Knowledge Graph Project (by FORWARD Data Lab)

Part 1. ETL Pipeline

Load libraries

In [1]:

```
import pyspark as sp
import numpy as np
import string
import re
```

Set environment variable (optional)

In [2]:

```
import os
os.environ["PYSPARK_PYTHON"]="/usr/local/bin/python3"
os.environ["PYSPARK_DRIVER_PYTHON"]="/usr/local/bin/python3"
```

Setup cluster

In [3]:

```
from pyspark.sql import SparkSession

spark = SparkSession \
    .builder \
    .appName("Python Knowledge Graph Project") \
    .master("local[*]") \
    .config("spark.some.config.option", "some-value") \
    .getOrCreate()
```

Load dataset

- Documents: `1.7m` documents (arXiv dataset)
- Keyword list: `100,000` keywords (FORWARD Data Lab)
- Download your documents here: [https://www.kaggle.com/Cornell-University/arxiv (https://www.kaggle.com/Cornell-University/arxiv)](https://www.kaggle.com/Cornell-University/arxiv).

In [4]:
```
df_keywords = spark.read.csv("./mag_cs_keywords.csv",header=True)
df_arxiv = spark.read.json("./original/arxiv-metadata-oai-snapshot.jso
n")
```

In [5]:
```
df_keywords = df_keywords.repartition(8)
df_arxiv = df_arxiv.repartition(8)
```

In [6]:
```
df_keywords.rdd.getNumPartitions()
```

Out[6]: 8

In [7]:
```
df_keywords.count()
```

Out[7]: 104654

In [8]:
```
abstracts = df_arxiv.select("id","abstract")
keywords = df_keywords.select("normalizedName")
```

Cleaning & Normalization

In [9]:
```
from pyspark.sql.functions import udf, col
from pyspark.sql import Row
from pyspark.sql.types import ArrayType, StructField, StructType, Stri
ngType, IntegerType

# get only lowercase alphabets
def strip_non_ascii(data_str):
    ''' Returns the string without non ASCII characters'''
    stripped = (c.lower() for c in data_str if 96 < ord(c.lower()) < 1
23 or ord(c)==32) #alphabets

    return ''.join(stripped)
# setup pyspark udf function
strip_non_ascii_udf = udf(strip_non_ascii, StringType())
```

In [10]:
```
abstracts = abstracts.withColumn('normalized', strip_non_ascii_udf(abs
tracts['abstract']))
abstracts = abstracts.select("id","normalized")
```

In [11]:
```
abstracts.show()
```

```
+---------+--------------------+
|       id|          normalized|
+---------+--------------------+
|0809.3647|  in this paper w...|
|0809.1984|  quantum fluctua...|
|0710.3204|  we show how com...|
|0704.3898|  we give two cla...|
|0807.4706|  let g be a grou...|
|0809.2915|  the h and zeus ...|
|0803.3905|  when designing ...|
|0807.0026|  radio telescope...|
|0804.1504|  in  an internat...|
|0802.4266|  we study group ...|
|0802.3187|  the role of neu...|
|0710.2708|  given a project...|
|0706.0677|  this is the thi...|
|0707.1652|  the pierre auge...|
|0809.1051|  we present a ve...|
|0704.3951|  ramification in...|
|0805.4670|  based on firstp...|
|0710.4428|  an asymptotic m...|
|0712.1683|  recently the in...|
|0810.0015|  experiments in ...|
+---------+--------------------+
only showing top 20 rows
```

Keyword List for Query

- `keywords_dict` : Hash table is used to find whether documents contain keywords
- My frist attempt was using regular expression (re.findall()).
- When using regular expression, there could be a time complexity issue due to unnecessary computational overhead
- To prevent optimize algorithm, we should search `from document to word`.

