize(text)
    # Remove stopwords and stem
    tokens = [stemmer.stem(word) for word in tokens if word not in stop_words]
    # Join back into a single string
    return ' '.join(tokens)

# Apply preprocessing to title and abstract
df['cleaned_title'] = df['title'].apply(preprocess_text)
df['cleaned_abstract'] = df['abstract'].apply(preprocess_text)

# Save the cleaned data for EDA and further processing
df.to_csv("cleaned_dataset.csv", index=False)
print("Preprocessing completed and saved.")
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\hashw\AppData\Roaming\nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package punkt to
[nltk_data]     C:\Users\hashw\AppData\Roaming\nltk_data...
[nltk_data]   Package punkt is already up-to-date!
Preprocessing completed and saved.
```

In [22]:
```
pip install wordcloud
```

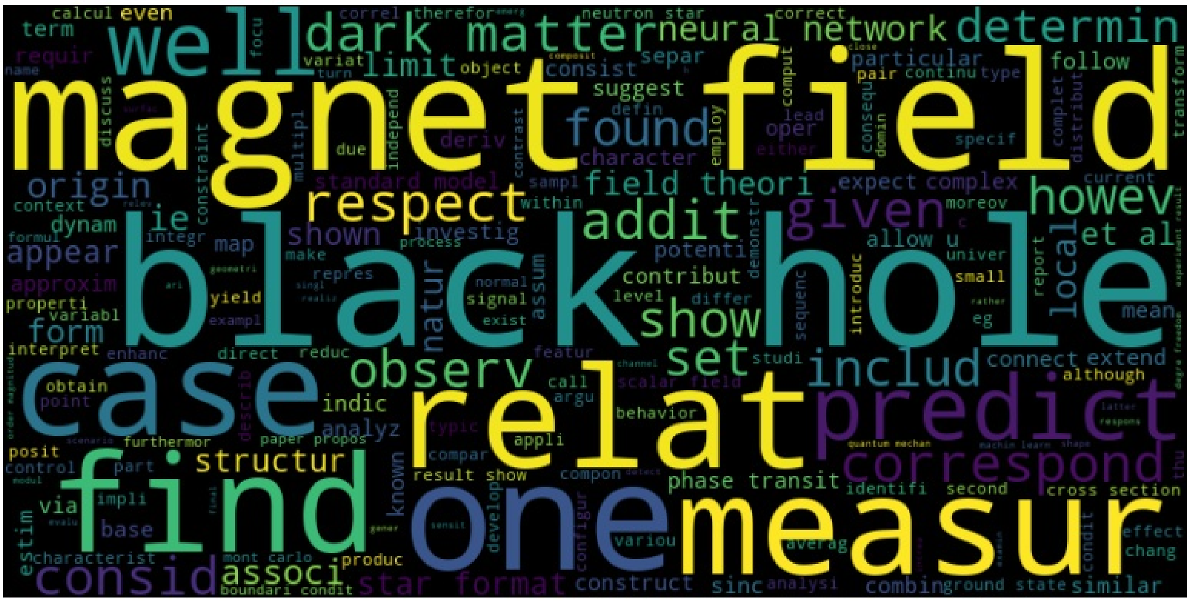
```
Requirement already satisfied: wordcloud in c:\users\hashw\anaconda3\lib\site-packages (1.9.4)
Requirement already satisfied: numpy>=1.6.1 in c:\users\hashw\anaconda3\lib\site-packages (from wordcloud) (1.2
6.4)
Requirement already satisfied: pillow in c:\users\hashw\anaconda3\lib\site-packages (from wordcloud) (9.4.0)
Requirement already satisfied: matplotlib in c:\users\hashw\anaconda3\lib\site-packages (from wordcloud) (3.7.1
)
Requirement already satisfied: contourpy>=1.0.1 in c:\users\hashw\anaconda3\lib\site-packages (from matplotlib-
>wordcloud) (1.0.5)
Requirement already satisfied: cycler>=0.10 in c:\users\hashw\anaconda3\lib\site-packages (from matplotlib->wor
dcloud) (0.11.0)
Requirement already satisfied: fonttools>=4.22.0 in c:\users\hashw\anaconda3\lib\site-packages (from matplotlib
->wordcloud) (4.25.0)
Requirement already satisfied: kiwisolver>=1.0.1 in c:\users\hashw\anaconda3\lib\site-packages (from matplotlib
->wordcloud) (1.4.4)
Requirement already satisfied: packaging>=20.0 in c:\users\hashw\anaconda3\lib\site-packages (from matplotlib->
wordcloud) (23.0)
Requirement already satisfied: pyparsing>=2.3.1 in c:\users\hashw\anaconda3\lib\site-packages (from matplotlib-
>wordcloud) (3.0.9)
Requirement already satisfied: python-dateutil>=2.7 in c:\users\hashw\anaconda3\lib\site-packages (from matplot
lib->wordcloud) (2.8.2)
Requirement already satisfied: six>=1.5 in c:\users\hashw\anaconda3\lib\site-packages (from python-dateutil>=2.
7->matplotlib->wordcloud) (1.16.0)
Note: you may need to restart the kernel to use updated packages.
```

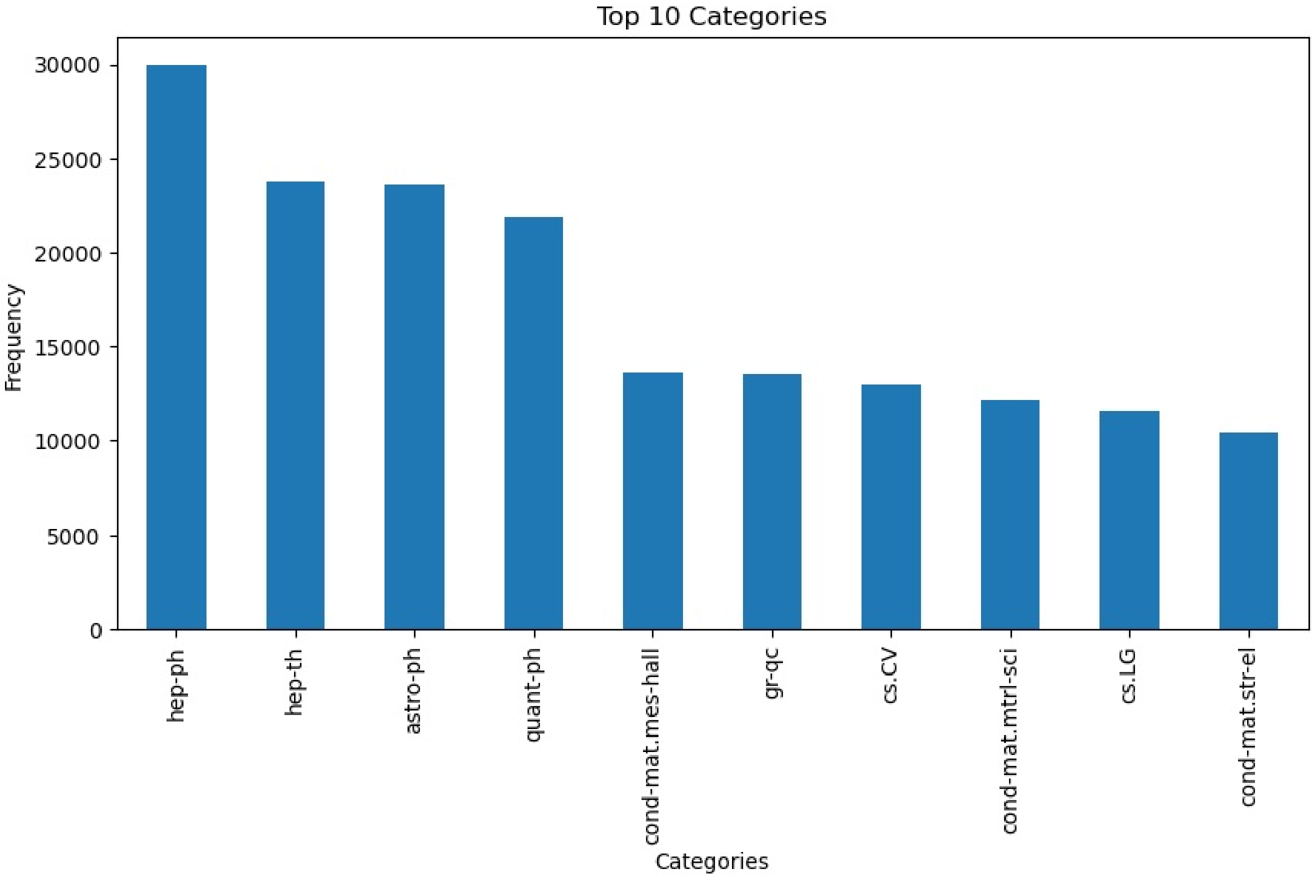
EDA

In [23]:

