# Laporan Topic Modelling & Keywords Extraction

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Notebook: notebook.ipynb

## Load library

```
!pip install yake -qqq
!pip install keybert -qqq
!pip install gensim
```

```
import pandas as pd
import re
import nltk
from nltk.corpus import stopwords

from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.decomposition import NMF, LatentDirichletAllocation, TruncatedSVD
import matplotlib.pyplot as plt
import yake
from keybert import KeyBERT
import numpy as np
from gensim.models.coherencemodel import CoherenceModel
from gensim.corpora import Dictionary

nltk.download('stopwords')
nltk.download('words')
nltk.download('punkt_tab')
```

## Baca data

```
# read data
df = pd.read_csv('data-nlp.csv')
df.head()
```

| | Title | Abstract | Keywords |
|---|---|---|---|
| 0 | Prediction of a natural clay membrane selectiv... | Heavy metals such as cadmium (Cd), lead (Pb), ... | Ceramic membrane; Clay mineral; Electrochemica... |
| 1 | IOT Based Smart Hydroponics System | Currently traditional agriculture soil based m... | Arduino; automated; Hydroponics; Mobileapp; Se... |
| 2 | Optimizing photocatalytic dye degradation: A m... | Dye contamination in water sources has severe ... | Bayesian Optimization; HistGradientBoosting (H... |
| 3 | Hybrid Intelligent Technique between Supervise... | Water is the secret of life and occupies over ... | Artificial Intelligent; Camel Herd Algorithm; ... |
| 4 | Advanced machine vision techniques for groundw... | This study utilizes three models, namely Weigh... | Comparative Statistical Modeling; Earth observ... |

## Preprocessing

```
# preprocessing

# case folding
df['Title'] = df['Title'].str.lower()
df['Abstract'] = df['Abstract'].str.lower()
df['Keywords'] = df['Keywords'].str.lower()

# hapus special characters and numbers
def clean_text(text):
    text = re.sub(r'[^a-zA-Z\s]', '', text)
    text = re.sub(r'\s+', ' ', text).strip()
    return text

df['Title'] = df['Title'].apply(clean_text)
df['Abstract'] = df['Abstract'].apply(clean_text)
df['Keywords'] = df['Keywords'].apply(clean_text)

# hapus kata-kata non-english
def remove_non_english(text):
    words = nltk.word_tokenize(text)
    english_words = set(nltk.corpus.words.words())
    words = [w for w in words if w.lower() in english_words]
    return ' '.join(words)

df['Title'] = df['Title'].apply(remove_non_english)
df['Abstract'] = df['Abstract'].apply(remove_non_english)
df['Keywords'] = df['Keywords'].apply(remove_non_english)

# hapus stopwords
stop_words = set(stopwords.words('english'))

def remove_stopwords(text):
    words = text.split()
    words = [w for w in words if w not in stop_words]
    return ' '.join(words)

df['Title'] = df['Title'].apply(remove_stopwords)
df['Abstract'] = df['Abstract'].apply(remove_stopwords)
df['Keywords'] = df['Keywords'].apply(remove_stopwords)
```

```
df.head()
```

| | Title | Abstract | Keywords |
|---|---|---|---|
| 0 | prediction natural clay membrane selectivity t... | heavy cadmium lead copper among toxic environm... | ceramic membrane clay mineral electrochemical ... |
| 1 | based smart hydroponics system | currently traditional agriculture soil based m... | hydroponics sensor web interface |
| 2 | photocatalytic dye degradation machine learnin... | dye contamination water severe environmental p... | optimization model machine learning methylene ... |
| 3 | hybrid intelligent technique unsupervised mach... | water secret life surface become necessary pro... | artificial intelligent camel herd algorithm ma... |
| 4 | advanced machine vision level prediction model... | study three namely weight evidence woe frequen... | comparative statistical modeling earth observa... |

**Feature extraction**

```
# feature extraction
text_data = df['Title'] + ' ' + df['Abstract'] + ' ' + df['Keywords']

# TF-IDF
tfidf_vectorizer = TfidfVectorizer(max_features=1000)
tfidf_matrix = tfidf_vectorizer.fit_transform(text_data)
```

Dilakukan proses feature extraction dengan menggabungkan teks dari kolom Title, Abstract, dan Keywords menjadi satu teks, kemudian dilakukan TF-IDF vectorization menggunakan TfidfVectorizer dengan batasan 1000 fitur untuk mengubah teks menjadi representasi numerik yang dapat digunakan untuk analisis lebih lanjut.