In [12]:
```
keywords_list = list(keywords.select('normalizedName').toPandas()['nor
malizedName'])
keyword_dict = {word:0 for word in keywords_list}
```

Extract Keyword from the keyword list

In [13]:
```python
import re

# Define the function you want to return
def extract(s):
    all_matches = set()
    for word in s.split(" "):
        if keyword_dict.get(word, -1) >=0:
            keyword_dict[word] += 1
            all_matches.add(word)
    return ','.join(all_matches)

# Create the UDF, note that you need to declare the return schema matc
hing the returned type
extract_udf = udf(extract, StringType())

# Apply it
df = abstracts.withColumn('extracted', extract_udf(abstracts['normaliz
ed']))
```

In [14]:
```python
df.show()
```

```
+---------+--------------------+--------------------+
|       id|          normalized|           extracted|
+---------+--------------------+--------------------+
|0809.3647|  in this paper w...|size,algorithm,pr...|
|0809.1984|  quantum fluctua...|quantum,field,res...|
|0710.3204|  we show how com...|current,scatterin...|
|0704.3898|  we give two cla...|set,metric,functi...|
|0807.4706|  let g be a grou...|product,cluster,q...|
|0809.2915|  the h and zeus ...|scattering,mass,q...|
|0803.3905|  when designing ...|set,art,modelling...|
|0807.0026|  radio telescope...|range,leakage,pos...|
|0804.1504|  in  an internat...|imagination,refle...|
|0802.4266|  we study group ...|  bimodule,skew,group|
|0802.3187|  the role of neu...|quark,phase,gauge...|
|0710.2708|  given a project...|bundle,decomposit...|
|0706.0677|  this is the thi...|geodesic,link,ser...|
|0707.1652|  the pierre auge...|pose,unit,distrib...|
|0809.1051|  we present a ve...|range,quantum,res...|
|0704.3951|  ramification in...|filtration,struct...|
|0805.4670|  based on firstp...|character,layers,...|
|0710.4428|  an asymptotic m...|structures,dynami...|
|0712.1683|  recently the in...|wave,molecule,dif...|
|0810.0015|  experiments in ...|cell,relation,low...|
+---------+--------------------+--------------------+
only showing top 20 rows
```

Drop Empty Rows where no keyword exists

In [15]:
```
from pyspark.sql.functions import length
df = df.filter(length('extracted')>2)
```

In [16]:
```
df.show()
```

```
+---------+--------------------+--------------------+
|       id|          normalized|           extracted|
+---------+--------------------+--------------------+
|0809.3647|  in this paper w...|size,algorithm,pr...|
|0809.1984|  quantum fluctua...|quantum,field,res...|
|0710.3204|  we show how com...|current,scatterin...|
|0704.3898|  we give two cla...|set,metric,functi...|
|0807.4706|  let g be a grou...|product,cluster,q...|
|0809.2915|  the h and zeus ...|scattering,mass,q...|
|0803.3905|  when designing ...|set,art,modelling...|
|0807.0026|  radio telescope...|range,leakage,pos...|
|0804.1504|  in  an internat...|imagination,refle...|
|0802.4266|  we study group ...| bimodule,skew,group|
|0802.3187|  the role of neu...|quark,phase,gauge...|
|0710.2708|  given a project...|bundle,decomposit...|
|0706.0677|  this is the thi...|geodesic,link,ser...|
|0707.1652|  the pierre auge...|pose,unit,distrib...|
|0809.1051|  we present a ve...|range,quantum,res...|
|0704.3951|  ramification in...|filtration,struct...|
|0805.4670|  based on firstp...|character,layers,...|
|0710.4428|  an asymptotic m...|structures,dynami...|
|0712.1683|  recently the in...|wave,molecule,dif...|
|0810.0015|  experiments in ...|cell,relation,low...|
+---------+--------------------+--------------------+
only showing top 20 rows
```

$$PMI(A, B) = \frac{P(A, B)}{P(A) * P(B)}$$

$$P(A, B) = \frac{c((A, B), C_{\text{pairs}})}{c(C_{\text{pairs}})}$$

$$P(A) = \frac{c(A)}{c(C)}, P(B) = \frac{c(B)}{c(C)}$$

where C stands for word collection

1. Get Word Count

- `corpus` : It is a dictionary of unigram count

```
defaultdict(int,
            {'conjugate': 4041,
             'quantum': 162709,
             'lambda': 18154,
             'method': 195849,
             'quantization': 11050,
             ...
             }
```

In [17]:
```
corpus_temp = df.select("extracted").rdd.repartition(32).flatMap(lambda x: (x["extracted"].split(",")))
corpus = corpus_temp.countByValue()
```

2. Get Cooccurence Count

- `corpus2` : It is a dictionary where key is tuple (pair of unigrams) and value is frequency

```
defaultdict(int,
            {('conjugate', 'quantum'): 490,
             ('conjugate', 'lambda'): 60,
             ('conjugate', 'method'): 606,
             ('conjugate', 'quantization'): 82,
             ...
             }
```

