

Kecerdasan Bisnis dalam Praktek

Predictive Analytics II

Text, Web, and Social Media Analytics

Husni

Lab. Riset JTIF UTM

Business Intelligence (BI)

1 Introduction to BI and Data Science

2 Descriptive Analytics

③ Predictive Analytics

4 Prescriptive Analytics

5 Big Data Analytics

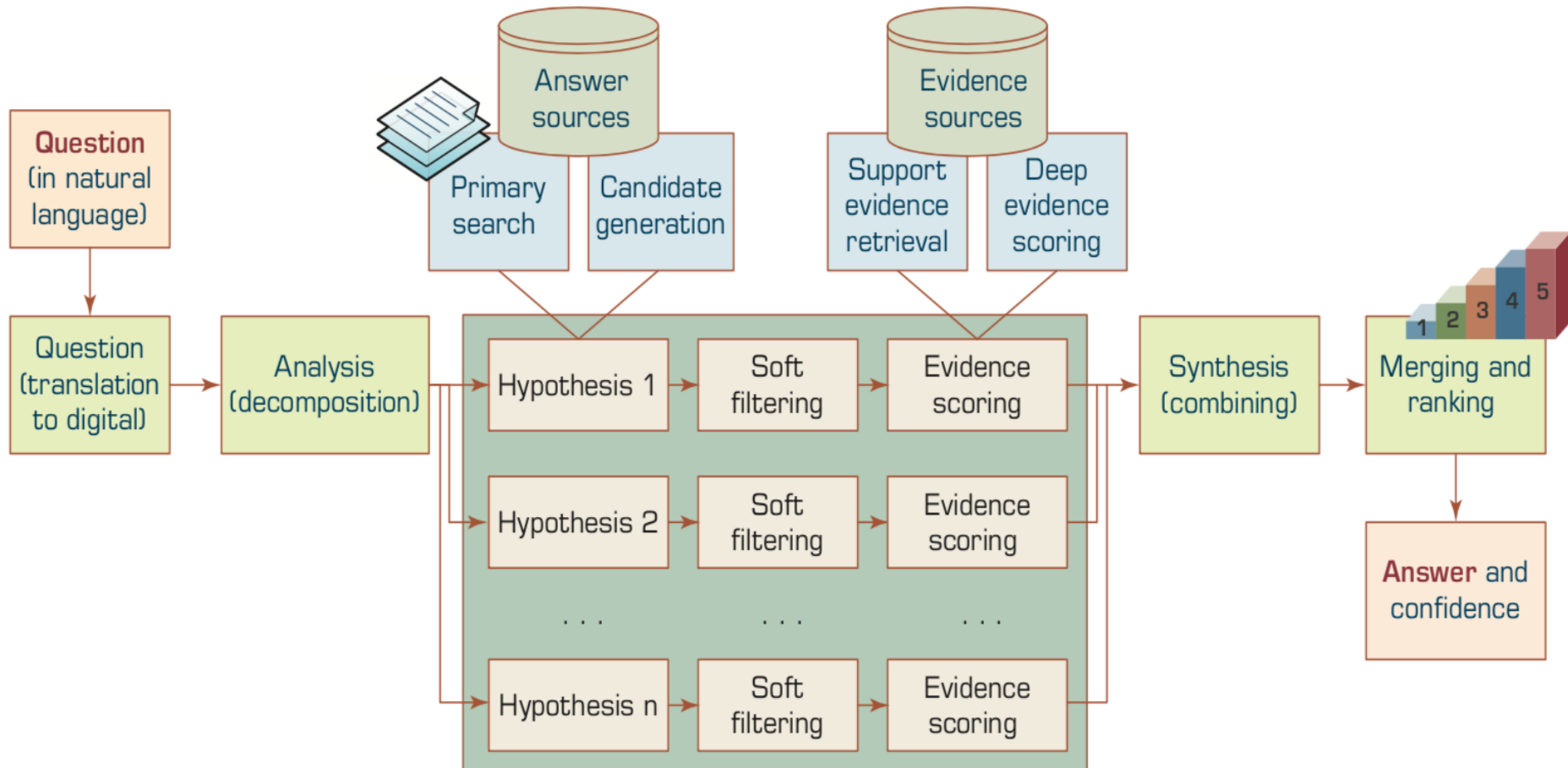
6 Future Trends

Predictive Analytics II: Text, Web, and Social Media Analytics

Outline

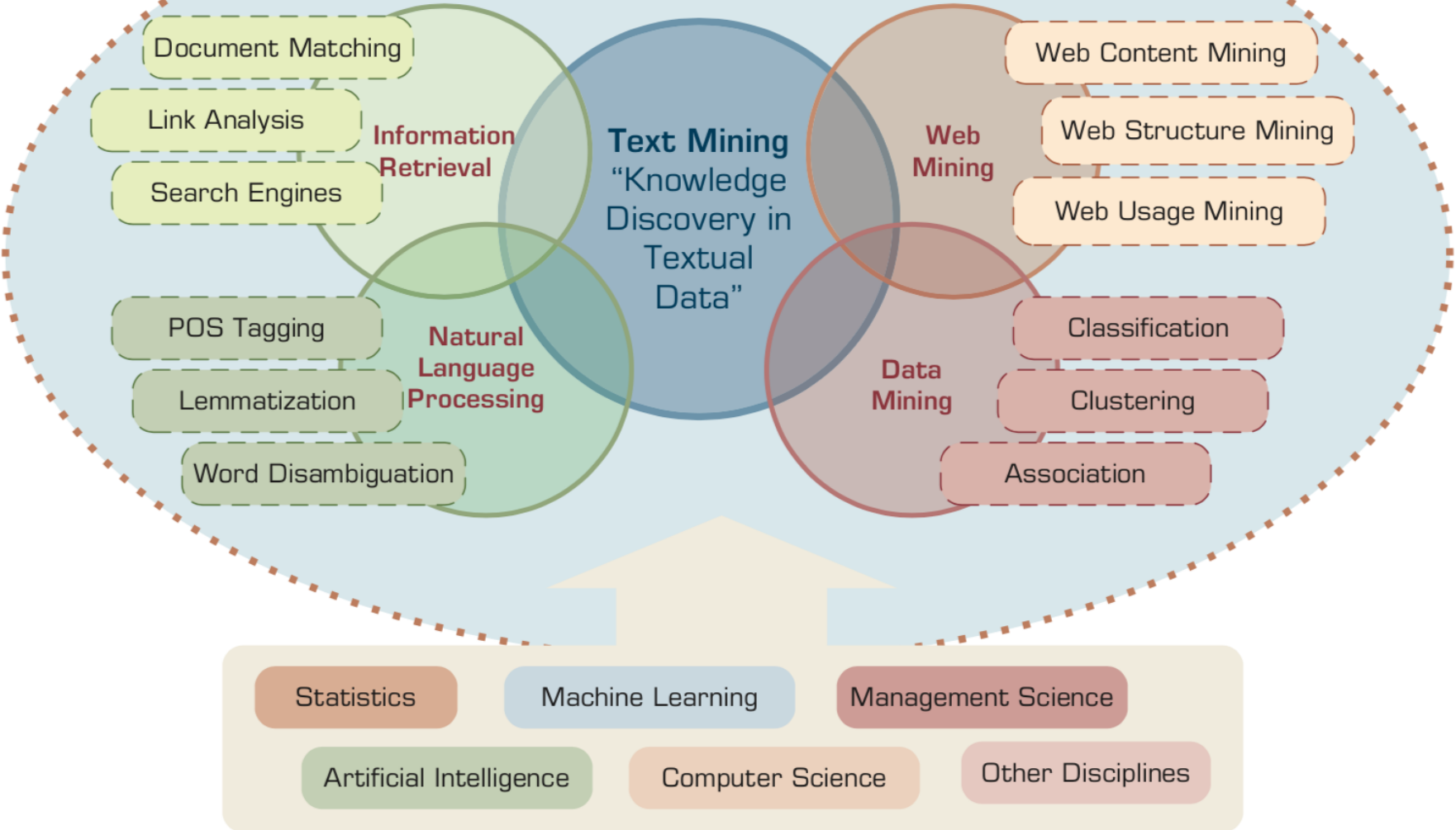
- Text Analytics and Text Mining Overview
 - Natural Language Processing (NLP)
 - Text Mining Applications
 - Text Mining Process
 - Sentiment Analysis
- Web Mining Overview
 - Search Engines
 - Web Usage Mining (Web Analytics)
- Social Analytics

A High-Level Depiction of DeepQA Architecture



Text Analytics and Text Mining

TEXT ANALYTICS



Text Analytics

- **Text Analytics =**
Information Retrieval +
Information Extraction +
Data Mining +
Web Mining
- **Text Analytics =**
Information Retrieval +
Text Mining

Text mining

- Text Data Mining
- Knowledge Discovery in Textual Databases

Application Areas of Text Mining

- Information extraction
- Topic tracking
- Summarization
- Categorization
- Clustering
- Concept linking
- Question answering

Natural Language Processing (NLP)

- Natural language processing (NLP) is an important component of text mining and is a subfield of artificial intelligence and computational linguistics.

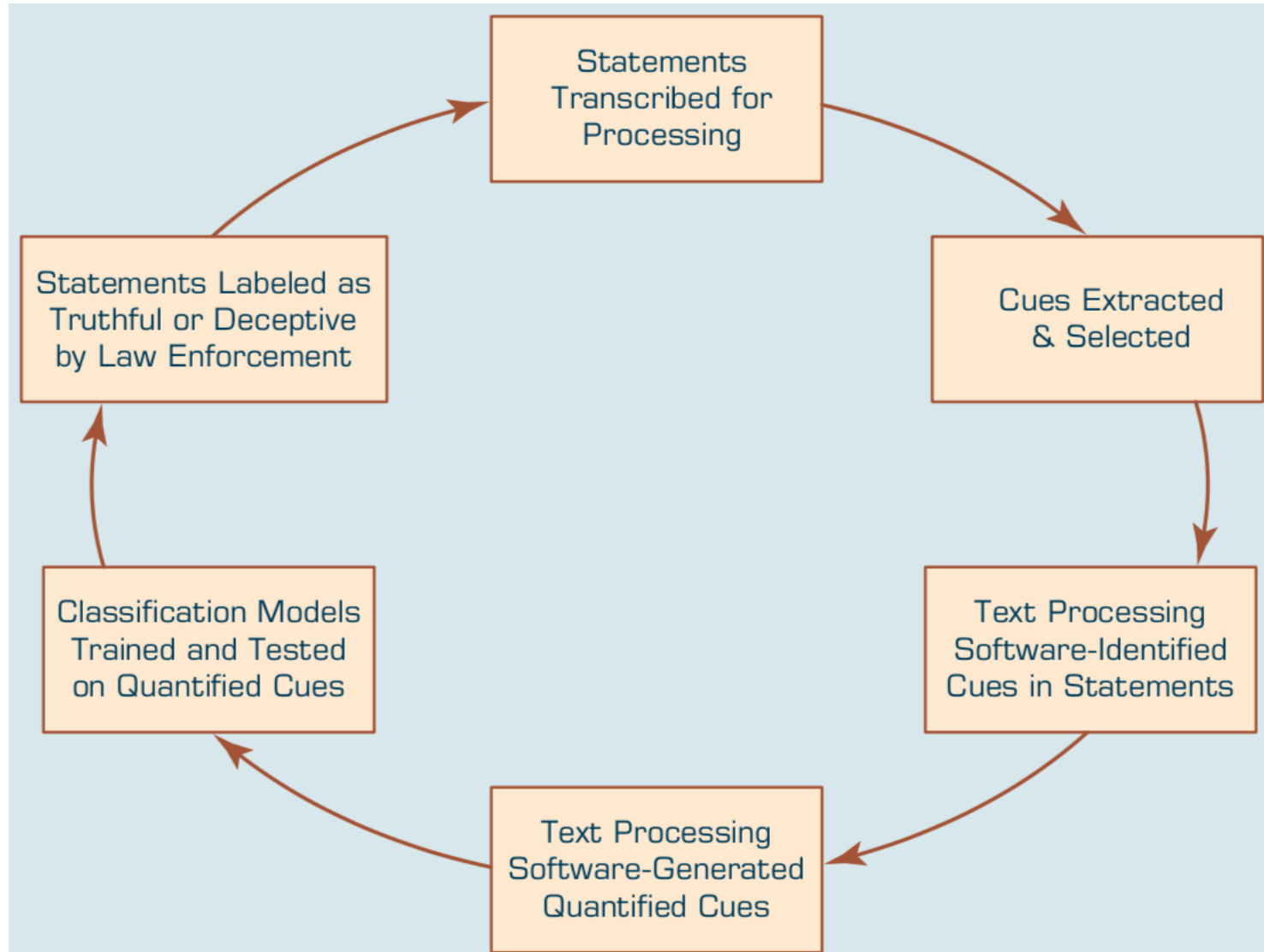
Natural Language Processing (NLP)

