Knowledge Graph

June 23, 2021

1 Preprocessing

1.1 Requisite Resources and Knowledge

Important libraries we will use is `spacy`, `pandas`, `networkx` and `matplotlib`. `spacy` is the NLP package that will handle the knowledge extraction that will feed into the subject, predicate, object (SPO) triples. `pandas` is used for creating a dataframe that contains the SPO triples which are used for graphing and statistical analysis. `networkx` and `matplotlib` are the primary sources of visual analysis of these knowledge graphs. To utilize these libraries effectively, we will need to be familiar with the resource description framework (RDF), parts of speech (POS) tagging, sentence segmenetation, dependency parsing, entity recognition & linking, SPO triples, and data engineering.

`bs4, requests` are supplementary libraries that are not used in this notebook but can be extremely useful when performing HTML/XML parsing and performing HTTP requests, respectfully.

`tqdm` is a library that creates a smart progress meter. It is unnecessary but useful when determing the progress made on an iterable and also estimation of time left.

1.2 Loading Libraries

[1]:
```
# !pip install spacy
# !python -m spacy download en_core_web_sm
import re
import pandas as pd
# import bs4
# import requests
import spacy
from spacy import displacy
nlp = spacy.load('en_core_web_sm')

from spacy.matcher import Matcher
from spacy.tokens import Span

import networkx as nx

import matplotlib.pyplot as plt
from tqdm import tqdm
```

```
pd.set_option('display.max_colwidth', 200)
%matplotlib inline
```

1.3 Reading and Sampling the sample data

[2]:
```
# import wikipedia sentences
candidate_sentences = pd.read_csv("wiki_sentences_v2.csv")
candidate_sentences.shape
```

[2]:
```
(4318, 1)
```

[3]:
```
candidate_sentences['sentence'].sample(5)
```

[3]:
```
3006                                        and it took 3 weeks to wrap up.
1120    in august 2013 he was declared india's most searched celebrity online.
256          prometheus  and alien: covenant  address extraterrestrial themes.
2717                                 the film was released on 6 january 2017.
2349                          cooper and tars are ejected from the tesseract.
Name: sentence, dtype: object
```

2 Entities Extraction

Entities are the nodes of our Knowledge Graph (KG). We can extract a single word entity from a sentence with the help of parts of speech (POS) tags. The noun and proper nouns will be our entities. However, when an entity spans across multiple words we need to parse the dependency tree of the sentence. We can accomplish this by creating a rule to extract such entities: ***extract the subject/object along with its modifiers, compound words and also extract the punctuation marks between them.*** This isn't necessarily complete, but it is a good place to start.

[4]:
```
doc = nlp("the drawdown process is governed by astm standard d823")

for tok in doc:
  print(tok.text, "...", tok.dep_)
```

```
the … det
drawdown … compound
process … nsubjpass
is … auxpass
governed … ROOT
by … agent
astm … compound
standard … pobj
d823 … punct
```

The following function extracts the subject and object entities from the sentence as they are encountered.

[5]:
```
def get_entities(sent):
  ## chunk 1
  ent1 = ""
  ent2 = ""

  prv_tok_dep = ""    # dependency tag of previous token in the sentence
  prv_tok_text = ""   # previous token in the sentence

  prefix = ""
  modifier = ""

  #############################################################

  for tok in nlp(sent):
    ## chunk 2
    # if token is a punctuation mark then move on to the next token
    if tok.dep_ != "punct":
      # check: token is a compound word or not
      if tok.dep_ == "compound":
        prefix = tok.text
        # if the previous word was also a 'compound' then add the current word␣
↪to it
        if prv_tok_dep == "compound":
          prefix = prv_tok_text + " "+ tok.text

      # check: token is a modifier or not
      if tok.dep_.endswith("mod") == True:
        modifier = tok.text
        # if the previous word was also a 'compound' then add the current word␣
↪to it
        if prv_tok_dep == "compound":
          modifier = prv_tok_text + " "+ tok.text

      ## chunk 3
      if tok.dep_.find("subj") == True:
        ent1 = modifier +" "+ prefix + " "+ tok.text
        prefix = ""
        modifier = ""
        prv_tok_dep = ""
        prv_tok_text = ""

      ## chunk 4
      if tok.dep_.find("obj") == True:
        ent2 = modifier +" "+ prefix +" "+ tok.text
```

```
    ## chunk 5
    # update variables
    prv_tok_dep = tok.dep_
    prv_tok_text = tok.text
  #############################################################

  return [ent1.strip(), ent2.strip()]
```