# 1. Perbandingan dengan Groundtruth UTS

```
groundtruth_df = pd.read_csv("Excel_Groundtruth_F_Final_Kelompok F.csv")

# ekstrak kata kunci/frasa unik dari groundtruth
unique_keywords = groundtruth_df['Keyword / Phrase'].unique()
print(unique_keywords[:10])
```

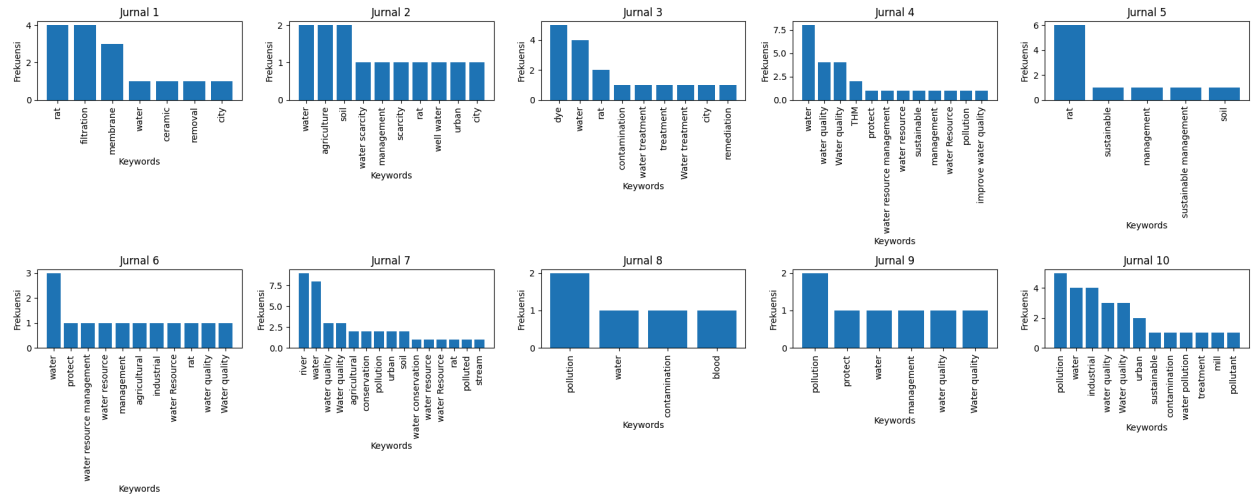
```
['riparian zone restoration' 'lakes' 'lake' 'ecosystem rehabilitation'
 'rehabilitation of water ecosystem' 'rehabilitation of water ecosystems'
 'rehabilitation of the water ecosystem'
 'rehabilitation of the water ecosystems' 'rehabilitate water ecosystem'
 'rehabilitate water ecosystems']
```

```
for idx, row in enumerate(text_data):
    matching_keywords = []
    text = row.lower()

    for keyword in unique_keywords:
        if str(keyword).lower() in text:
            matching_keywords.append(keyword)

    print(f"Jurnal {idx + 1}: {len(matching_keywords)} keyword groundtruth ditemukan")
    if matching_keywords:
        print(f"Keywords: {', '.join(matching_keywords)}")
    print()
```

```
Jurnal 1: 7 keyword groundtruth ditemukan
Keywords: water, rat, ceramic, filtration, removal, membrane, city

Jurnal 2: 10 keyword groundtruth ditemukan
Keywords: water, agriculture, water scarcity, management, scarcity, rat, well water, urban, city, soil

Jurnal 3: 9 keyword groundtruth ditemukan
Keywords: water, contamination, rat, water treatment, treatment, Water treatment, dye, city, remediation

Jurnal 4: 12 keyword groundtruth ditemukan
Keywords: protect, water, water resource management, water resource, sustainable, management, water Resource, water quality, pollution, improve water quali

Jurnal 5: 5 keyword groundtruth ditemukan
Keywords: sustainable, management, sustainable management, rat, soil

Jurnal 6: 11 keyword groundtruth ditemukan
Keywords: protect, water, water resource management, water resource, management, agricultural, industrial, water Resource, rat, water quality, Water quali

Jurnal 7: 15 keyword groundtruth ditemukan
Keywords: river, water, water conservation, water resource, agricultural, conservation, water Resource, rat, water quality, polluted, pollution, stream, u

Jurnal 8: 4 keyword groundtruth ditemukan
Keywords: water, contamination, pollution, blood

Jurnal 9: 6 keyword groundtruth ditemukan
Keywords: protect, water, management, water quality, pollution, Water quality

Jurnal 10: 12 keyword groundtruth ditemukan
Keywords: water, sustainable, industrial, contamination, water quality, water pollution, treatment, pollution, urban, Water quality, mill, pollutant
```

```
journal_keyword_counts = {}

# hitung frekuensi keyword untuk setiap jurnal
for idx, row in df.iterrows():
    combined_text = f"{row['Title']} {row['Abstract']} {row['Keywords']}".lower()
    keyword_counts = {}

    for keyword in unique_keywords:
```

```
        keyword_lower = str(keyword).lower()
        if keyword_lower in combined_text:
            keyword_counts[keyword] = combined_text.count(keyword_lower)

    journal_keyword_counts[idx] = dict(sorted(keyword_counts.items(), key=lambda x: x[1],
reverse=True))

plt.figure(figsize=(20, 8))
for idx in range(len(df)):
    plt.subplot(2, 5, idx+1)

    if len(journal_keyword_counts[idx]) > 0:
        plt.bar(range(len(journal_keyword_counts[idx])),
                list(journal_keyword_counts[idx].values()))
        plt.xticks(range(len(journal_keyword_counts[idx])),
                   list(journal_keyword_counts[idx].keys()),
                   rotation=90)

    plt.title(f'Jurnal {idx+1}')
    plt.xlabel('Keywords')
    plt.ylabel('Frekuensi')

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




Berdasarkan analisis perbandingan antara dataset jurnal dengan *groundtruth* SDG 6, terlihat bahwa semua jurnal memiliki tingkat kesesuaian yang bervariasi dengan tujuan pembangunan berkelanjutan untuk air bersih dan sanitasi. Secara keseluruhan, jurnal-jurnal tersebut menunjukkan kontribusi yang signifikan terhadap berbagai aspek SDG 6, mulai dari konservasi air, pengelolaan polusi, hingga pengolahan air untuk keberlanjutan.

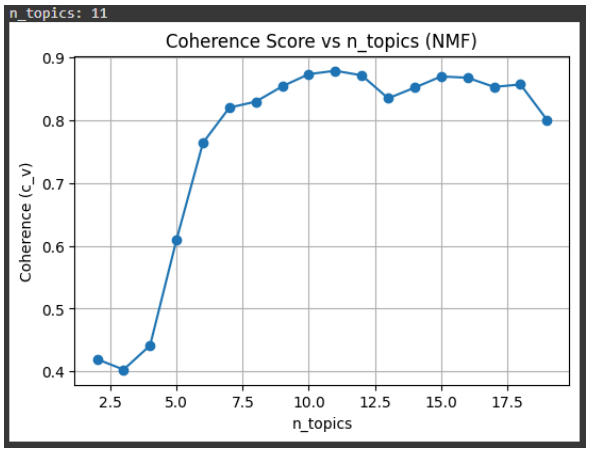
## 2. Topic Modelling

### 2.1 Non-negative Matrix Factorization (NMF)