```python
# Shell 3: Exploratory Data Analysis (EDA)
import matplotlib.pyplot as plt
from wordcloud import WordCloud
from collections import Counter

# Word Cloud for Abstracts
abstract_text = " ".join(df['cleaned_abstract'])
wordcloud = WordCloud(width=800, height=400).generate(abstract_text)

plt.figure(figsize=(10, 5))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis('off')
plt.title("Word Cloud of Abstracts")
plt.show()

# Top Categories Bar Chart
category_counts = df['categories'].value_counts()
plt.figure(figsize=(10, 5))
category_counts.head(10).plot(kind='bar')
plt.title("Top 10 Categories")
plt.xlabel("Categories")
plt.ylabel("Frequency")
plt.show()
```

Word Cloud of Abstracts





Recommendation Engine using BERT

In [24]:
```
pip install transformers
```

```
Requirement already satisfied: transformers in c:\users\hashw\anaconda3\lib\site-packages (4.46.3)
Requirement already satisfied: filelock in c:\users\hashw\anaconda3\lib\site-packages (from transformers) (3.9.
0)
Requirement already satisfied: huggingface-hub<1.0,>=0.23.2 in c:\users\hashw\anaconda3\lib\site-packages (from
transformers) (0.25.2)
Requirement already satisfied: numpy>=1.17 in c:\users\hashw\anaconda3\lib\site-packages (from transformers) (1
.26.4)
Requirement already satisfied: packaging>=20.0 in c:\users\hashw\anaconda3\lib\site-packages (from transformers
) (23.0)
Requirement already satisfied: pyyaml>=5.1 in c:\users\hashw\anaconda3\lib\site-packages (from transformers) (6
.0)
Requirement already satisfied: regex!=2019.12.17 in c:\users\hashw\anaconda3\lib\site-packages (from transforme
rs) (2022.7.9)
Requirement already satisfied: requests in c:\users\hashw\anaconda3\lib\site-packages (from transformers) (2.32
.3)
Requirement already satisfied: tokenizers<0.21,>=0.20 in c:\users\hashw\anaconda3\lib\site-packages (from trans
formers) (0.20.3)
Requirement already satisfied: safetensors>=0.4.1 in c:\users\hashw\anaconda3\lib\site-packages (from transform
ers) (0.4.5)
Requirement already satisfied: tqdm>=4.27 in c:\users\hashw\anaconda3\lib\site-packages (from transformers) (4.
66.5)
Requirement already satisfied: fsspec>=2023.5.0 in c:\users\hashw\anaconda3\lib\site-packages (from huggingface
-hub<1.0,>=0.23.2->transformers) (2024.6.1)
Requirement already satisfied: typing-extensions>=3.7.4.3 in c:\users\hashw\anaconda3\lib\site-packages (from h
uggingface-hub<1.0,>=0.23.2->transformers) (4.12.2)
Requirement already satisfied: colorama in c:\users\hashw\anaconda3\lib\site-packages (from tqdm>=4.27->transfo
rmers) (0.4.6)
Requirement already satisfied: charset-normalizer<4,>=2 in c:\users\hashw\anaconda3\lib\site-packages (from req
uests->transformers) (2.0.4)
Requirement already satisfied: idna<4,>=2.5 in c:\users\hashw\anaconda3\lib\site-packages (from requests->trans
formers) (3.4)
Requirement already satisfied: urllib3<3,>=1.21.1 in c:\users\hashw\anaconda3\lib\site-packages (from requests-
>transformers) (1.26.16)
Requirement already satisfied: certifi>=2017.4.17 in c:\users\hashw\anaconda3\lib\site-packages (from requests-
>transformers) (2023.7.22)
Note: you may need to restart the kernel to use updated packages.
```

In [25]:

```python
# Shell 4: Recommendation Engine Using BERT
from transformers import BertTokenizer, BertModel
from sklearn.metrics.pairwise import cosine_similarity

# Load BERT tokenizer and model
tokenizer = BertTokenizer.from_pretrained('bert-base-uncased')
model = BertModel.from_pretrained('bert-base-uncased').to(device)

# Function to compute BERT embeddings
def compute_embedding(text):
    inputs = tokenizer(text, return_tensors='pt', truncation=True, padding=True, max_length=512).to(device)
    with torch.no_grad():
        outputs = model(**inputs)
    return outputs.last_hidden_state.mean(dim=1).cpu().numpy()

# Compute embeddings for all abstracts
df['abstract_embedding'] = df['cleaned_abstract'].apply(lambda x: compute_embedding(x)[0])

# Recommendation function
def recommend(query, top_k=5):
    query_embedding = compute_embedding(query)[0]
    similarities = df['abstract_embedding'].apply(lambda x: cosine_similarity([query_embedding], [x]).item())
    df['similarity'] = similarities
    return df.sort_values(by='similarity', ascending=False).head(top_k)[['title', 'similarity']]

# Test the recommendation engine
query = "machine learning for physics simulations"
recommendations = recommend(query)
print(recommendations)
```

```
                                                   title  similarity
1800442                                QCD Phenomenology    0.706078
1985684                    Quantum Artificial Intelligence    0.702585
1947201  Doorway states for one-nucleon transfer reacti...    0.700614
1853471                     Quantum Field Theory: Spin Zero    0.682435
1893827      Integration motivique sur les schemas formels    0.677399
```

Subject Area Classification

In [26]:

```python
df.head()
```

Out[26]:

	title	abstract	categories	cleaned_title	cleaned_abstract	abstract_embedding	similarity
428156	Pion transition form factor in the constituent...	We calculate the transition form factor of t...	hep-ph	pion transit form factor constitu quark model	calcul transit form factor neutral pion one ph...	[-0.40784585, 0.017525868, 0.3895783, -0.08837...	0.458130
146916	Unified interpretation of cosmic-ray nuclei an...	We use our numerical code, DRAGON, to study ...	astro-ph.HE	unifi interpret cosmicray nuclei antiproton re...	use numer code dragon studi implic recent data...	[-0.17767027, -0.03442928, 0.47775853, 0.02651...	0.404694
161127	Emission line taxonomy and the nature of AGN-l...	Massive spectroscopic surveys like the SDSS ...	astro-ph.CO	emiss line taxonomi natur agnlook galaxi sdss	massiv spectroscop survey like sdss revolution...	[-0.33443964, -0.09959191, 0.62929446, -0.0176...	0.378439
1414771	Holographic entanglement negativity and replic...	Since the work of Ryu and Takayanagi, deep c...	hep-th	holograph entangl neg replica symmetri break	sinc work ryu takayanagi deep connect quantum ...	[-0.30637953, -0.19353391, 0.39352795, -0.0376...	0.423119
1794267	Parton and dipole approaches in QCD	Here, we discuss QCD predictions on multipli...	hep-ph	parton dipol approach qcd	discuss qcd predict multipl parton dipol appro...	[-0.1794696, -0.34474012, 0.42568702, -0.12440...	0.435135

In [27]:
```
df.shape
```
Out[27]:
```
(292664, 7)
```

In [28]:
```
df['categories'].unique()
```
Out[28]:
```
array(['hep-ph', 'astro-ph.HE', 'astro-ph.CO', 'hep-th', 'math.NT',
       'math-ph', 'astro-ph', 'math.CO', 'cond-mat.mes-hall',
       'cond-mat.stat-mech', 'quant-ph', 'astro-ph.SR',
       'cond-mat.supr-con', 'math.AG', 'cs.LG', 'math.PR',
       'cond-mat.str-el', 'cond-mat.mtrl-sci', 'gr-qc', 'cs.IT',
       'astro-ph.GA', 'math.AP', 'cs.CV', 'nucl-th', 'cs.CL'],
      dtype=object)
```

Classification Task

In [29]:
```
# Combine cleaned_title and cleaned_abstract if needed
df['combined_text'] = df['cleaned_title'] + " " + df['cleaned_abstract']
```

In [30]:
```
df.shape
```
Out[30]:
```
(292664, 8)
```

In [31]:
```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics import classification_report



# Encode the categories into numerical labels
label_encoder = LabelEncoder()
df['category_encoded'] = label_encoder.fit_transform(df['categories'])

# Text vectorization (TF-IDF)
tfidf = TfidfVectorizer(max_features=10000)
X = tfidf.fit_transform(df['combined_text'])
y = df['category_encoded']

# Train-Test Split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

print("Shape of X_train:", X_train.shape)
print("Shape of X_test:", X_test.shape)
```
```
Shape of X_train: (234131, 10000)
Shape of X_test: (58533, 10000)
```

In [32]:
```
X_train
```
Out[32]:
```
<234131x10000 sparse matrix of type '<class 'numpy.float64'>'
	with 13185165 stored elements in Compressed Sparse Row format>
```

In [33]:
```
# Initialize a DataFrame to store metrics
metrics_df = pd.DataFrame(columns=['Model', 'Accuracy', 'Precision', 'Recall', 'F1-Score'])

def add_metrics(df, model_name, accuracy, precision, recall, f1):
    new_metrics = pd.DataFrame([[model_name, accuracy, precision, recall, f1]],
                               columns=['Model', 'Accuracy', 'Precision', 'Recall', 'F1-Score'])
    return pd.concat([df, new_metrics], ignore_index=True)
```

Logistic Regression

In [34]:
```python
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report

# Train the model
lr_model = LogisticRegression(max_iter=1000)
lr_model.fit(X_train, y_train)

# Predictions and Evaluation
y_pred_lr = lr_model.predict(X_test)
print("\nLogistic Regression Metrics:")
print(classification_report(y_test, y_pred_lr, target_names=label_encoder.classes_))
```