- Part-of-speech tagging
- Text segmentation
- Word sense disambiguation
- Syntactic ambiguity
- Imperfect or irregular input
- Speech acts

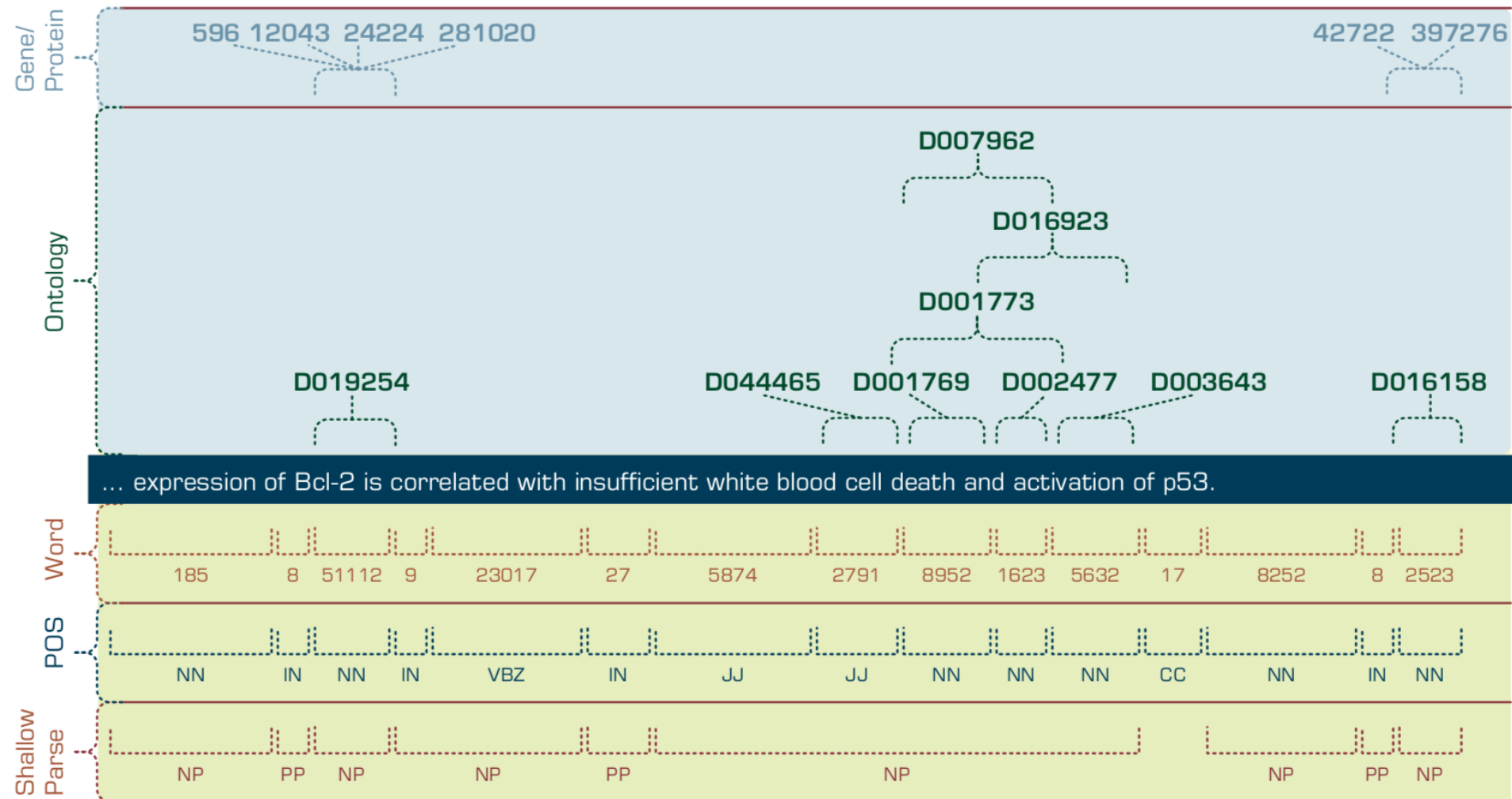
NLP Tasks

- Question answering
- Automatic summarization
- Natural language generation
- Natural language understanding
- Machine translation
- Foreign language reading
- Foreign language writing.
- Speech recognition
- Text-to-speech
- Text proofing
- Optical character recognition

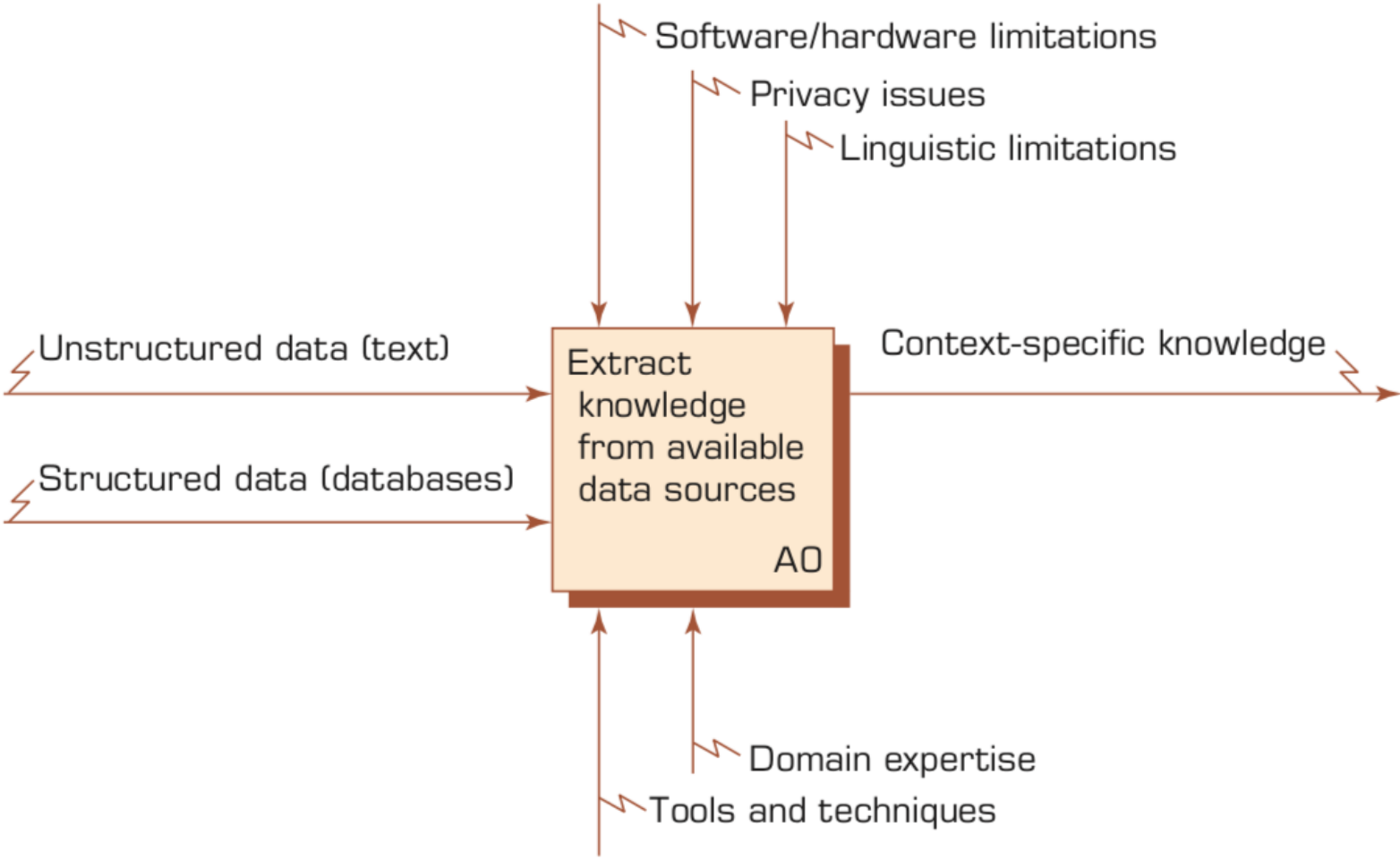
Text-Based Deception-Detection Process



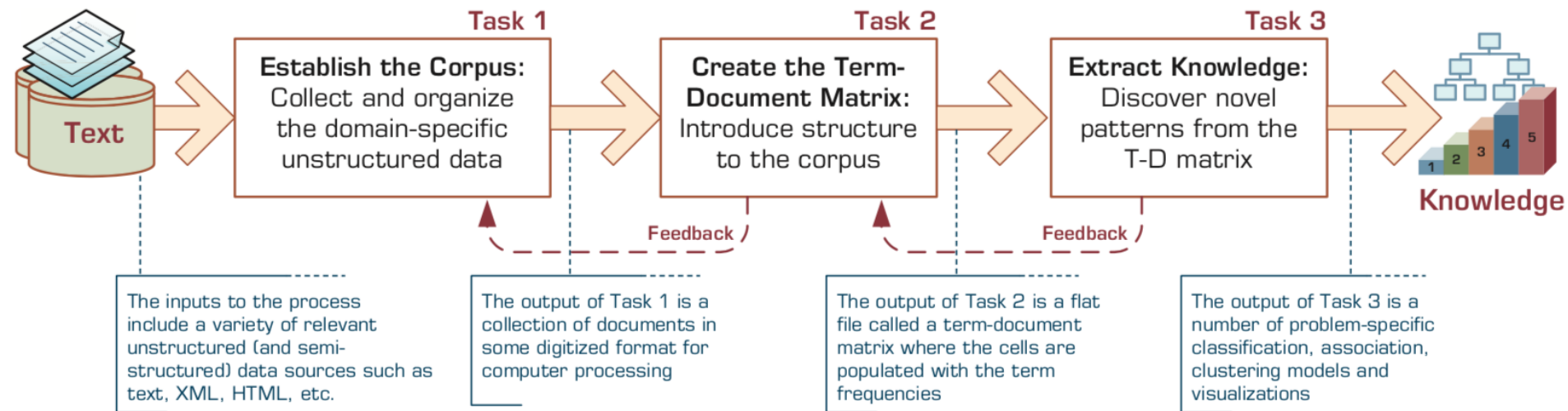
Multilevel Analysis of Text for Gene/Protein Interaction Identification