```
# membuat fungsi untuk menghitung coherence score

tokens_list = [text.split() for text in text_data]
dictionary = Dictionary(tokens_list)

def get_topics_words_from_components(components_matrix, feature_names, topn=10):
    topics = []
    for topic_vec in components_matrix:
        top_indices = topic_vec.argsort()[-topn:][::-1]
        topics.append([feature_names[i] for i in top_indices])
    return topics

def compute_coherence_over_k(method, k_values, vector_matrix, feature_names, topn=10,
random_state=42):
    scores = []
    topics_per_k = {}
    for k in k_values:
        if method == 'nmf':
            model = NMF(n_components=k, random_state=random_state)
            model.fit(vector_matrix)
            components = model.components_
        elif method == 'lda':
            model = LatentDirichletAllocation(n_components=k, random_state=random_state)
            model.fit(vector_matrix)
            components = model.components_
        elif method == 'lsa':
            model = TruncatedSVD(n_components=k, random_state=random_state)
            model.fit(vector_matrix)
            components = model.components_
        else:
            raise ValueError('Unknown method')

        topics = get_topics_words_from_components(components, feature_names, topn=topn)
        topics_per_k[k] = topics

        cm = CoherenceModel(
            topics=topics,
            texts=tokens_list,
            dictionary=dictionary,
            coherence='c_v'
        )
        scores.append(cm.get_coherence())