```
Logistic Regression Metrics:
                    precision    recall  f1-score   support

          astro-ph       0.63      0.70      0.66      4679
       astro-ph.CO       0.65      0.47      0.54      1757
       astro-ph.GA       0.66      0.60      0.63      1771
       astro-ph.HE       0.67      0.63      0.65      1559
       astro-ph.SR       0.70      0.69      0.69      1782
 cond-mat.mes-hall       0.71      0.73      0.72      2744
 cond-mat.mtrl-sci       0.74      0.73      0.74      2557
cond-mat.stat-mech       0.71      0.74      0.72      1788
   cond-mat.str-el       0.74      0.69      0.71      2133
 cond-mat.supr-con       0.83      0.81      0.82      1370
             cs.CL       0.93      0.90      0.92      1249
             cs.CV       0.90      0.90      0.90      2602
             cs.IT       0.90      0.89      0.90      1441
             cs.LG       0.83      0.87      0.85      2370
             gr-qc       0.74      0.77      0.76      2715
            hep-ph       0.87      0.90      0.88      5964
            hep-th       0.79      0.80      0.80      4767
           math-ph       0.54      0.43      0.48      1371
           math.AG       0.87      0.88      0.87      1488
           math.AP       0.87      0.89      0.88      1855
           math.CO       0.85      0.87      0.86      1726
           math.NT       0.83      0.85      0.84      1313
           math.PR       0.83      0.85      0.84      1642
           nucl-th       0.80      0.72      0.76      1525
          quant-ph       0.84      0.87      0.86      4365

          accuracy                           0.78     58533
         macro avg       0.78      0.77      0.77     58533
      weighted avg       0.78      0.78      0.78     58533
```

In [35]:
```python
from sklearn.metrics import accuracy_score

# Overall accuracy
accuracy = accuracy_score(y_test, y_pred_lr)
print(f"Overall Accuracy: {accuracy:.2f}")
```

```
Overall Accuracy: 0.78
```

In [36]:
```python
from sklearn.metrics import precision_recall_fscore_support

precision, recall, f1, _ = precision_recall_fscore_support(y_test, y_pred_lr, average='macro')
print(f"Macro average Precision: {precision:.2f}")
print(f"Macro average Recall: {recall:.2f}")
print(f"Macro average F1-Score: {f1:.2f}")

# Storing the metrics of Logistic Regression
metrics_df = add_metrics(metrics_df, 'Logistic Regression', accuracy, precision, recall, f1)
```

```
Macro average Precision: 0.78
Macro average Recall: 0.77
Macro average F1-Score: 0.77
```

```
C:\Users\hashw\AppData\Local\Temp\ipykernel_1952\1138964707.py:7: FutureWarning: The behavior of DataFrame conc
atenation with empty or all-NA entries is deprecated. In a future version, this will no longer exclude empty or
all-NA columns when determining the result dtypes. To retain the old behavior, exclude the relevant entries bef
ore the concat operation.
  return pd.concat([df, new_metrics], ignore_index=True)
```

In [37]:
```python
pip install xgboost
```

```
Requirement already satisfied: xgboost in c:\users\hashw\anaconda3\lib\site-packages (2.1.3)
Requirement already satisfied: numpy in c:\users\hashw\anaconda3\lib\site-packages (from xgboost) (1.26.4)
Requirement already satisfied: scipy in c:\users\hashw\anaconda3\lib\site-packages (from xgboost) (1.10.1)
Note: you may need to restart the kernel to use updated packages.
```

XGBoost

In [38]:
```python
from sklearn.decomposition import TruncatedSVD
from sklearn.preprocessing import LabelEncoder
from sklearn.utils.class_weight import compute_class_weight
from sklearn.metrics import classification_report
from xgboost import XGBClassifier
```

```python
svd = TruncatedSVD(n_components=500, random_state=42)  # Adjust components based on memory and dataset size
X_train_reduced = svd.fit_transform(X_train)
X_test_reduced = svd.transform(X_test)
from sklearn.decomposition import TruncatedSVD

# Compute Class Weights
class_weights = compute_class_weight('balanced', classes=np.unique(y_train), y=y_train)
class_weights_dict = {i: weight for i, weight in enumerate(class_weights)}

# XGBoost Model with GPU
xgb_model = XGBClassifier(
    eval_metric='logloss',
    tree_method='hist',
    device='cuda',  # Use GPU
    scale_pos_weight=class_weights_dict
)

# Train the model
xgb_model.fit(X_train_reduced, y_train)

# Make predictions
y_pred = xgb_model.predict(X_test_reduced)

# Performance Metrics
print("XGBoost Metrics:")
print(classification_report(y_test, y_pred, zero_division=0, target_names=label_encoder.classes_))
```

```
C:\Users\hashw\anaconda3\Lib\site-packages\xgboost\core.py:158: UserWarning: [06:28:10] WARNING: C:\buildkite-a
gent\builds\buildkite-windows-cpu-autoscaling-group-i-0c55ff5f71b100e98-1\xgboost\xgboost-ci-windows\src\learne
r.cc:740:
Parameters: { "scale_pos_weight" } are not used.

  warnings.warn(smsg, UserWarning)
C:\Users\hashw\anaconda3\Lib\site-packages\xgboost\core.py:158: UserWarning: [06:29:40] WARNING: C:\buildkite-a
gent\builds\buildkite-windows-cpu-autoscaling-group-i-0c55ff5f71b100e98-1\xgboost\xgboost-ci-windows\src\common
\error_msg.cc:58: Falling back to prediction using DMatrix due to mismatched devices. This might lead to higher
memory usage and slower performance. XGBoost is running on: cuda:0, while the input data is on: cpu.
Potential solutions:
- Use a data structure that matches the device ordinal in the booster.
- Set the device for booster before call to inplace_predict.