Context Diagram for the Text Mining Process



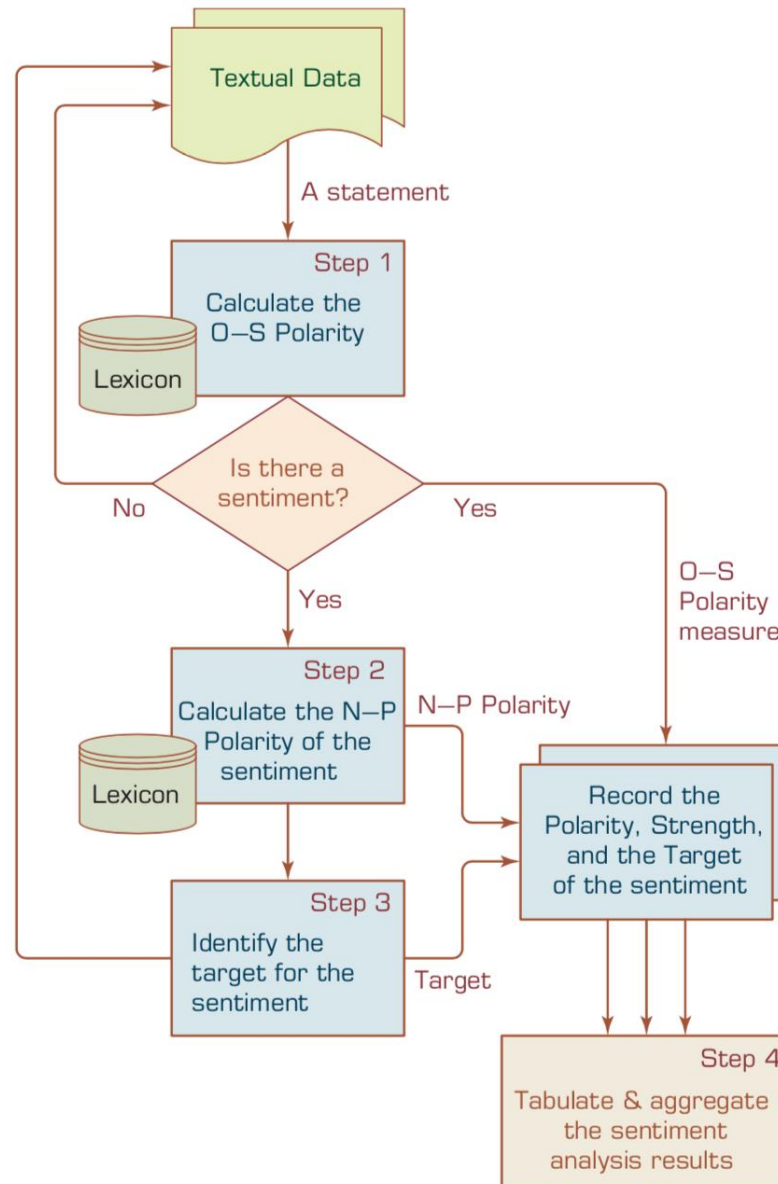
The Three-Step/Task Text Mining Process



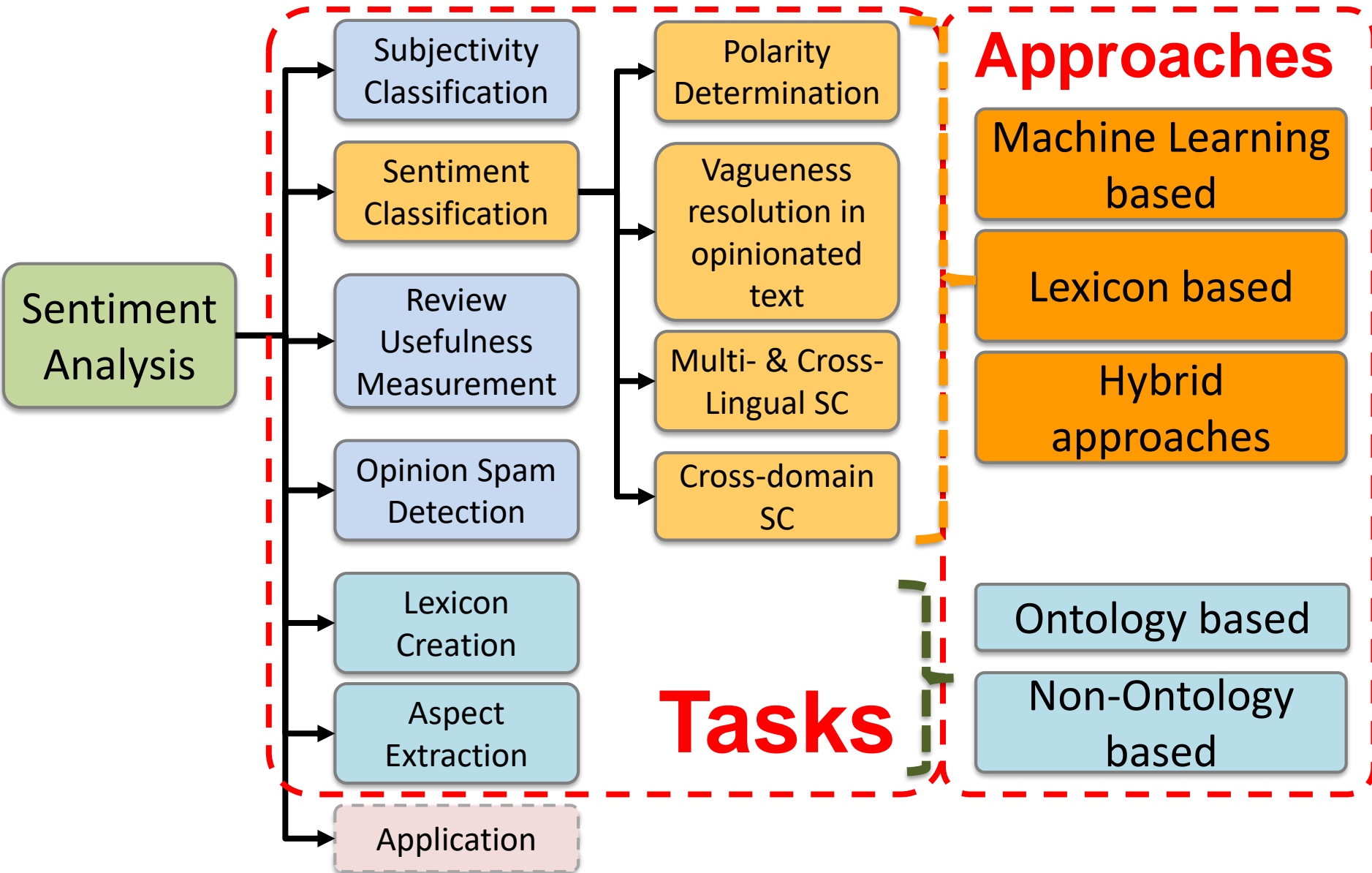
Term–Document Matrix

Terms \ Documents	Investment Risk	Project Management	Software Engineering	Development	SAP	...
Document 1	1			1		
Document 2		1				
Document 3			3		1	
Document 4		1				
Document 5			2	1		
Document 6	1			1		
...						

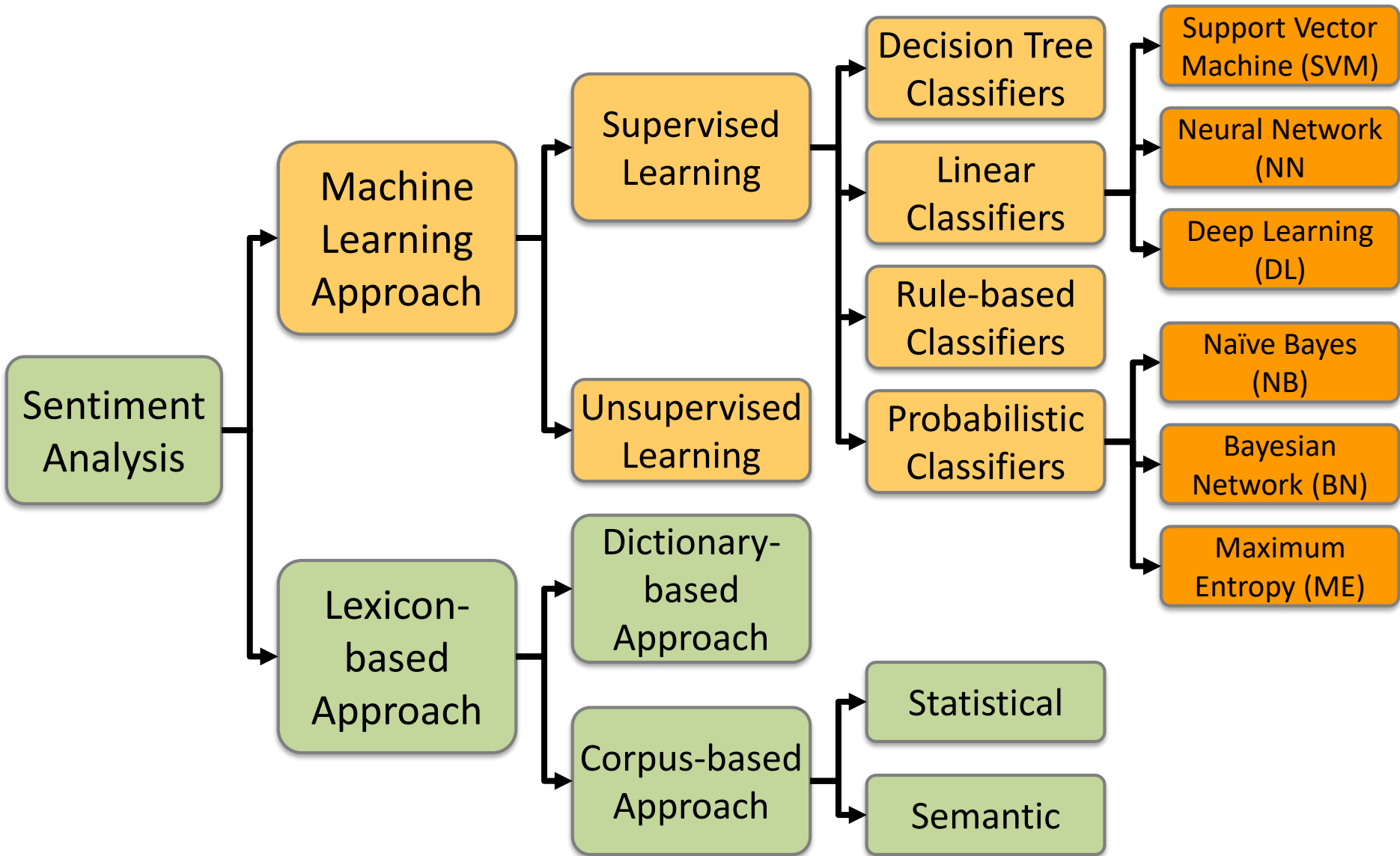
A Multistep Process to Sentiment Analysis



Sentiment Analysis



Sentiment Classification Techniques





Example of Opinion: review segment on iPhone



“I bought an iPhone a few days ago.

It was such a nice phone.

The touch screen was really cool.

The voice quality was clear too.

However, my mother was mad with me as I did not tell her before I bought it.

She also thought the phone was too expensive, and wanted me to return it to the shop. ... ”

Example of Opinion: review segment on iPhone

“(1) I bought an iPhone a few days ago.

(2) It was such a **nice** phone.

(3) The touch screen was really **cool**.

(4) The voice quality was **clear** too.

(5) However, my mother was mad with me as I did not tell her before I bought it.

(6) She also thought the phone was too expensive, and wanted me to return it to the shop. ...”