    return np.array(k_values), np.array(scores), topics_per_k

# coherence score untuk NMF
k_values = list(range(2, 20))
feature_names = tfidf_vectorizer.get_feature_names_out()
```

```
k_arr, coh_scores, nmf_topics_dict = compute_coherence_over_k(
    method='nmf',
    k_values=k_values,
    vector_matrix=tfidf_matrix,
    feature_names=feature_names,
    topn=10,
    random_state=42,
)

best_k_nmf = int(k_arr[np.argmax(coh_scores)])
print(f'n_topics: {best_k_nmf}')

plt.figure(figsize=(6,4))
plt.plot(k_arr, coh_scores, marker='o')
plt.title('Coherence Score vs n_topics (NMF)')
plt.xlabel('n_topics')
plt.ylabel('Coherence (c_v)')
plt.grid(True)
plt.show()
```

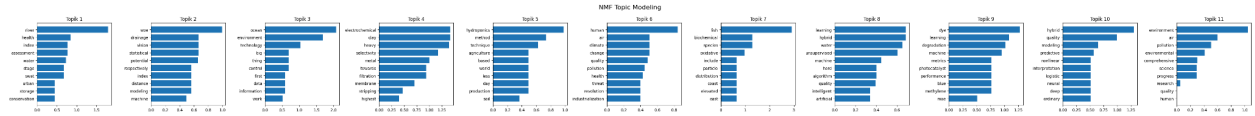
```
n_topics: 11
```




Jumlah topik optimal adalah 11.

```
n_topics = best_k_nmf
nmf_model = NMF(n_components=n_topics, random_state=42)
doc_topics = nmf_model.fit_transform(tfidf_matrix)

# ambil feature names dan kata teratas untuk tiap topik
feature_names = tfidf_vectorizer.get_feature_names_out()
n_top_words = 10

fig, axes = plt.subplots(1, n_topics, figsize=(4*n_topics, 4))
fig.suptitle('NMF Topic Modeling', fontsize=16)

for topic_idx, topic in enumerate(nmf_model.components_):
    top_words_idx = topic.argsort()[:-n_top_words-1:-1]
    top_words = [feature_names[i] for i in top_words_idx]
    top_scores = [topic[i] for i in top_words_idx]
```

```
    axes[topic_idx].barh(range(len(top_words)), top_scores)
    axes[topic_idx].set_yticks(range(len(top_words)))
    axes[topic_idx].set_yticklabels(top_words)
    axes[topic_idx].set_title(f'Topik {topic_idx + 1}')
    axes[topic_idx].invert_yaxis()

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



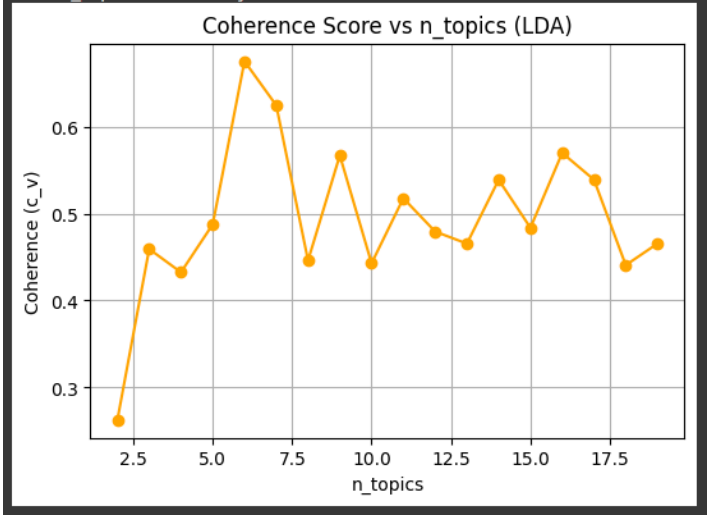

```
for idx, doc_topics in enumerate(doc_topics):
    dominant_topic = doc_topics.argmax() + 1
    print(f"Jurnal {idx + 1}: Topik {dominant_topic}")
```

```
Jurnal 1: Topik 4
Jurnal 2: Topik 5
Jurnal 3: Topik 9
Jurnal 4: Topik 8
Jurnal 5: Topik 2
Jurnal 6: Topik 10
Jurnal 7: Topik 1
Jurnal 8: Topik 7
Jurnal 9: Topik 3
Jurnal 10: Topik 6
```