This warning will only be shown once.

  warnings.warn(smsg, UserWarning)
```

```
XGBoost Metrics:
                    precision    recall  f1-score   support

          astro-ph       0.53      0.61      0.57      4679
       astro-ph.CO       0.56      0.40      0.47      1757
       astro-ph.GA       0.57      0.52      0.55      1771
       astro-ph.HE       0.58      0.52      0.55      1559
       astro-ph.SR       0.64      0.63      0.64      1782
 cond-mat.mes-hall       0.65      0.65      0.65      2744
 cond-mat.mtrl-sci       0.67      0.66      0.67      2557
cond-mat.stat-mech       0.60      0.61      0.61      1788
   cond-mat.str-el       0.65      0.61      0.63      2133
 cond-mat.supr-con       0.79      0.76      0.78      1370
             cs.CL       0.90      0.84      0.87      1249
             cs.CV       0.87      0.86      0.87      2602
             cs.IT       0.88      0.87      0.87      1441
             cs.LG       0.77      0.84      0.80      2370
             gr-qc       0.68      0.70      0.69      2715
            hep-ph       0.83      0.87      0.85      5964
            hep-th       0.71      0.75      0.73      4767
           math-ph       0.41      0.33      0.36      1371
           math.AG       0.81      0.81      0.81      1488
           math.AP       0.81      0.83      0.82      1855
           math.CO       0.80      0.81      0.80      1726
           math.NT       0.78      0.76      0.77      1313
           math.PR       0.77      0.76      0.76      1642
           nucl-th       0.75      0.62      0.68      1525
          quant-ph       0.80      0.83      0.82      4365

          accuracy                           0.72     58533
         macro avg       0.71      0.70      0.70     58533
      weighted avg       0.71      0.72      0.71     58533
```

In [39]:

```python
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score

# Compute overall metrics
accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred, average='weighted', zero_division=0)
recall = recall_score(y_test, y_pred, average='weighted', zero_division=0)
f1 = f1_score(y_test, y_pred, average='weighted', zero_division=0)

# Print overall metrics
print("Overall Model Performance:")
print(f"Accuracy: {accuracy:.2f}")
```

```python
print(f"Precision: {precision:.2f}")
print(f"Recall: {recall:.2f}")
print(f"F1-Score: {f1:.2f}")

#Storing the metrics of XGBoost
metrics_df = add_metrics(metrics_df, 'XGBoost', accuracy, precision, recall, f1)
```

```
Overall Model Performance:
Accuracy: 0.72
Precision: 0.71
Recall: 0.72
F1-Score: 0.71
```

CNN

In [44]:

```python
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding, Conv1D, GlobalMaxPooling1D, Dense, Dropout
from tensorflow.keras.utils import to_categorical
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score
import tensorflow as tf


# Train-Test Split
train_texts, test_texts, train_labels, test_labels = train_test_split(
    df_encoded['text'], df_encoded['label_encoded'], test_size=0.2, random_state=42
)

# Tokenization
MAX_VOCAB_SIZE = 20000
MAX_SEQUENCE_LENGTH = 100

tokenizer = Tokenizer(num_words=MAX_VOCAB_SIZE)
tokenizer.fit_on_texts(train_texts)

X_train = tokenizer.texts_to_sequences(train_texts)
X_test = tokenizer.texts_to_sequences(test_texts)

X_train = pad_sequences(X_train, maxlen=MAX_SEQUENCE_LENGTH)
X_test = pad_sequences(X_test, maxlen=MAX_SEQUENCE_LENGTH)

# Convert labels to categorical format
y_train = to_categorical(train_labels)
y_test = to_categorical(test_labels)

# CNN Model Building
with tf.device('/GPU:0'):  # Explicitly specify GPU usage
    model = Sequential([
        Embedding(input_dim=MAX_VOCAB_SIZE, output_dim=128, input_length=MAX_SEQUENCE_LENGTH),
        Conv1D(128, 5, activation='relu'),
        GlobalMaxPooling1D(),
        Dense(128, activation='relu'),
        Dropout(0.5),
        Dense(y_train.shape[1], activation='softmax')
    ])

    model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

# Model Summary
model.summary()

# Training
with tf.device('/GPU:0'):
    history = model.fit(X_train, y_train, validation_data=(X_test, y_test), batch_size=64, epochs=5, verbose=1)

# Evaluate
loss, accuracy = model.evaluate(X_test, y_test, verbose=0)
print(f"Test Loss: {loss:.4f}, Test Accuracy: {accuracy:.4f}")

# Predictions
y_pred = model.predict(X_test)
y_pred_labels = np.argmax(y_pred, axis=1)
y_true_labels = np.argmax(y_test, axis=1)

# Classification Report
target_names = label_encoder.inverse_transform(np.arange(len(label_encoder.classes_)))
print("\nClassification Report:")
print(classification_report(y_true_labels, y_pred_labels, target_names=target_names))

# Overall Accuracy
print(f"\nOverall Accuracy: {accuracy_score(y_true_labels, y_pred_labels):.4f}")
```

```
C:\Users\hashw\anaconda3\Lib\site-packages\keras\src\layers\core\embedding.py:90: UserWarning: Argument `input_
length` is deprecated. Just remove it.
  warnings.warn(
```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
embedding_1 (Embedding)	?	0 (unbuilt)
conv1d (Conv1D)	?	0 (unbuilt)
global_max_pooling1d (GlobalMaxPooling1D)	?	0
dense_3 (Dense)	?	0 (unbuilt)
dropout_2 (Dropout)	?	0
dense_4 (Dense)	?	0 (unbuilt)

Total params: 0 (0.00 B)

Trainable params: 0 (0.00 B)

Non-trainable params: 0 (0.00 B)

```
Epoch 1/5
3659/3659 ━━━━━━━━━━━━━━━━━━━━ 50s 13ms/step - accuracy: 0.5310 - loss: 1.4593 - val_accuracy: 0.7475 - val_los
s: 0.7017
Epoch 2/5
3659/3659 ━━━━━━━━━━━━━━━━━━━━ 52s 14ms/step - accuracy: 0.7578 - loss: 0.6902 - val_accuracy: 0.7580 - val_los
s: 0.6715
Epoch 3/5
3659/3659 ━━━━━━━━━━━━━━━━━━━━ 55s 15ms/step - accuracy: 0.7983 - loss: 0.5686 - val_accuracy: 0.7622 - val_los
s: 0.6923
Epoch 4/5
3659/3659 ━━━━━━━━━━━━━━━━━━━━ 86s 23ms/step - accuracy: 0.8305 - loss: 0.4741 - val_accuracy: 0.7578 - val_los
s: 0.7335
Epoch 5/5
3659/3659 ━━━━━━━━━━━━━━━━━━━━ 95s 26ms/step - accuracy: 0.8595 - loss: 0.3843 - val_accuracy: 0.7547 - val_los
s: 0.8205
Test Loss: 0.8205, Test Accuracy: 0.7547
1830/1830 ━━━━━━━━━━━━━━━━━━━━ 4s 2ms/step