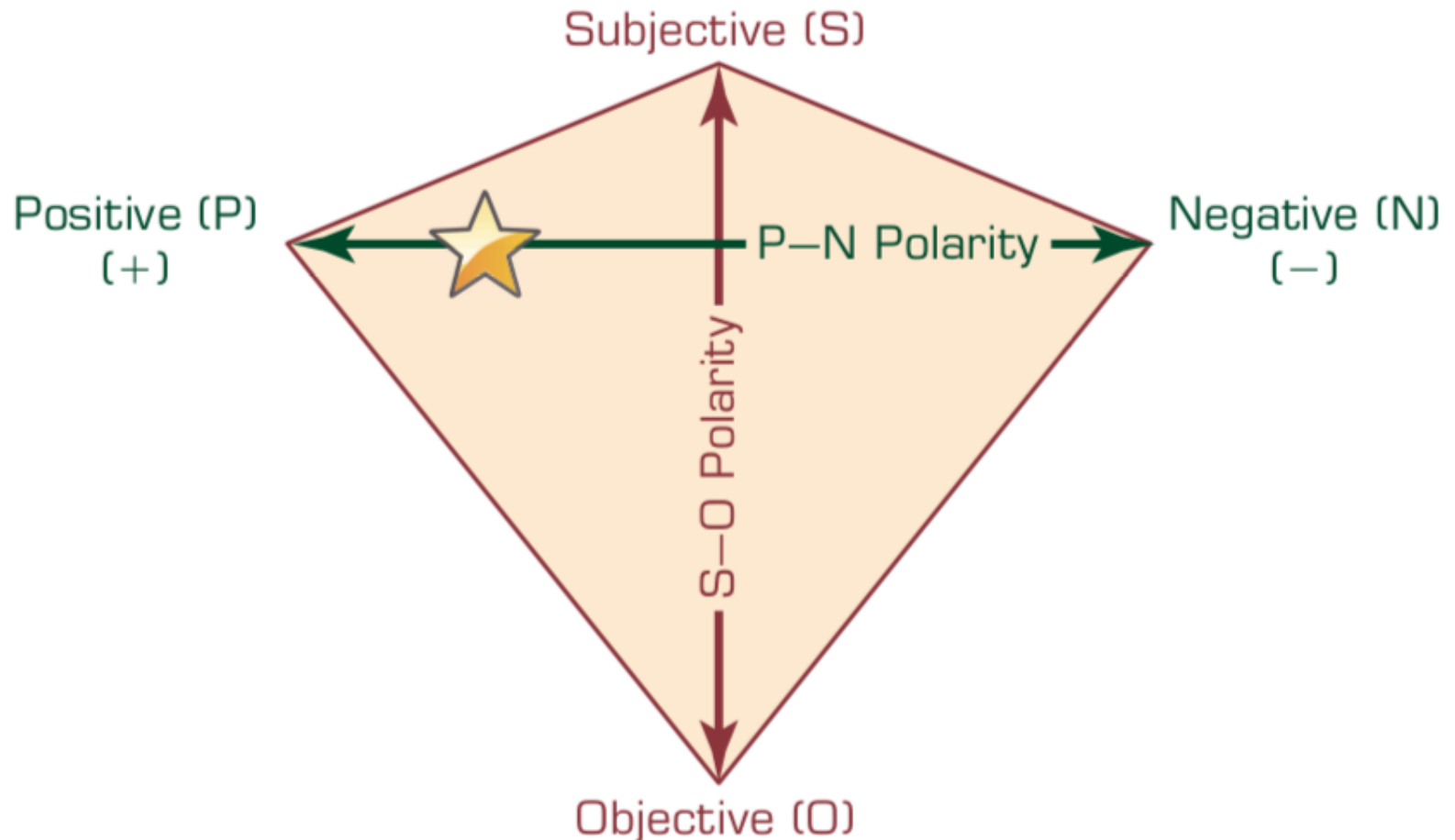


+Positive
Opinion

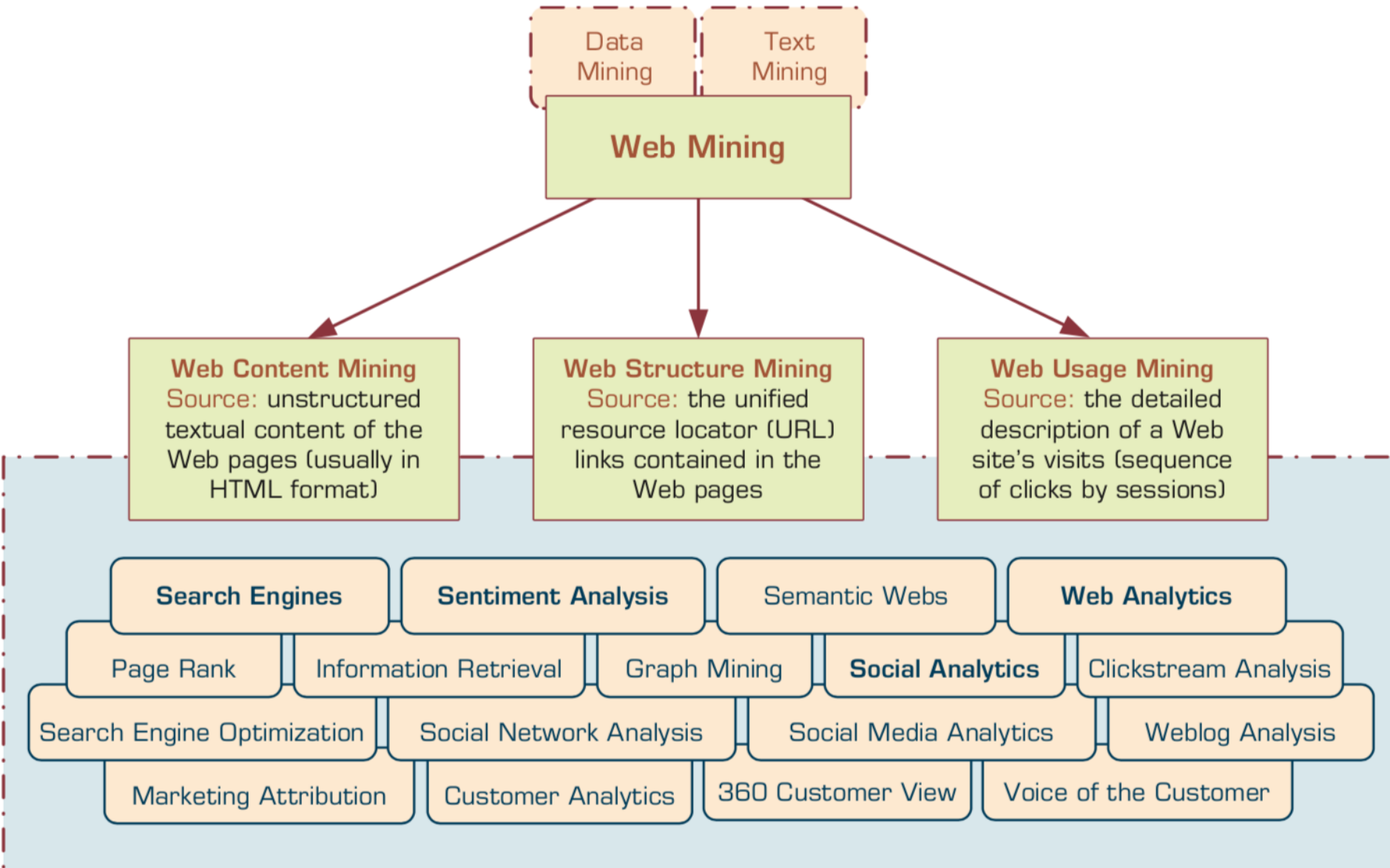


-Negative
Opinion

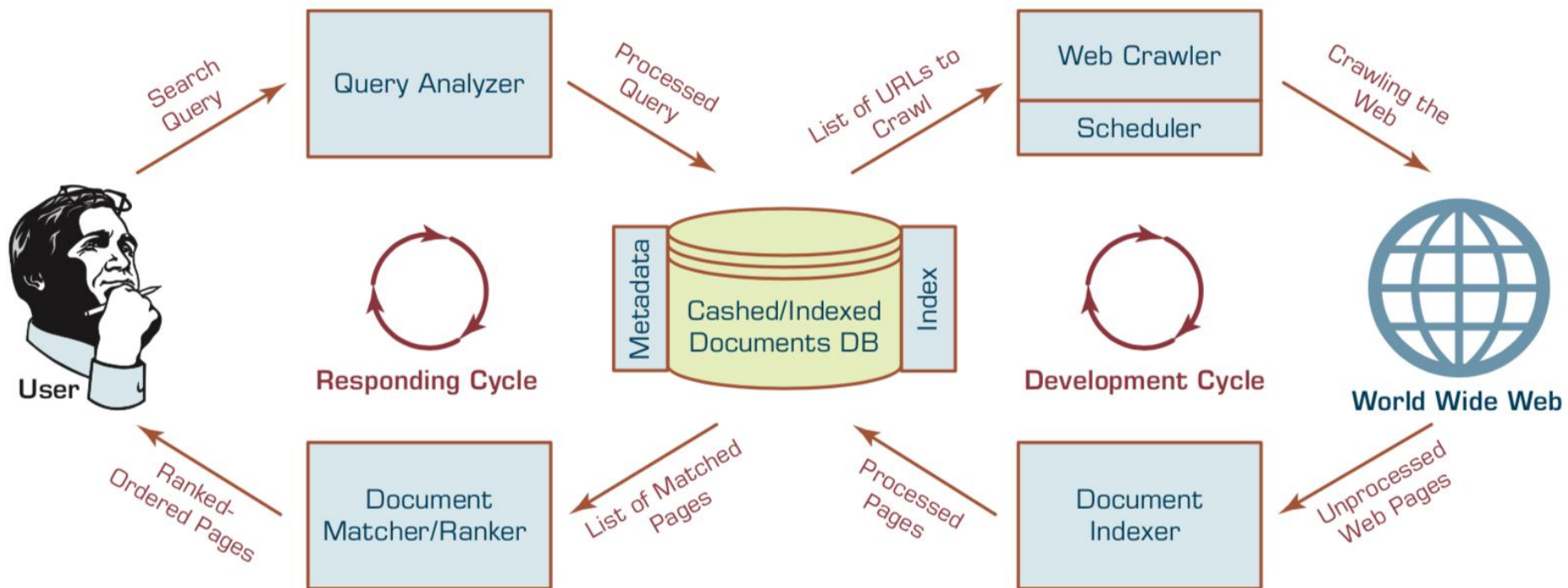
P–N Polarity and S–O Polarity Relationship



Taxonomy of Web Mining



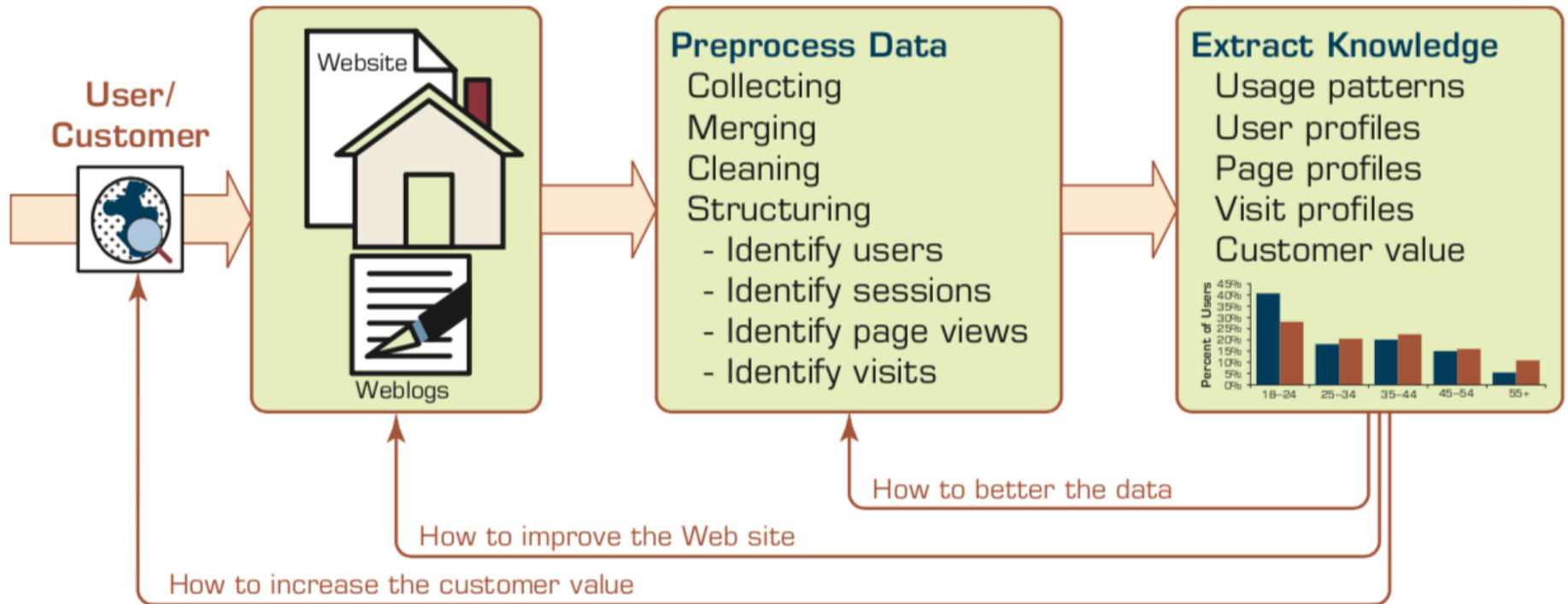
Structure of a Typical Internet Search Engine