[6]:
```
entity_pairs = []

for i in tqdm(candidate_sentences["sentence"]):
  entity_pairs.append(get_entities(i))
```

```
100%|      | 4318/4318 [00:22<00:00, 188.68it/s]
```

For most sentences, our function works. Below, we will see that the sentence `"We are working towards the future"` correctly outputs `['We', 'Future']` as the subject and object respectively.

[7]:
```
get_entities("We are working towards the future")
```

[7]:
```
['We', 'future']
```

However, there are sentences that deviate from what we expect, for example the sentence `"c. mackenzie, and craig vincent joined the cast."` should output something along the lines of `['c. mackenzie and craig vincent', 'cast']`:

[8]:
```
print(candidate_sentences[6:7])
entity_pairs[6:7]
```

```
                                            sentence
6  c. mackenzie, and craig vincent joined the cast.
```

[8]:
```
[['c. mackenzie', 'craig  cast']]
```

3 Relation Extraction

Relations between entities are the edges of our KE. We can extract these through an unsupervised manner, by using the grammar of the setences, i.e., identifying the ROOT POS tag in a sentence.

The following function extracts the relation of the sentence, which is the ROOT/predicate of the sentence. The `Matcher()` function is part of the `spaCy` package and allows you to perform token-based matching.

[9]:
```
def get_relation(sent):

  doc = nlp(sent)
```

```python
    # Matcher class object
    matcher = Matcher(nlp.vocab)

    #define the pattern
    pattern = [{'DEP':'ROOT'},
               {'DEP':'prep','OP':"?"},
               {'DEP':'agent','OP':"?"},
               {'POS':'ADJ','OP':"?"}]

    matcher.add("matching_1",[pattern])

    matches = matcher(doc)
    k = len(matches) - 1

    span = doc[matches[k][1]:matches[k][2]]

    return(span.text)
```

[10]:
```python
get_relation("John completed the task")
```

[10]: 'completed'

[11]:
```python
relations = [get_relation(i) for i in tqdm(candidate_sentences['sentence'])]
```

```
100%|      | 4318/4318 [00:23<00:00, 184.20it/s]
```

[12]:
```python
pd.Series(relations).value_counts()[:50]
```

[12]:
```
is              348
was             283
released on      82
are              73
were             67
include          61
                 50
's               41
released         39
have             31
became           29
has              29
released in      26
become           26
composed by      26
included         22
produced         21
called           21
```

```
been               20
considered         19
used               18
had                18
be                 16
made               16
received           15
went               14
scheduled          14
hired              14
wrote              13
introduced in      13
directed by        13
set                12
wanted             11
won                11
produced by        11
began              11
began in           11
\n                 10
features           10
sold               10
cast as            10
written by         10
stars              10
gave               10
gives               9
includes            9
going               9
known as            9
reported            9
produced in         9
dtype: int64
```