## 2.2 Latent Dirichlet Allocation (LDA)

```
# coherence untuk LDA
k_values = list(range(2, 20))
feature_names = tfidf_vectorizer.get_feature_names_out()

k_arr_lda, coh_scores_lda, lda_topics_dict = compute_coherence_over_k(
    method='lda',
    k_values=k_values,
    vector_matrix=tfidf_matrix,
    feature_names=feature_names,
    topn=10,
    random_state=42,
)

best_k_lda = int(k_arr_lda[np.argmax(coh_scores_lda)])
print(f'Best n_topics for LDA by coherence: {best_k_lda}')

plt.figure(figsize=(6,4))
plt.plot(k_arr_lda, coh_scores_lda, marker='o', color='orange')
plt.title('Coherence Score vs n_topics (LDA)')
plt.xlabel('n_topics')
plt.ylabel('Coherence (c_v)')
plt.grid(True)
plt.show()
```

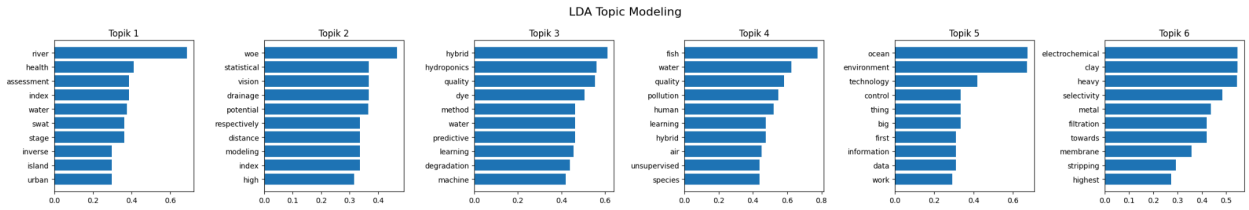
```
Best n_topics for LDA by coherence: 6
```




Jumlah topik optimal adalah 6.

```
n_topics = best_k_lda
lda_model = LatentDirichletAllocation(n_components=n_topics, random_state=42)
lda_output = lda_model.fit_transform(tfidf_matrix)

fig, axes = plt.subplots(1, n_topics, figsize=(4*n_topics, 4))
fig.suptitle('LDA Topic Modeling', fontsize=16)

for topic_idx, topic in enumerate(lda_model.components_):
    top_words_idx = topic.argsort()[:-n_top_words-1:-1]
```

```
    top_words = [feature_names[i] for i in top_words_idx]
    top_scores = [topic[i] for i in top_words_idx]

    axes[topic_idx].barh(range(len(top_words)), top_scores)
    axes[topic_idx].set_yticks(range(len(top_words)))
    axes[topic_idx].set_yticklabels(top_words)
    axes[topic_idx].set_title(f'Topik {topic_idx + 1}')
    axes[topic_idx].invert_yaxis()

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



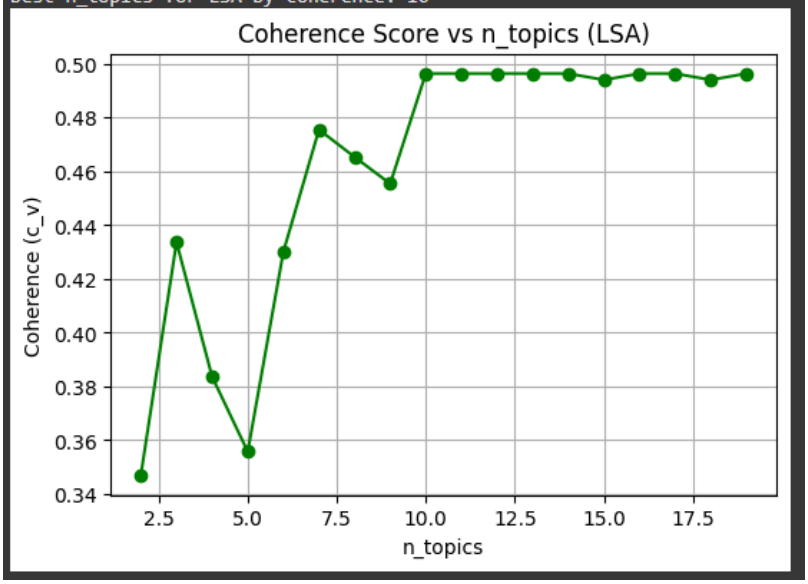

```
for idx, doc_topics in enumerate(lda_output):
    dominant_topic = doc_topics.argmax() + 1
    print(f"Jurnal {idx + 1}: Topik {dominant_topic}")
```