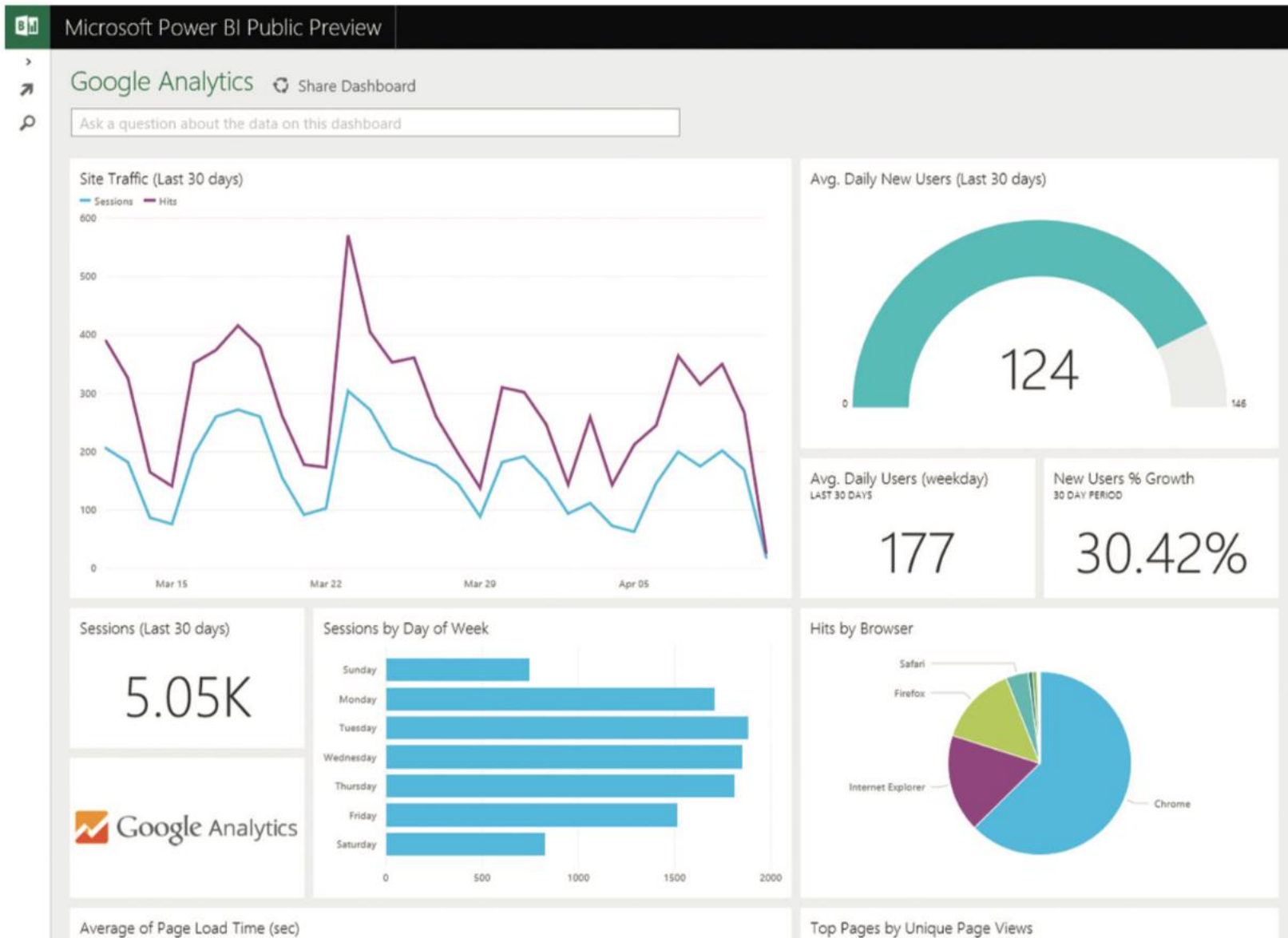
Web Usage Mining (Web Analytics)

- **Web usage mining (Web analytics)** is the extraction of useful information from data generated through Web page visits and transactions.
- **Clickstream Analysis**

Extraction of Knowledge from Web Usage Data



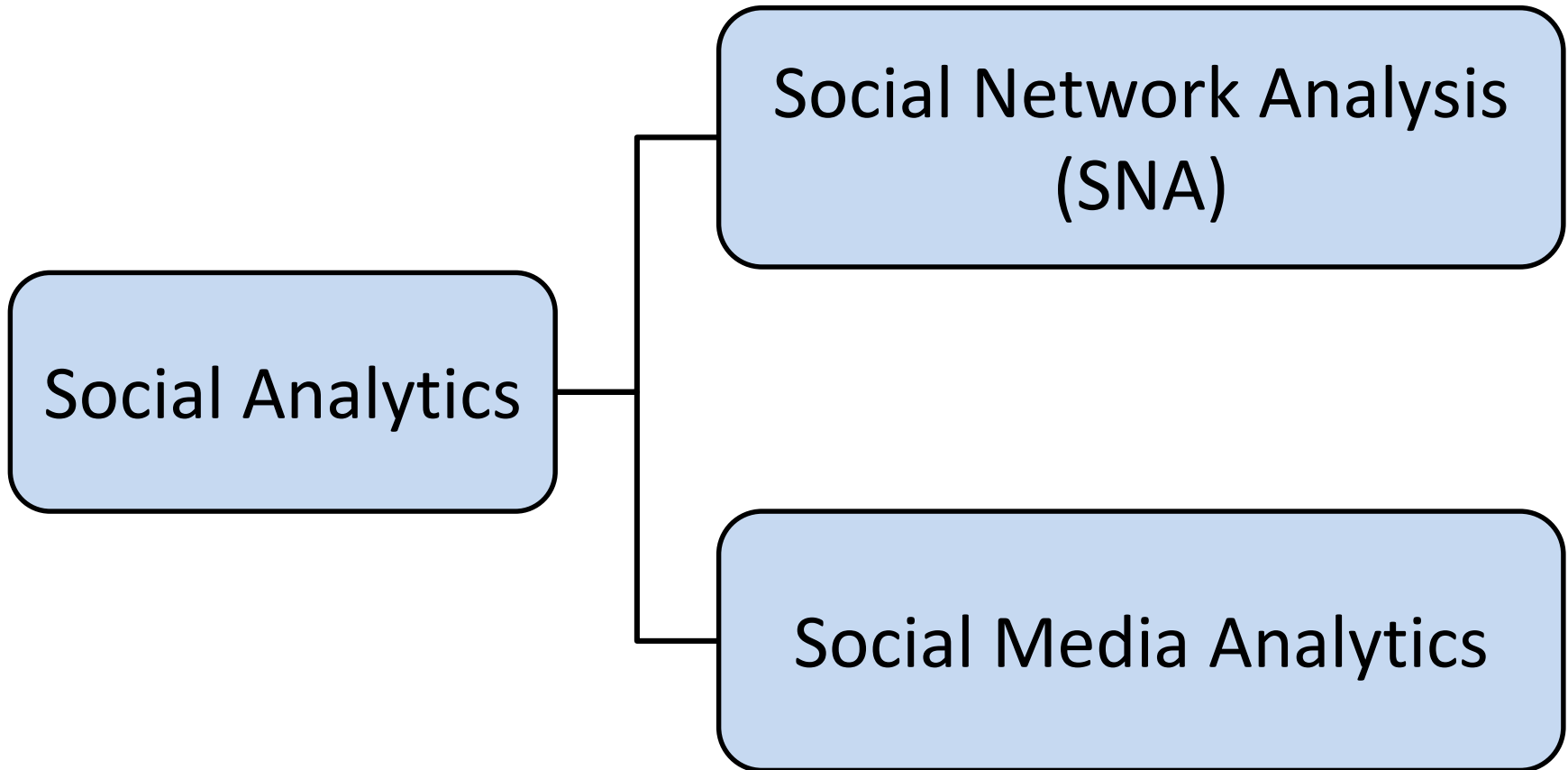
Web Analytics Dashboard



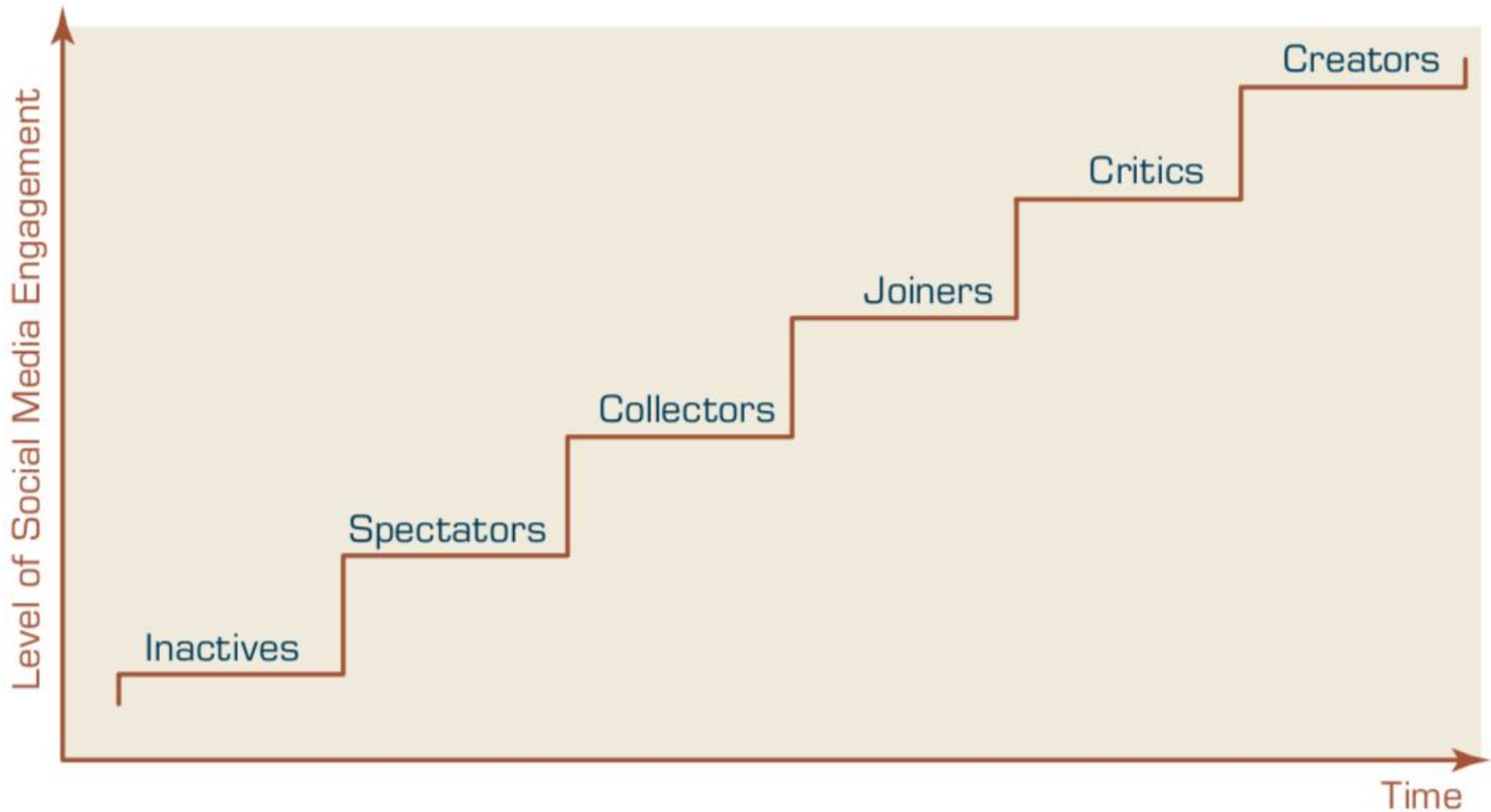
Social Analytics

- Social analytics is defined as monitoring, analyzing, measuring and interpreting digital interactions and relationships of people, topics, ideas and content.