4 Creating the Graph

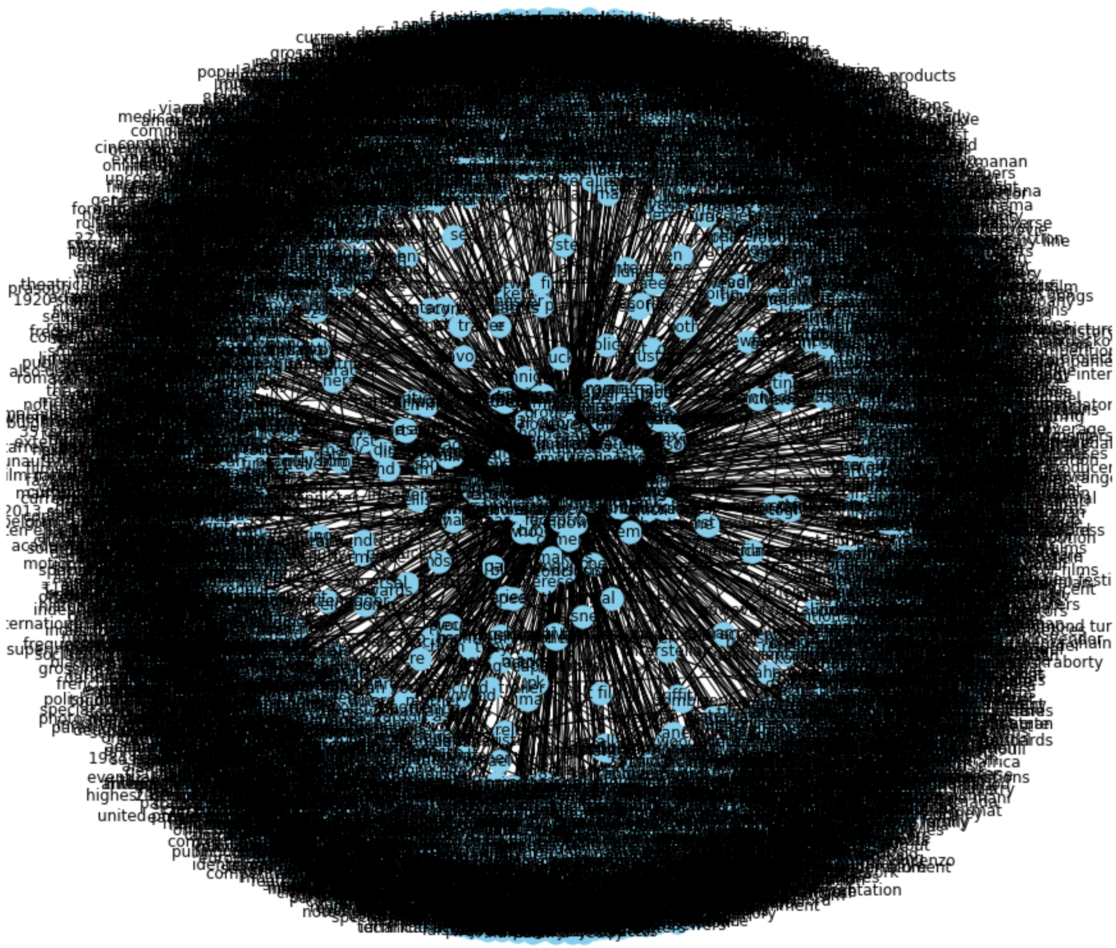
[13]:
```
# extract subject
source = [i[0] for i in entity_pairs]

# extract object
target = [i[1] for i in entity_pairs]

kg_df = pd.DataFrame({'source':source, 'target':target, 'edge':relations})
```

[14]:
```
# create a directed-graph from a dataframe
G=nx.from_pandas_edgelist(kg_df, "source", "target",
                          edge_attr=True, create_using=nx.MultiDiGraph())
```

[15]:
```
# !pip install -U decorator
!pip install 'decorator == 5.0.7'
```

```
Requirement already satisfied: decorator==5.0.7 in
/Users/jiesenzhang/opt/anaconda3/lib/python3.8/site-packages (5.0.7)
```

[16]:
```
plt.figure(figsize=(12,12))

pos = nx.spring_layout(G)
nx.draw(G, with_labels=True, node_color='skyblue', edge_cmap=plt.cm.Blues, pos␣
 ↪= pos)
plt.show()
```