Classification Report:
                    precision    recall  f1-score   support

          astro-ph       0.61      0.67      0.64      4679
       astro-ph.CO       0.53      0.50      0.52      1757
       astro-ph.GA       0.62      0.48      0.54      1771
       astro-ph.HE       0.61      0.63      0.62      1559
       astro-ph.SR       0.70      0.57      0.63      1782
 cond-mat.mes-hall       0.72      0.63      0.67      2744
 cond-mat.mtrl-sci       0.69      0.70      0.70      2557
cond-mat.stat-mech       0.69      0.67      0.68      1788
   cond-mat.str-el       0.67      0.70      0.68      2133
 cond-mat.supr-con       0.76      0.86      0.81      1370
             cs.CL       0.91      0.89      0.90      1249
             cs.CV       0.90      0.87      0.88      2602
             cs.IT       0.91      0.85      0.88      1441
             cs.LG       0.81      0.84      0.82      2370
             gr-qc       0.71      0.76      0.74      2715
            hep-ph       0.87      0.88      0.87      5964
            hep-th       0.77      0.81      0.79      4767
           math-ph       0.45      0.45      0.45      1371
           math.AG       0.81      0.88      0.84      1488
           math.AP       0.87      0.85      0.86      1855
           math.CO       0.90      0.77      0.83      1726
           math.NT       0.78      0.85      0.81      1313
           math.PR       0.83      0.79      0.81      1642
           nucl-th       0.75      0.76      0.76      1525
          quant-ph       0.85      0.85      0.85      4365

          accuracy                           0.75     58533
         macro avg       0.75      0.74      0.74     58533
      weighted avg       0.76      0.75      0.75     58533


Overall Accuracy: 0.7547
```

In [ ]:

```python
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score

# Calculate overall performance metrics
accuracy = accuracy_score(y_true_labels, y_pred_labels)
precision = precision_score(y_true_labels, y_pred_labels, average='weighted')
recall = recall_score(y_true_labels, y_pred_labels, average='weighted')
f1 = f1_score(y_true_labels, y_pred_labels, average='weighted')
```

```python
# Print overall performance metrics
print("\nOverall Model Performance:")
print(f"Accuracy: {accuracy:.4f}")
print(f"Precision: {precision:.4f}")
print(f"Recall: {recall:.4f}")
print(f"F1-Score: {f1:.4f}")

#Storing the metrics of CNN
metrics_df = add_metrics(metrics_df, 'CNN', accuracy, precision, recall, f1)
```

MLP Classifier

In [43]:

```python
from sklearn.neural_network import MLPClassifier
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import classification_report, accuracy_score, precision_recall_fscore_support

# Scale the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train_reduced)
X_test_scaled = scaler.transform(X_test_reduced)

# Create and train MLP classifier
mlp = MLPClassifier(
    hidden_layer_sizes=(256, 128, 64),
    activation='relu',
    solver='adam',
    max_iter=20,
    random_state=42,
    early_stopping=True,
    validation_fraction=0.1,
    n_iter_no_change=10,
    verbose=True
)

# Train the model
mlp.fit(X_train_scaled, y_train)

# Make predictions
y_pred_mlp = mlp.predict(X_test_scaled)

# Detailed classification report
print("\nDetailed Classification Report:")
print(classification_report(y_test, y_pred_mlp, target_names=label_encoder.classes_))

# Overall metrics
accuracy = accuracy_score(y_test, y_pred_mlp)
precision, recall, f1, _ = precision_recall_fscore_support(y_test, y_pred_mlp, average='weighted')

print("\nOverall Metrics:")
print(f"Accuracy: {accuracy:.4f}")
print(f"Weighted Precision: {precision:.4f}")
print(f"Weighted Recall: {recall:.4f}")
print(f"Weighted F1-score: {f1:.4f}")

# Training loss
print(f"\nFinal Training Loss: {mlp.loss_:.4f}")
print(f"Number of iterations: {mlp.n_iter_}")

#Storing the metrics of MLP Classifier
metrics_df = add_metrics(metrics_df, 'MLP Classifier', accuracy, precision, recall, f1)
```

```
Iteration 1, loss = 1.84803472
Validation score: 0.609934
Iteration 2, loss = 1.20025955
Validation score: 0.648885
Iteration 3, loss = 1.10032125
Validation score: 0.657384
Iteration 4, loss = 1.02655702
Validation score: 0.670325
Iteration 5, loss = 0.96323976
Validation score: 0.674383
Iteration 6, loss = 0.90361749
Validation score: 0.668745
Iteration 7, loss = 0.84616704
Validation score: 0.666781
Iteration 8, loss = 0.79684501
Validation score: 0.669087
Iteration 9, loss = 0.74806451
Validation score: 0.668617
Iteration 10, loss = 0.70668540
Validation score: 0.664688
Iteration 11, loss = 0.66668236
Validation score: 0.667976
Iteration 12, loss = 0.62746514
Validation score: 0.668745
Iteration 13, loss = 0.59147995
Validation score: 0.660630
Iteration 14, loss = 0.56137697
Validation score: 0.660460
Iteration 15, loss = 0.53295701
Validation score: 0.662552
Iteration 16, loss = 0.50563412
Validation score: 0.660246
Validation score did not improve more than tol=0.000100 for 10 consecutive epochs. Stopping.