Branches of Social Analytics



Evolution of Social Media User Engagement



Python in Google Colab

<https://colab.research.google.com/drive/1FEG6DnGvwfUbeo4zJ1zTunjMqf2RkCrT>



python101.ipynb ☆

File Edit View Insert Runtime Tools Help

COMMENT

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A

CODE TEXT CELL CELL

CONNECT

EDITING

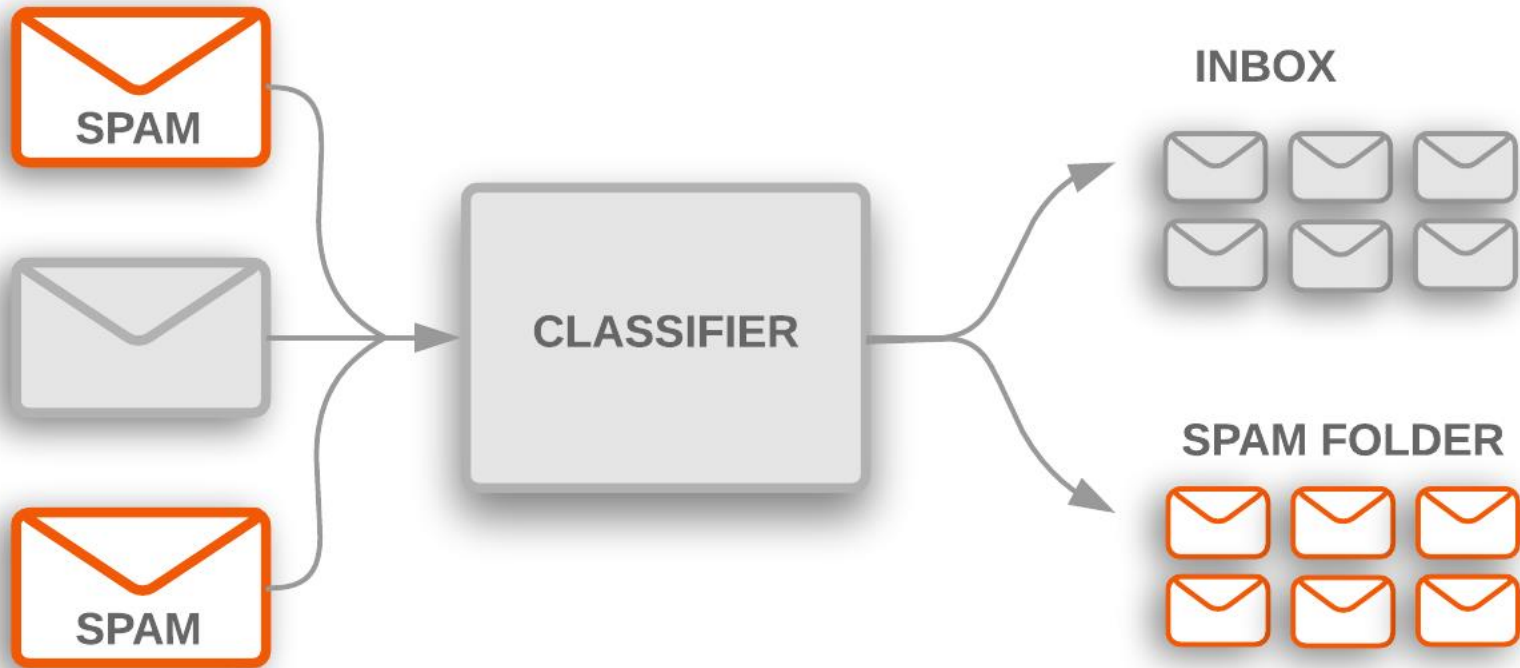
Keras preprocessing text

```
1 # keras.preprocessing.text Tokenizer
2 from keras.preprocessing.text import Tokenizer
3 # define 5 documents
4 docs = ['Well done!', 'Good work', 'Great effort', 'nice work', 'Excellent!']
5 # create the tokenizer
6 t = Tokenizer()
7 # fit the tokenizer on the documents
8 t.fit_on_texts(docs)
9 print('docs:', docs)
10 print('word_counts:', t.word_counts)
11 print('document_count:', t.document_count)
12 print('word_index:', t.word_index)
13 print('word_docs:', t.word_docs)
14 # integer encode documents
15 texts_to_matrix = t.texts_to_matrix(docs, mode='count')
16 print('texts_to_matrix:')
17 print(texts_to_matrix)
```

Using TensorFlow backend.

```
docs: ['Well done!', 'Good work', 'Great effort', 'nice work', 'Excellent!']
word_counts: OrderedDict([('well', 1), ('done', 1), ('good', 1), ('work', 2), ('great', 1), ('effort', 1), ('nice', 1), ('excellent', 1)])
document_count: 5
word_index: {'work': 1, 'well': 2, 'done': 3, 'good': 4, 'great': 5, 'effort': 6, 'nice': 7, 'excellent': 8}
word_docs: {'done': 1, 'well': 1, 'work': 2, 'good': 1, 'great': 1, 'effort': 1, 'nice': 1, 'excellent': 1}
texts_to_matrix:
[[0. 0. 1. 1. 0. 0. 0. 0. 0.]
 [0. 1. 0. 0. 1. 0. 0. 0. 0.]
 [0. 0. 0. 0. 0. 1. 1. 0. 0.]
 [0. 1. 0. 0. 0. 0. 0. 0. 1. 0.]
 [0. 0. 0. 0. 0. 0. 0. 0. 0. 1.]]
```


Text Classification

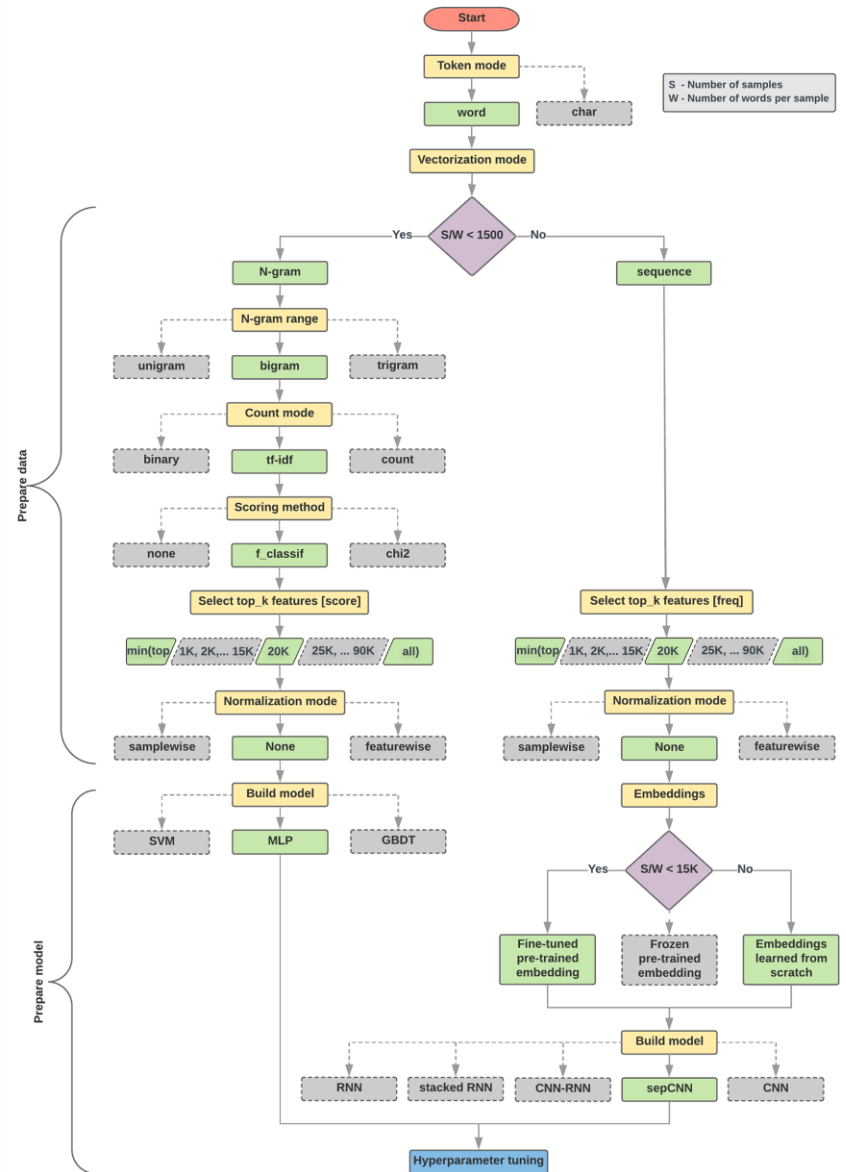


Text Classification Workflow

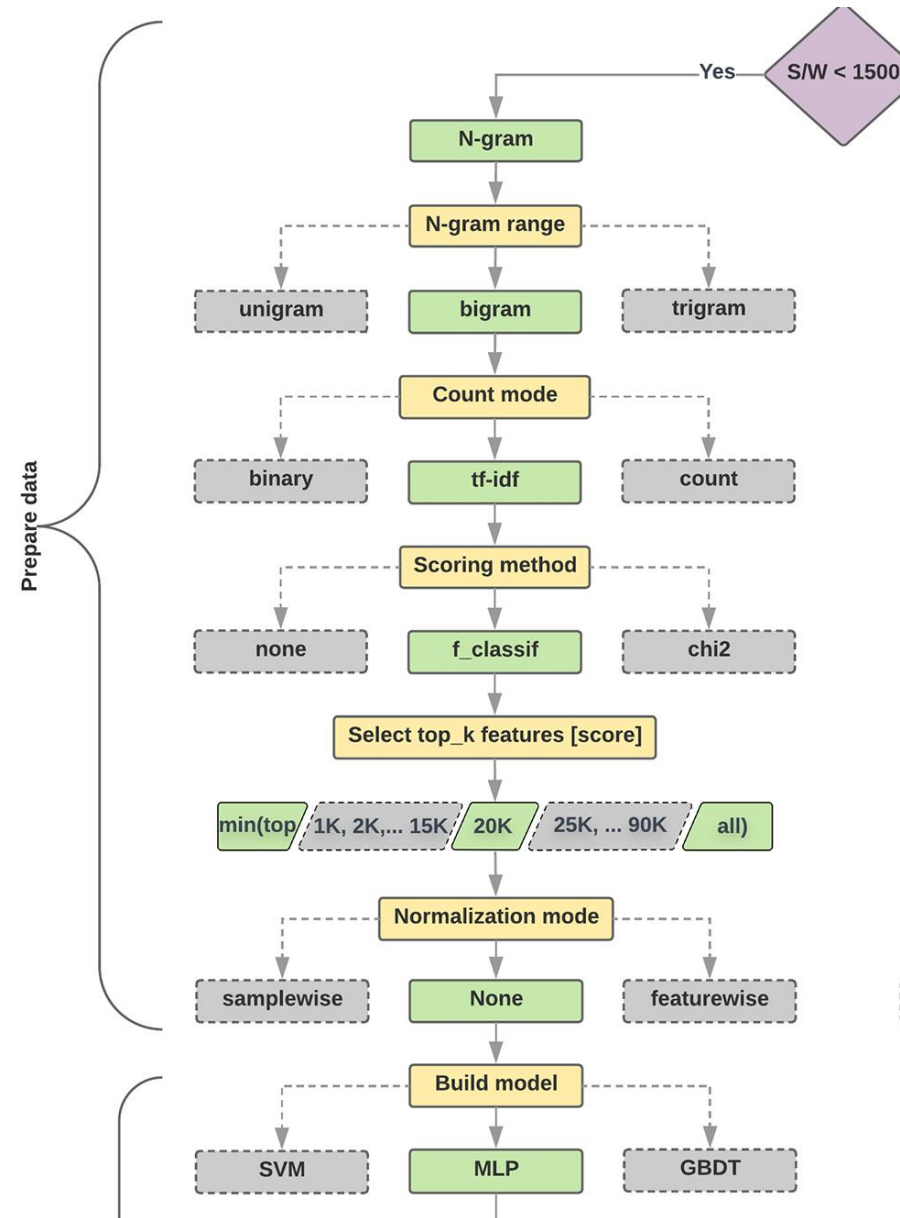
- Step 1: Gather Data
- Step 2: Explore Your Data
- Step 2.5: Choose a Model*
- Step 3: Prepare Your Data
- Step 4: Build, Train, and Evaluate Your Model
- Step 5: Tune Hyperparameters
- Step 6: Deploy Your Model