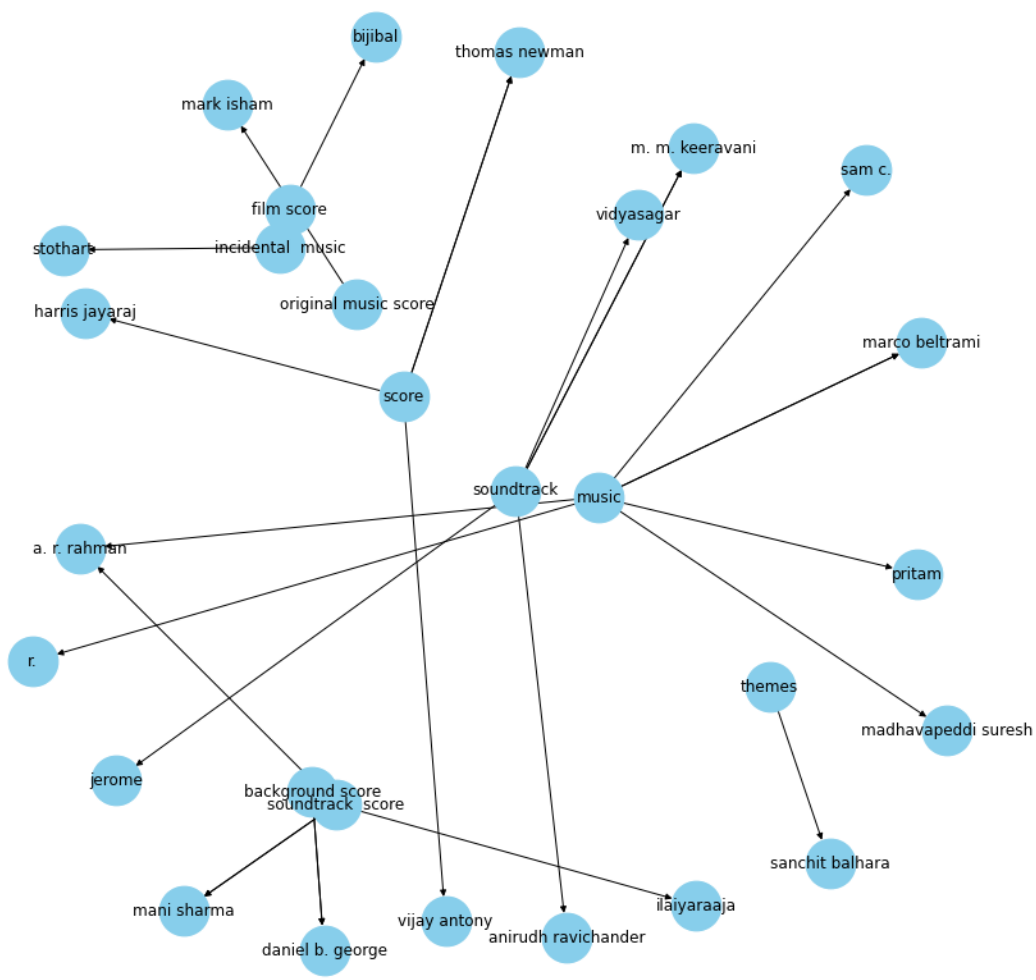


This is the entire knowledge graph with every single usage relation, however, this isn't useful for our understanding. We can single out certain relations of interest.

"composed by"