```
Jurnal 1: Topik 6
Jurnal 2: Topik 3
Jurnal 3: Topik 3
Jurnal 4: Topik 4
Jurnal 5: Topik 2
Jurnal 6: Topik 3
Jurnal 7: Topik 1
Jurnal 8: Topik 4
Jurnal 9: Topik 5
Jurnal 10: Topik 4
```

## 2.3 Latent Semantic Analysis (LSA)

```
# coherence untuk LSA
k_values = list(range(2, 20))
feature_names = tfidf_vectorizer.get_feature_names_out()

k_arr_lsa, coh_scores_lsa, lsa_topics_dict = compute_coherence_over_k(
    method='lsa',
    k_values=k_values,
    vector_matrix=tfidf_matrix,
    feature_names=feature_names,
    topn=10,
    random_state=42,
)

best_k_lsa = int(k_arr_lsa[np.argmax(coh_scores_lsa)])
print(f'Best n_topics for LSA by coherence: {best_k_lsa}')

plt.figure(figsize=(6,4))
plt.plot(k_arr_lsa, coh_scores_lsa, marker='o', color='green')
plt.title('Coherence Score vs n_topics (LSA)')
plt.xlabel('n_topics')
plt.ylabel('Coherence (c_v)')
plt.grid(True)
plt.show()
```

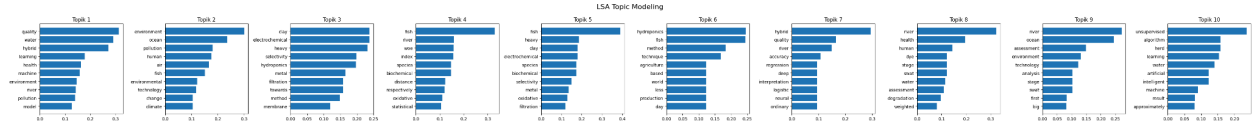
```
Best n_topics for LSA by coherence: 10
```




Jumlah topik optimal adalah 11.

```
n_topics = best_k_lsa
lsa_model = TruncatedSVD(n_components=n_topics, random_state=42)
lsa_output = lsa_model.fit_transform(tfidf_matrix)

fig, axes = plt.subplots(1, n_topics, figsize=(4*n_topics, 4))
fig.suptitle('LSA Topic Modeling', fontsize=16)
```

```
for topic_idx, topic in enumerate(lsa_model.components_):
    top_words_idx = topic.argsort()[:-n_top_words-1:-1]
    top_words = [feature_names[i] for i in top_words_idx]
    top_scores = [topic[i] for i in top_words_idx]

    axes[topic_idx].barh(range(len(top_words)), top_scores)
    axes[topic_idx].set_yticks(range(len(top_words)))
    axes[topic_idx].set_yticklabels(top_words)
    axes[topic_idx].set_title(f'Topik {topic_idx + 1}')
    axes[topic_idx].invert_yaxis()

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



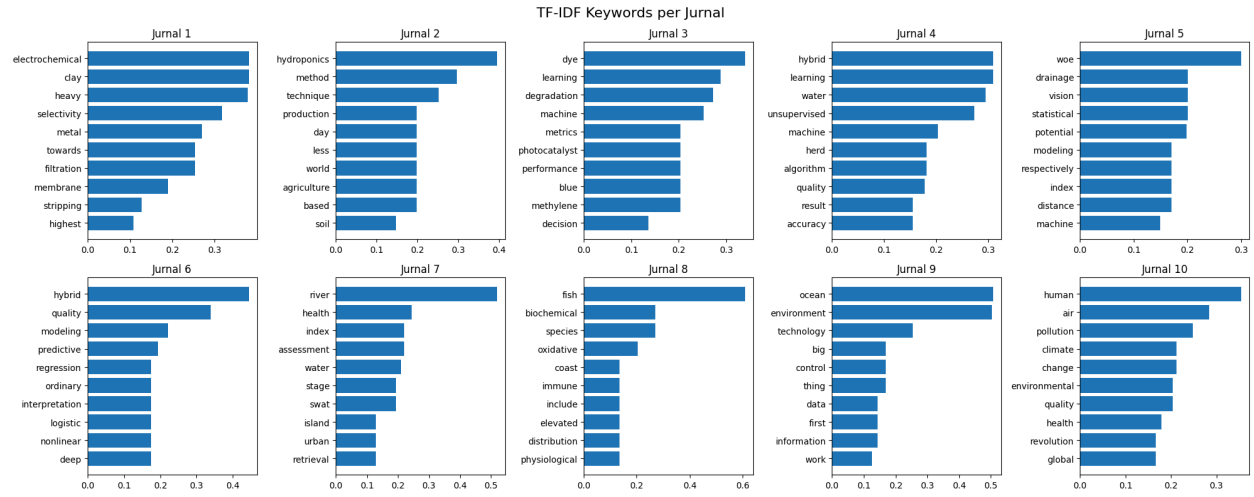

```
for idx, doc_topics in enumerate(lsa_output):
    dominant_topic = doc_topics.argmax() + 1
    print(f"Jurnal {idx + 1}: Topik {dominant_topic}")
```

```
Jurnal 1: Topik 3
Jurnal 2: Topik 6
Jurnal 3: Topik 1
Jurnal 4: Topik 1
Jurnal 5: Topik 4
Jurnal 6: Topik 1
Jurnal 7: Topik 8
Jurnal 8: Topik 5
Jurnal 9: Topik 2
Jurnal 10: Topik 2
```