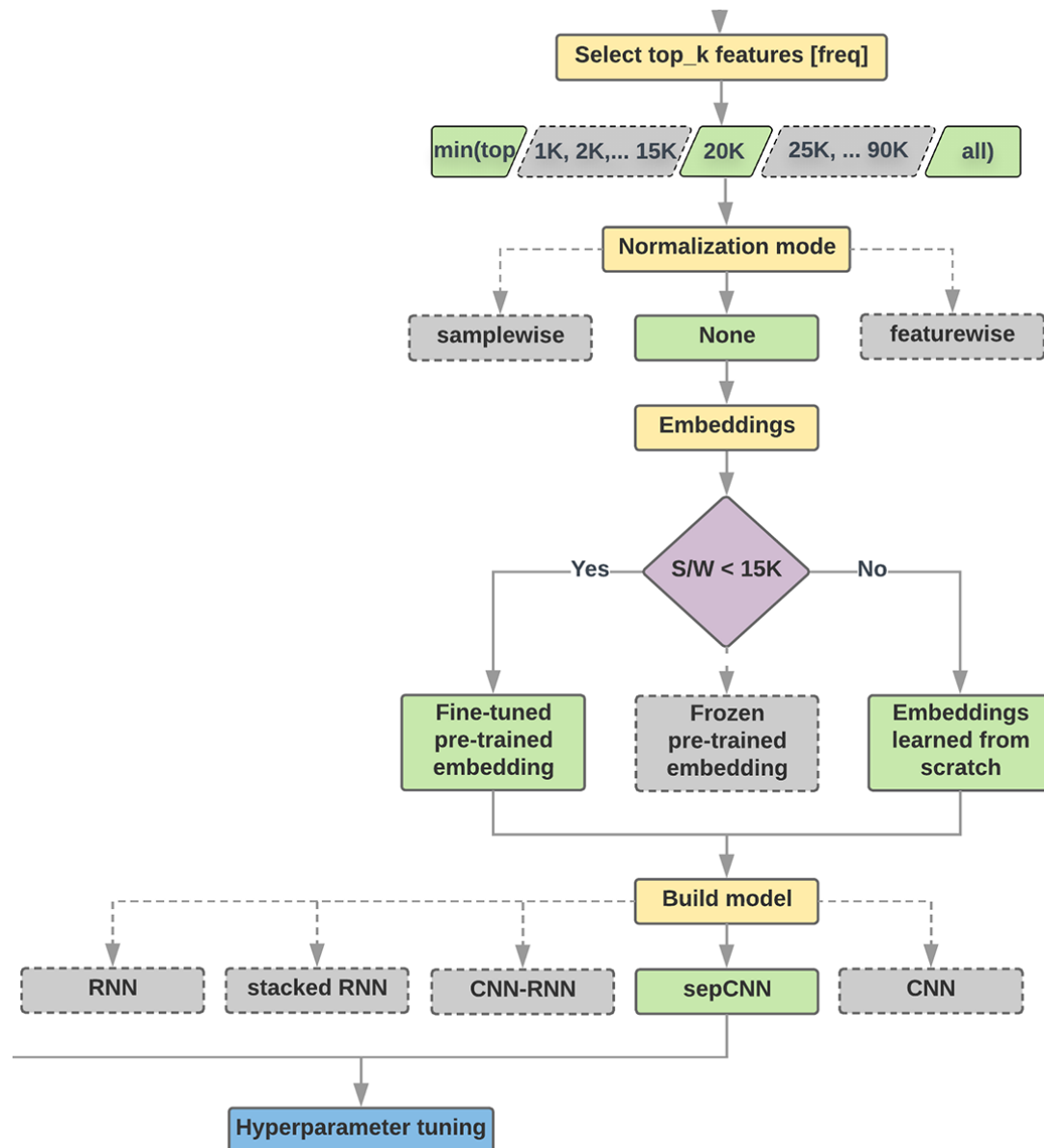
Text Classification Flowchart



Text Classification S/W<1500: N-gram



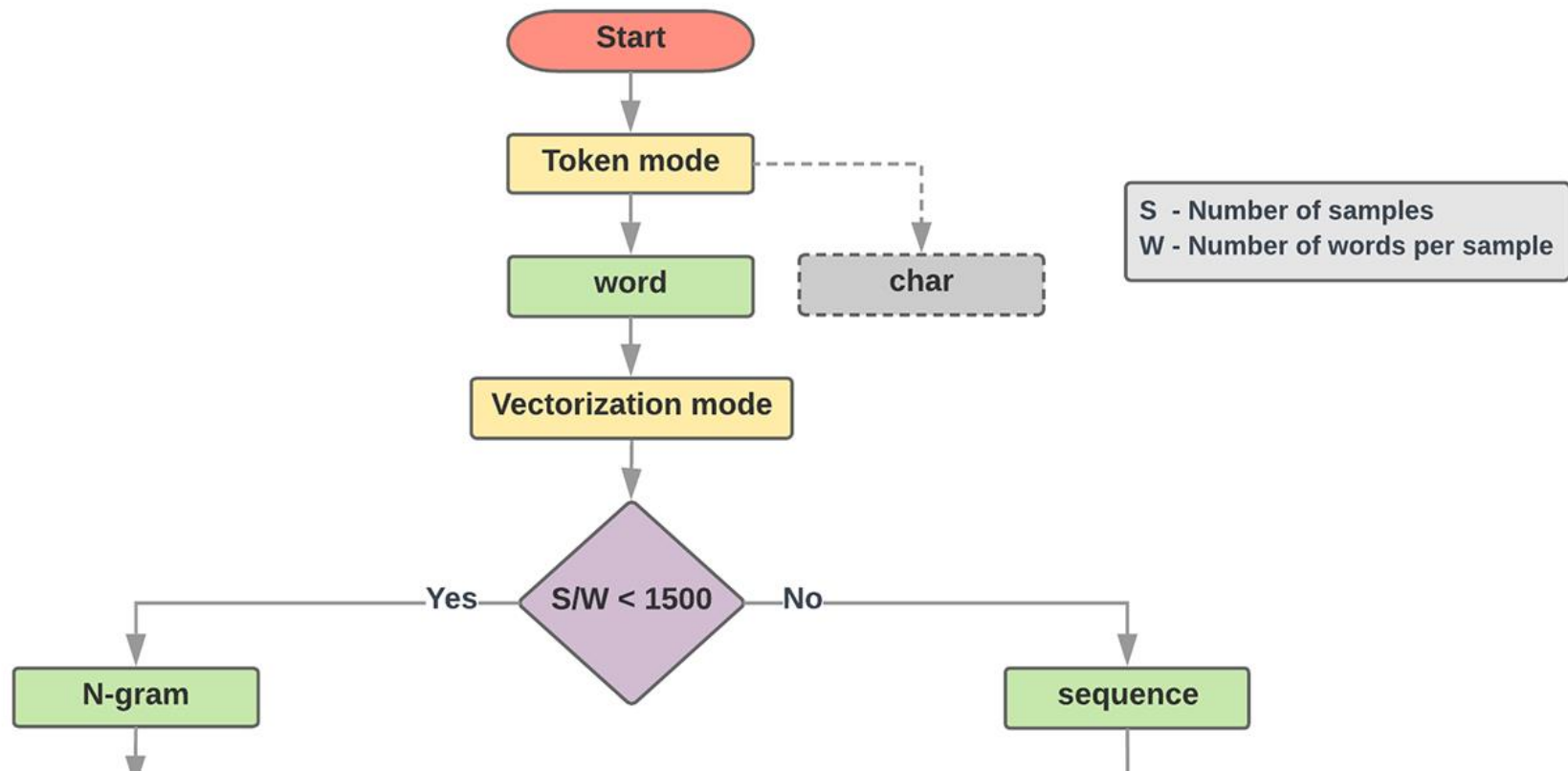
Text Classification $S/W \geq 1500$: Sequence



Step 2.5: Choose a Model

Samples/Words < 1500

$$150,000/100 = 1500$$

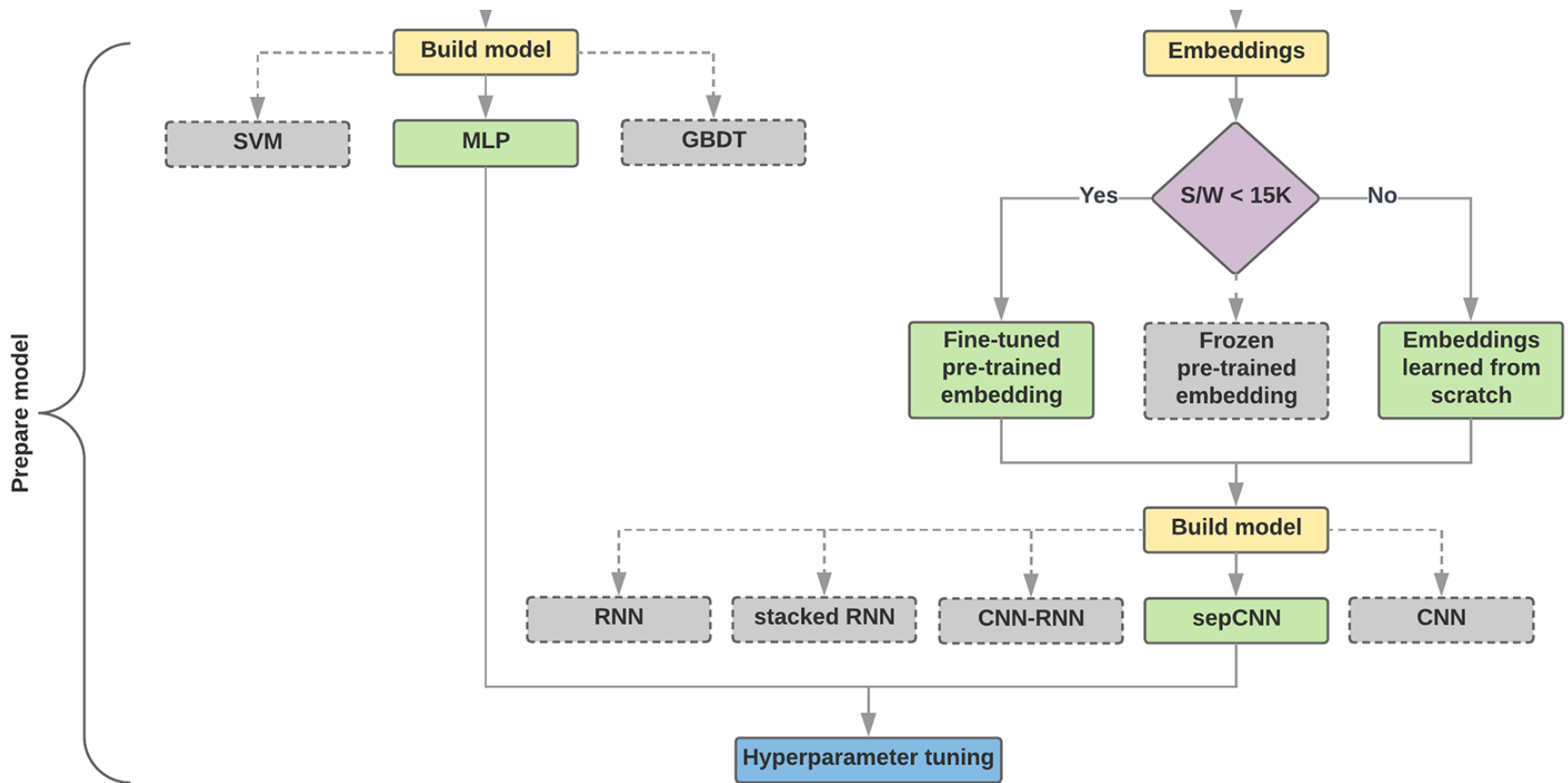


IMDb review dataset,
the samples/words-per-sample ratio is ~ 144

Step 2.5: Choose a Model

Samples/Words < 15,000

1,500,000/100 = 15,000



Step 3: Prepare Your Data

Texts:

T1: 'The mouse ran up the clock'

T2: 'The mouse ran down'

Token Index:

```
{'the': 1, 'mouse': 2, 'ran': 3, 'up': 4, 'clock': 5, 'down': 6,}.
```

NOTE: 'the' occurs most frequently,
so the index value of 1 is assigned to it.
Some libraries reserve index 0 for unknown tokens,
as is the case here.

Sequence of token indexes:

```
T1: 'The mouse ran up the clock' =  
    [1,  2,  3, 4,  1,  5]
```

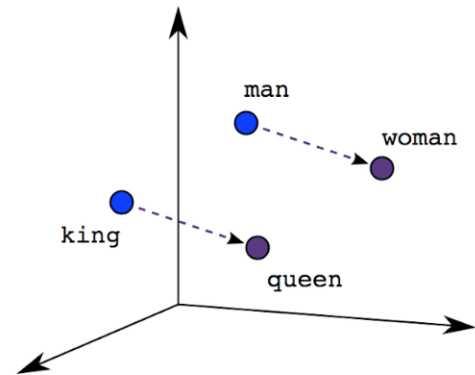
```
T2: 'The mouse ran down' =  
    [1,  2,  3,  6]
```


One-hot encoding

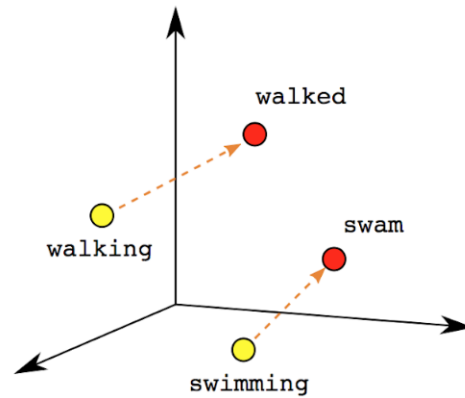
'The mouse ran up the clock' =

The	1	[[0, 1, 0, 0, 0, 0, 0],
mouse	2		[0, 0, 1, 0, 0, 0, 0],
ran	3		[0, 0, 0, 1, 0, 0, 0],
up	4		[0, 0, 0, 0, 1, 0, 0],
the	1		[0, 1, 0, 0, 0, 0, 0],
clock	5		[0, 0, 0, 0, 0, 1, 0]]
			[0, 1, 2, 3, 4, 5, 6]