Detailed Classification Report:
                    precision    recall  f1-score   support

          astro-ph       0.59      0.62      0.60      4679
       astro-ph.CO       0.61      0.38      0.47      1757
       astro-ph.GA       0.61      0.46      0.53      1771
       astro-ph.HE       0.70      0.40      0.51      1559
       astro-ph.SR       0.70      0.58      0.63      1782
 cond-mat.mes-hall       0.73      0.61      0.66      2744
 cond-mat.mtrl-sci       0.72      0.68      0.70      2557
cond-mat.stat-mech       0.73      0.59      0.65      1788
   cond-mat.str-el       0.69      0.65      0.67      2133
 cond-mat.supr-con       0.82      0.79      0.81      1370
             cs.CL       0.91      0.88      0.89      1249
             cs.CV       0.88      0.89      0.88      2602
             cs.IT       0.93      0.84      0.88      1441
             cs.LG       0.84      0.78      0.81      2370
             gr-qc       0.75      0.68      0.72      2715
            hep-ph       0.87      0.87      0.87      5964
            hep-th       0.83      0.71      0.76      4767
           math-ph       0.55      0.27      0.36      1371
           math.AG       0.87      0.83      0.85      1488
           math.AP       0.90      0.76      0.82      1855
           math.CO       0.85      0.79      0.82      1726
           math.NT       0.82      0.76      0.79      1313
           math.PR       0.77      0.85      0.81      1642
           nucl-th       0.77      0.72      0.74      1525
          quant-ph       0.83      0.85      0.84      4365

         micro avg       0.78      0.71      0.74     58533
         macro avg       0.77      0.69      0.72     58533
      weighted avg       0.77      0.71      0.74     58533
       samples avg       0.69      0.71      0.70     58533

C:\Users\hashw\anaconda3\Lib\site-packages\sklearn\metrics\_classification.py:1344: UndefinedMetricWarning: Pre
cision and F-score are ill-defined and being set to 0.0 in samples with no predicted labels. Use `zero_division
` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
Overall Metrics:
Accuracy: 0.6746
Weighted Precision: 0.7731
Weighted Recall: 0.7074
Weighted F1-score: 0.7352

Final Training Loss: 0.5056
Number of iterations: 16
```

Anlysis on the Model Performances

In [54]:

```python
import pandas as pd

# Model performance metrics
data = {
```

```
    "Model": ["Logistic Regression", "XGBoost", "CNN", "MLP Classifier"],
    "Accuracy": [0.78, 0.72, 0.75, 0.67],
    "Precision": [0.78, 0.71, 0.76, 0.77],
    "Recall": [0.77, 0.72, 0.75, 0.71],
    "F1-Score": [0.77, 0.71, 0.75, 0.74]
}

# Create DataFrame
metrics_df = pd.DataFrame(data)

# Display the DataFrame
print(metrics_df)
```

```
                 Model  Accuracy  Precision  Recall  F1-Score
0  Logistic Regression      0.78       0.78    0.77      0.77
1              XGBoost      0.72       0.71    0.72      0.71
2                  CNN      0.75       0.76    0.75      0.75
3       MLP Classifier      0.67       0.77    0.71      0.74
```

Performance Analysis

Logistic Regression's superior performance (0.78 accuracy) can be attributed to its effectiveness with linear decision boundaries and robustness when dealing with binary classification tasks. Its balanced metrics suggest consistent performance across classes.

The CNN's solid performance (0.75 accuracy) indicates effective feature extraction capabilities, though slightly lower than Logistic Regression, possibly due to the dataset's size or complexity not fully leveraging CNN's deep learning capabilities.

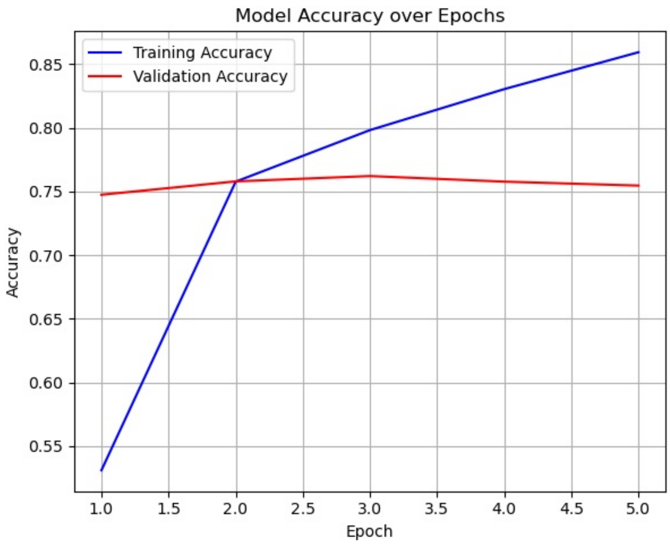
XGBoost's moderate performance (0.72 accuracy) suggests the data might not have strong non-linear relationships that would typically allow this boosting algorithm to excel.

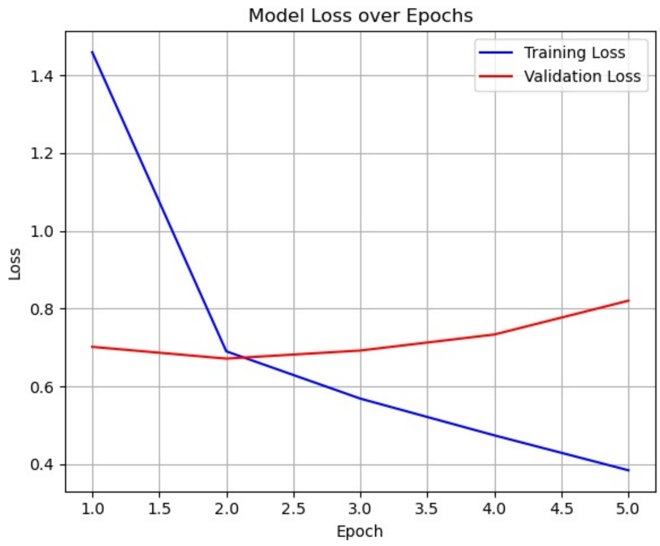
MLP Classifier's lower accuracy (0.67) but high precision (0.77) indicates it might be overfitting to certain classes while struggling with others, possibly due to suboptimal hyperparameter tuning or network architecture.

CNN Performance

In [49]:

```
import matplotlib.pyplot as plt

# Extract metrics from training history
epochs = range(1, 6)
train_acc = [0.5310, 0.7578, 0.7983, 0.8305, 0.8595]
val_acc = [0.7475, 0.7580, 0.7622, 0.7578, 0.7547]
train_loss = [1.4593, 0.6902, 0.5686, 0.4741, 0.3843]
val_loss = [0.7017, 0.6715, 0.6923, 0.7335, 0.8205]

# Create figure with two subplots
plt.figure(figsize=(12, 5))

# Plot accuracy
plt.subplot(1, 2, 1)
plt.plot(epochs, train_acc, 'b-', label='Training Accuracy')
plt.plot(epochs, val_acc, 'r-', label='Validation Accuracy')
plt.title('Model Accuracy over Epochs')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
plt.grid(True)