# 3. Keyword Extraction

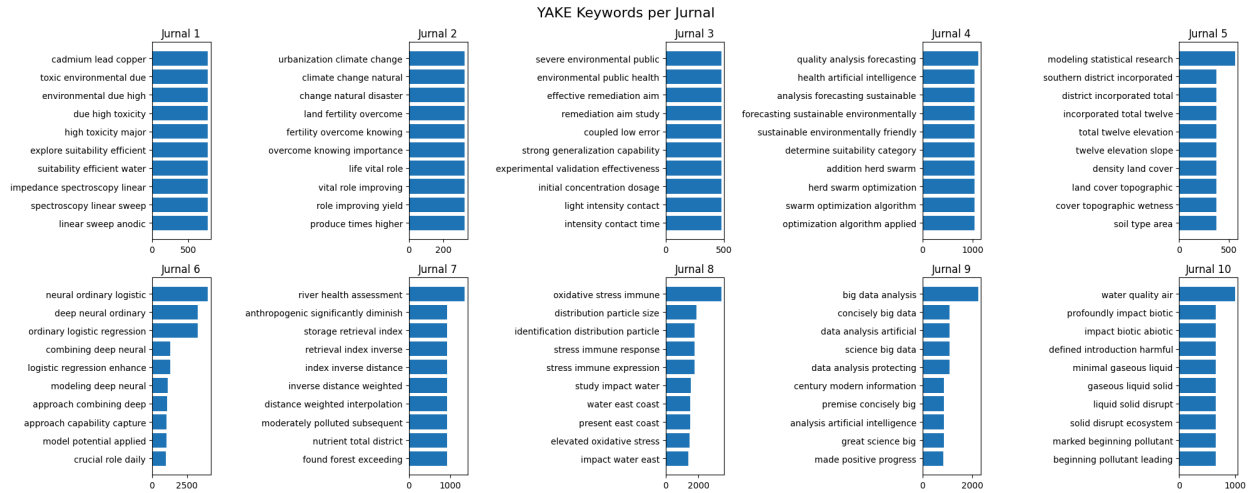
## 3.1 TF-IDF

```
n_keywords = 10

fig, axes = plt.subplots(2, 5, figsize=(20, 8))
fig.suptitle('TF-IDF Keywords per Jurnal', fontsize=16)

for i in range(10):
    doc_tfidf = tfidf_matrix[i].toarray()[0]
    top_indices = doc_tfidf.argsort()[-n_keywords:][::-1]

    top_words = [feature_names[idx] for idx in top_indices]
    top_scores = [doc_tfidf[idx] for idx in top_indices]

    row = i // 5
    col = i % 5

    axes[row, col].barh(range(len(top_words)), top_scores)
    axes[row, col].set_yticks(range(len(top_words)))
    axes[row, col].set_yticklabels(top_words)
    axes[row, col].set_title(f'Jurnal {i+1}')
    axes[row, col].invert_yaxis()

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



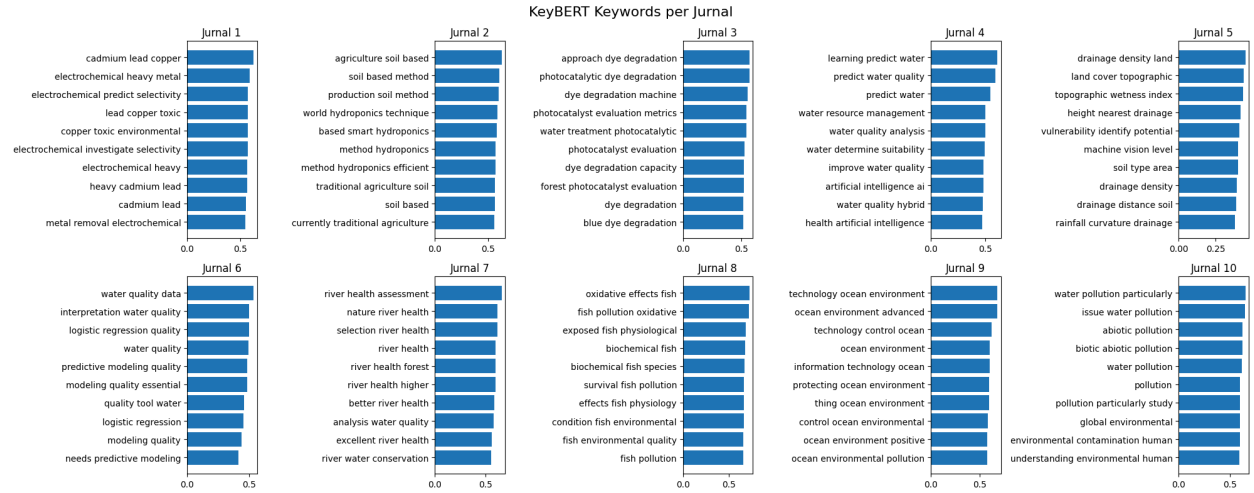
## 3.1 Yake