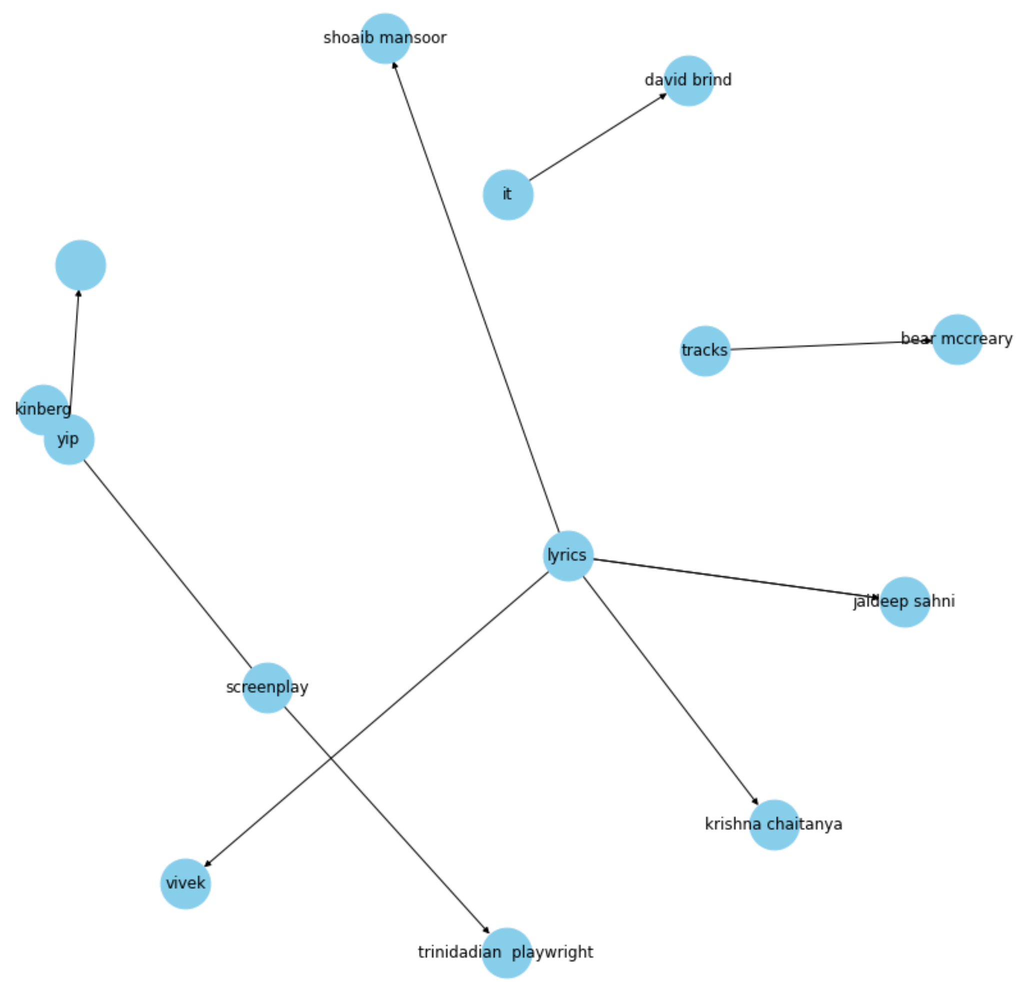
[17]:
```
G=nx.from_pandas_edgelist(kg_df[kg_df['edge']=="composed by"], "source",␣
↪"target",
                          edge_attr=True, create_using=nx.MultiDiGraph())

plt.figure(figsize=(12,12))
pos = nx.spring_layout(G, k = 0.5) # k regulates the distance between nodes
nx.draw(G, with_labels=True, node_color='skyblue', node_size=1500,␣
↪edge_cmap=plt.cm.Blues, pos = pos)
```

```
plt.show()
```