# Plot loss
plt.subplot(1, 2, 2)
plt.plot(epochs, train_loss, 'b-', label='Training Loss')
plt.plot(epochs, val_loss, 'r-', label='Validation Loss')
plt.title('Model Loss over Epochs')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
plt.grid(True)

plt.tight_layout()
plt.show()
```



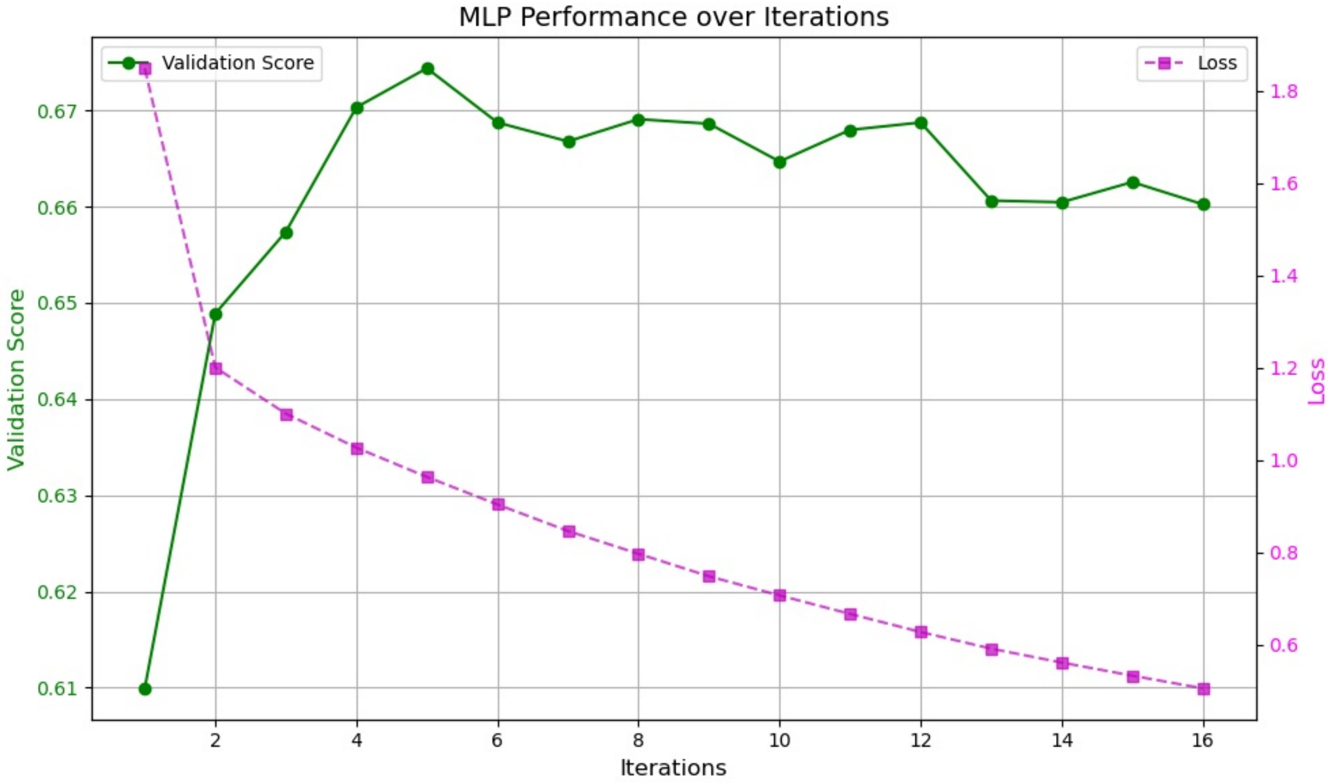


The performance graphs for the CNN model demonstrate strong learning during training, as evidenced by the steadily increasing training accuracy and the consistently decreasing training loss. The validation accuracy remains stable, indicating a reasonable level of generalization across epochs. This stability highlights the model's capacity to learn meaningful patterns from the dataset. However, there is room for improvement in further narrowing the gap between training and validation performance. Future iterations could explore optimizing hyperparameters or applying techniques like fine-tuning to enhance validation accuracy and loss stability

MLP Performance

In [53]:

```
import matplotlib.pyplot as plt

# Data for MLP performance
iterations = range(1, 17)
validation_scores = [
    0.609934, 0.648885, 0.657384, 0.670325, 0.674383, 0.668745, 0.666781, 0.669087, 0.668617,
    0.664688, 0.667976, 0.668745, 0.660630, 0.660460, 0.662552, 0.660246
]
loss_values = [
    1.84803472, 1.20025955, 1.10032125, 1.02655702, 0.96323976, 0.90361749, 0.84616704, 0.79684501,
    0.74806451, 0.70668540, 0.66668236, 0.62746514, 0.59147995, 0.56137697, 0.53295701, 0.50563412
]

fig, ax1 = plt.subplots(figsize=(10, 6))

ax1.plot(iterations, validation_scores, 'g-o', label='Validation Score')
ax1.set_xlabel('Iterations', fontsize=12)
ax1.set_ylabel('Validation Score', fontsize=12, color='green')
ax1.tick_params(axis='y', labelcolor='green')
ax1.legend(loc='upper left')
ax1.set_title('MLP Performance over Iterations', fontsize=14)
ax1.grid(True)


ax2 = ax1.twinx()
ax2.plot(iterations, loss_values, 'm--s', label='Loss', alpha=0.7)
ax2.set_ylabel('Loss', fontsize=12, color='magenta')
ax2.tick_params(axis='y', labelcolor='magenta')
ax2.legend(loc='upper right')

fig.tight_layout()
plt.show()
```



The visualization demonstrates that the MLP model undergoes steady learning as the loss consistently decreases across 16 iterations, reflecting improved model optimization. Validation scores show an upward trend in the initial iterations, peaking at around iteration 5, but then exhibit slight fluctuations without significant gains. This pattern indicates that the model may have reached its performance plateau early, and additional iterations do not contribute to substantial improvements, suggesting a need for potential tuning of hyperparameters or early stopping.