```
# inisialisasi yake keyword extractor
kw_extractor = yake.KeywordExtractor(
    lan="en",
    n=3,
    dedupLim=0.9,
    dedupFunc='seqm',
    windowsSize=1,
    top=10,
    features=None
)

fig, axes = plt.subplots(2, 5, figsize=(20, 8))
fig.suptitle('YAKE Keywords per Jurnal', fontsize=16)

# ekstraksi keyword untuk setiap dokumen
for i in range(10):
    # mendapatkan keyword menggunakan yake
    text = df['Abstract'].iloc[i] + " " + df['Title'].iloc[i]
    keywords = kw_extractor.extract_keywords(text)

    keywords.sort(key=lambda x: x[1])

    top_words = [kw[0] for kw in keywords[:n_keywords]]
    top_scores = [1/kw[1] for kw in keywords[:n_keywords]]

    row = i // 5
    col = i % 5

    axes[row, col].barh(range(len(top_words)), top_scores)
    axes[row, col].set_yticks(range(len(top_words)))
    axes[row, col].set_yticklabels(top_words)
    axes[row, col].set_title(f'Jurnal {i+1}')
    axes[row, col].invert_yaxis()

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



## 3.1 KeyBERT

```
# inisialisasi keybert keyword extractor
kw_extractor = KeyBERT()

fig, axes = plt.subplots(2, 5, figsize=(20, 8))
fig.suptitle('KeyBERT Keywords per Jurnal', fontsize=16)

# ekstraksi keyword untuk setiap dokumen
for i in range(10):
    # mendapatkan keyword menggunakan keybert
    text = df['Abstract'].iloc[i] + " " + df['Title'].iloc[i]
    keywords = kw_extractor.extract_keywords(text,
                                             keyphrase_ngram_range=(1, 3),
                                             stop_words='english',
                                             top_n=n_keywords)

    top_words = [kw[0] for kw in keywords]
    top_scores = [kw[1] for kw in keywords]

    row = i // 5
    col = i % 5

    axes[row, col].barh(range(len(top_words)), top_scores)
    axes[row, col].set_yticks(range(len(top_words)))
    axes[row, col].set_yticklabels(top_words)
    axes[row, col].set_title(f'Jurnal {i+1}')
    axes[row, col].invert_yaxis()

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



## 4. Analisis Hasil

- Berdasarkan analisis hasil topic modeling dengan tiga metode berbeda (NMF, LDA, dan LSA), dapat disimpulkan bahwa topik yang dihasilkan cukup masuk akal karena semua metode berhasil mengidentifikasi tema-tema yang konsisten dan relevan dengan domain penelitian lingkungan air. Namun, harus diakui bahwa antar topik masih tumpang tindih dan sulit diinterpretasi, hal ini mungkin bisa diakibatkan oleh jumlah data (artikel/jurnal) yang terbatas.
- KeyBERT menunjukkan performa terbaik untuk keyword extraction karena mampu menghasilkan keyphrase yang kontekstual. KeyBERT menunjukkan konsistensi yang baik dalam skor relevansi (sekitar 0.5).