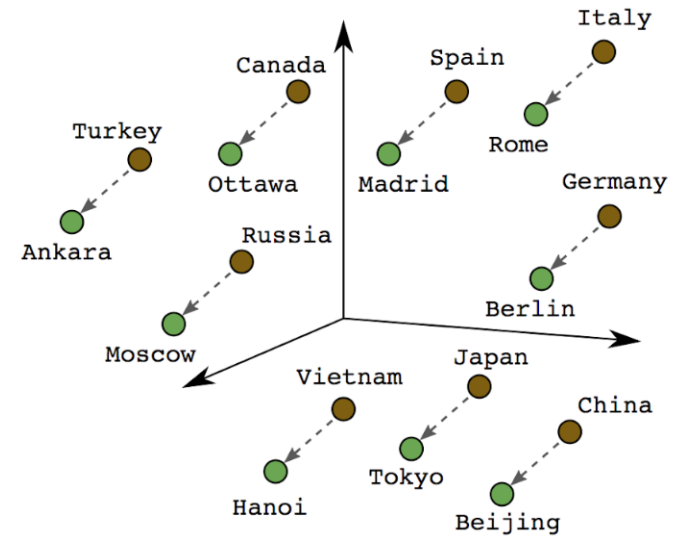
Word embeddings



Male-Female

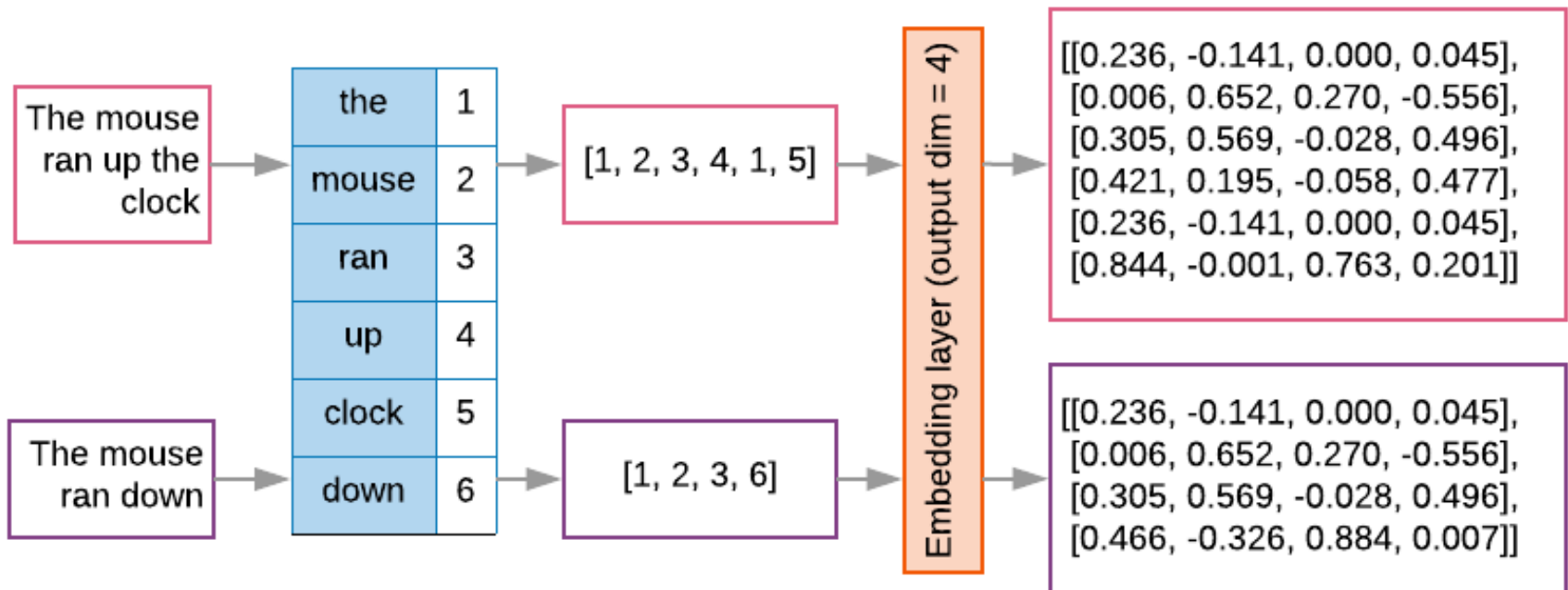


Verb Tense



Country-Capital

Word embeddings



```
t1 = 'The mouse ran up the clock'
t2 = 'The mouse ran down'
s1 = t1.lower().split(' ')
s2 = t2.lower().split(' ')
terms = s1 + s2
sortedset = sorted(set(terms))
print('terms =', terms)
print('sortedset =', sortedset)
```

```
1 t1 = 'The mouse ran up the clock'
2 t2 = 'The mouse ran down'
3 s1 = t1.lower().split(' ')
4 s2 = t2.lower().split(' ')
5 terms = s1 + s2
6 sortedset = sorted(set(terms))
7 print('terms =', terms)
8 print('sortedset =', sortedset)
```

```
terms = ['the', 'mouse', 'ran', 'up', 'the', 'clock', 'the', 'mouse', 'ran', 'down']
sortedset = ['clock', 'down', 'mouse', 'ran', 'the', 'up']
```

```
t1 = 'The mouse ran up the clock'
t2 = 'The mouse ran down'
s1 = t1.lower().split(' ')
s2 = t2.lower().split(' ')
terms = s1 + s2
print(terms)

tfdict = {}
for term in terms:
    if term not in tfdict:
        tfdict[term] = 1
    else:
        tfdict[term] += 1

a = []
for k,v in tfdict.items():
    a.append('{} , {}'.format(k,v))
print(a)
```

```
['the', 'mouse', 'ran', 'up', 'the', 'clock', 'the', 'mouse', 'ran', 'down']
['the, 3', 'mouse, 2', 'ran, 2', 'up, 1', 'clock, 1', 'down, 1']
```

```
sorted_by_value_reverse = sorted(tfdict.items(),
key=lambda kv: kv[1], reverse=True)
```

```
sorted_by_value_reverse_dict =
dict(sorted_by_value_reverse)
```

```
id2word = {id: word for id, word in
enumerate(sorted_by_value_reverse_dict)}
```

```
word2id = dict([(v, k) for (k, v) in
id2word.items()])
```

```
sorted_by_value: [('up', 1), ('clock', 1), ('down', 1), ('mouse', 2), ('ran', 2), ('the', 3)]
sorted_by_value2: ['the', 'mouse', 'ran', 'up', 'clock', 'down']
sorted_by_value_reverse: [('the', 3), ('mouse', 2), ('ran', 2), ('up', 1), ('clock', 1), ('down', 1)]
sorted_by_value_reverse_dict {'the': 3, 'mouse': 2, 'ran': 2, 'up': 1, 'clock': 1, 'down': 1}
id2word {0: 'the', 1: 'mouse', 2: 'ran', 3: 'up', 4: 'clock', 5: 'down'}
word2id {'the': 0, 'mouse': 1, 'ran': 2, 'up': 3, 'clock': 4, 'down': 5}
len_words: 6
sorted_by_key: [('clock', 1), ('down', 1), ('mouse', 2), ('ran', 2), ('the', 3), ('up', 1)]
the, 3
mouse, 2
ran, 2
up, 1
clock, 1
down, 1
```

```

sorted_by_value = sorted(tfdict.items(), key=lambda kv: kv[1])
print('sorted_by_value: ', sorted_by_value)
sorted_by_value2 = sorted(tfdict, key=tfdict.get, reverse=True)
print('sorted_by_value2: ', sorted_by_value2)
sorted_by_value_reverse = sorted(tfdict.items(), key=lambda kv: kv[1], reverse=True)
print('sorted_by_value_reverse: ', sorted_by_value_reverse)
sorted_by_value_reverse_dict = dict(sorted_by_value_reverse)
print('sorted_by_value_reverse_dict', sorted_by_value_reverse_dict)
id2word = {id: word for id, word in enumerate(sorted_by_value_reverse_dict)}
print('id2word', id2word)
word2id = dict([(v, k) for (k, v) in id2word.items()])
print('word2id', word2id)
print('len_words:', len(word2id))

```

```

sorted_by_key = sorted(tfdict.items(), key=lambda kv: kv[0])
print('sorted_by_key: ', sorted_by_key)

```

```

tfstring = '\n'.join(a)
print(tfstring)
tf = tfdict.get('mouse')
print(tf)

```

```

sorted_by_value: [('up', 1), ('clock', 1), ('down', 1), ('mouse', 2), ('ran', 2), ('the', 3)]
sorted_by_value2: ['the', 'mouse', 'ran', 'up', 'clock', 'down']
sorted_by_value_reverse: [('the', 3), ('mouse', 2), ('ran', 2), ('up', 1), ('clock', 1), ('down', 1)]
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id2word {0: 'the', 1: 'mouse', 2: 'ran', 3: 'up', 4: 'clock', 5: 'down'}
word2id {'the': 0, 'mouse': 1, 'ran': 2, 'up': 3, 'clock': 4, 'down': 5}
len_words: 6
sorted_by_key: [('clock', 1), ('down', 1), ('mouse', 2), ('ran', 2), ('the', 3), ('up', 1)]
the, 3
mouse, 2
ran, 2
up, 1
clock, 1
down, 1

```

from keras.preprocessing.text import Tokenizer

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13 # integer encode documents
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15 print('texts_to_matrix:')
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```

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docs: ['Well done!', 'Good work', 'Great effort', 'nice work', 'Excellent!']
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document_count: 5
word_index: {'work': 1, 'well': 2, 'done': 3, 'good': 4, 'great': 5, 'effort': 6, 'nice': 7, 'excellent': 8}
word_docs: {'done': 1, 'well': 1, 'work': 2, 'good': 1, 'great': 1, 'effort': 1, 'nice': 1, 'excellent': 1}
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[[0. 0. 1. 1. 0. 0. 0. 0. 0.]
 [0. 1. 0. 0. 1. 0. 0. 0. 0.]
 [0. 0. 0. 0. 0. 1. 1. 0. 0.]
 [0. 1. 0. 0. 0. 0. 0. 1. 0.]
 [0. 0. 0. 0. 0. 0. 0. 0. 1.]]
```


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```
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'nice work', 'Excellent!']  
word_counts: OrderedDict([('well', 1), ('done', 1),  
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( 'nice', 1), ('excellent', 1)])  
document_count: 5  
word_index: {'work': 1, 'well': 2, 'done': 3, 'good':  
4, 'great': 5, 'effort': 6, 'nice': 7, 'excellent': 8}  
word_docs: {'done': 1, 'well': 1, 'work': 2, 'good': 1,  
'great': 1, 'effort': 1, 'nice': 1, 'excellent': 1}  
texts_to_matrix:  
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 [0. 1. 0. 0. 1. 0. 0. 0. 0.]  
 [0. 0. 0. 0. 0. 1. 1. 0. 0.]  
 [0. 1. 0. 0. 0. 0. 0. 1. 0.]  
 [0. 0. 0. 0. 0. 0. 0. 0. 1.]]
```

t.texts_to_matrix(docs, mode='tfidf')

```
from keras.preprocessing.text import Tokenizer
# define 5 documents
docs = ['Well done!', 'Good work', 'Great effort', 'nice work',
        'Excellent!']
# create the tokenizer
t = Tokenizer()
# fit the tokenizer on the documents
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print('document_count:', t.document_count)
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print('word_docs:', t.word_docs)
# integer encode documents
texts_to_matrix = t.texts_to_matrix(docs, mode='tfidf')
print('texts_to_matrix:')
print(texts_to_matrix)
```

texts_to_matrix:

```
[[0.  0.  1.25276297  1.25276297  0.  0.  0.  0.  0. ]
 [0.  0.98082925  0.  0.  1.25276297  0.  0.  0.  0. ]
 [0.  0.  0.  0.  0.  1.25276297  1.25276297  0.  0. ]
 [0.  0.98082925  0.  0.  0.  0.  0.  0.  1.25276297  0. ]
 [0.  0.  0.  0.  0.  0.  0.  0.  0.  1.25276297]]
```

Summary

- Text Analytics and Text Mining Overview
 - Natural Language Processing (NLP)
 - Text Mining Applications
 - Text Mining Process
 - Sentiment Analysis
- Web Mining Overview
 - Search Engines
 - Web Usage Mining (Web Analytics)
- Social Analytics

References

- Ramesh Sharda, Dursun Delen, and Efraim Turban (2017), Business Intelligence, Analytics, and Data Science: A Managerial Perspective, 4th Edition, Pearson.
- Jake VanderPlas (2016), Python Data Science Handbook: Essential Tools for Working with Data, O'Reilly Media.