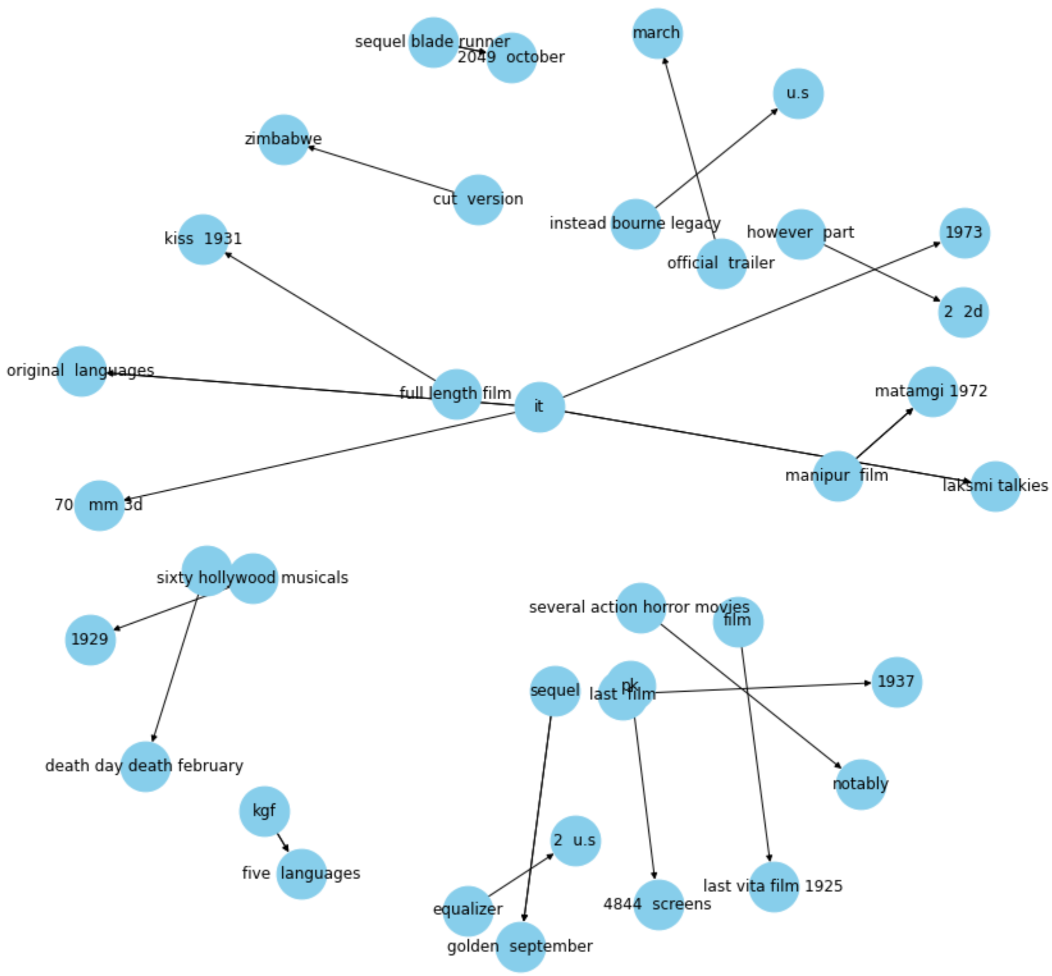
"written by"

```
[18]: G=nx.from_pandas_edgelist(kg_df[kg_df['edge']=="written by"], "source",␣
       ↪"target",
                                edge_attr=True, create_using=nx.MultiDiGraph())

      plt.figure(figsize=(12,12))
      pos = nx.spring_layout(G, k = 0.5)
      nx.draw(G, with_labels=True, node_color='skyblue', node_size=1500,␣
       ↪edge_cmap=plt.cm.Blues, pos = pos)
      plt.show()
```



"released in"

```
[19]: G=nx.from_pandas_edgelist(kg_df[kg_df['edge']=="released in"], "source",␣
      ↪"target",
                                  edge_attr=True, create_using=nx.MultiDiGraph())

      plt.figure(figsize=(12,12))
      pos = nx.spring_layout(G, k = 0.5)
      nx.draw(G, with_labels=True, node_color='skyblue', node_size=1500,␣
      ↪edge_cmap=plt.cm.Blues, pos = pos)
      plt.show()
```



While these graphs are not perfect, i.e., ‘it’ as an entity does not provide much insight as to what it is referring to, we can still gleam a lot of useful information.

5 Conclusion and Thoughts

1. One important thing to note is that our method of generating a knowledge graph is limited to sentence-level, which does not always provide complete knowledge extraction. There are many instances where entities can be referenced between sentences or even paragraphs.
2. The extraction rule we use “***extract the subject/object along with its modifiers, compound words and also extract the punctuation marks between them.***” isn’t complete. For example, the sentence “Mark Zuckerberg is the CEO of Facebook” classifies ‘Facebook’ as the object, but ‘CEO’ is an important relation that is not picked up. This can be fixed by

adding more rules.

3. We restricted ourselves to sentences with exactly two entities. Even so, we can still build an informative and complex networks.

6 References

- Knowledge Graph Tutorial
- Knowledge Graph Simple Understanding

6.1 Support Links

- Matcher.Add Issues
- Markdown Support
- networkx.decorator random_state_index error