In [18]:
```
rdds = df.select("extracted").rdd.repartition(32).map(lambda x: x['extracted'].split(","))
```

In [19]:
```
from itertools import combinations
corpus2_temp = rdds.flatMap(lambda x: combinations(x,2))
corpus2 = corpus2_temp.countByValue()
```

3. How to avoid bottleneck?

- Use clusters! (Amazon EMR, S3)

4. Save Result Here

- Uncomment to save to text file

In [20]:
```
# corpus_temp.repartition(8).saveAsTextFile("./corpus_final.txt")
# corpus2_temp.repartition(8).saveAsTextFile("./corpus2_final.txt")
```

5. Load From File

- Uncomment to load from file

In [21]:
```
# corpus = spark.sparkContext.textFile("./corpus_final.txt").countByVa
lue()
# corpus2 = spark.sparkContext.textFile("./corpus2_final.txt").countBy
Value()

"""
Clean corpus when read from file
Since we are loading from a textfile, tuples are converted into string
s
"""
# from collections import defaultdict
# corpus_temp = defaultdict(int)

# corpus = dict(map(lambda x: (x[0].strip(), x[1]), corpus.items()))
# for k, v in corpus2.items():
#     k1, k2 = re.sub("'", "", k.strip('"()')).split(",")
#     k2 = k2.strip()
#     w1, w2 = min(k1, k2), max(k1, k2)
#     corpus_temp[(w1, w2)] += v
# corpus2 = corpus_temp
```

Out[21]:
```
'\nClean corpus when read from file\nSince we are loading from a tex
tfile, tuples are converted into strings\n'
```

Part 2. Graph Visualization

Draw Graph

In [22]:
```
freq_threshold = 0
PMI_threshold = 10
```

In [23]:
```
import networkx as nx
import math
import pdb
G = nx.Graph()

total_word_freq = sum(corpus.values())
total_pair_freq = sum(corpus2.values())
for (n1, n2), cooccurence in corpus2.items():
    if corpus[n1] > freq_threshold and corpus[n2] > freq_threshold and
cooccurence:
        pa = corpus[n1] / total_word_freq
        pb = corpus[n2] / total_word_freq
        pab = cooccurence / total_pair_freq

        pmi = math.log(pab/(pa*pb), 2)
        G.add_edge(n1, n2, weight=pmi)
```

!! Test Your QUERY Here !!

- Type `your query` here
- Sample queries include

```
gene, class, theory, stat, dimension, state
```

In [24]:
```
query = 'colonialism'
sorted(G.adj[query].items(), key=lambda x: x[1]['weight'], reverse=Tru
e)[:10]
```

Out[24]:
```
[('patriarchy', {'weight': 21.569935731346103}),
 ('solidarity', {'weight': 17.400010729903787}),
 ('meter', {'weight': 11.037579806057254}),
 ('astronomy', {'weight': 9.556613057920654}),
 ('white', {'weight': 8.155514749599684}),
 ('center', {'weight': 7.155382616518959}),
 ('telescope', {'weight': 6.94331407898773}),
 ('impact', {'weight': 6.596238365040749}),
 ('support', {'weight': 6.590599858680719})]
```

- Higher than `10 pmi` demonstrates a strong relationship between the two words
- Below is the `sample pmi` table from the wikipiedia dataset.

word 1	word 2	count word 1	count word2	co-occurence	pmi
puerto	rico	1938	1311	1159	10.0349081703
car	driver	5578	2749	1384	8.41470768304
it	the	283891	3293296	3347	-1.72037278119
of	and	1761436	1375396	1190	-3.70663100173

- Reference: https://en.wikipedia.org/wiki/Pointwise_mutual_information (https://en.wikipedia.org/wiki/Pointwise_mutual_information)

Top 10 Related Words

- `Queries` and their `related keywords` are sorted here by pmi.
- Natural science domain seems to working well

In [25]:
```
result = list()
for i, q in enumerate(list(G.nodes)):
    weight = sorted(G.adj[q].items(), key=lambda x: x[1]['weight'], re
verse=True)[:3]

    if len(weight)==0:
        r1, r2, r3 = 0, 0, 0
        pmi = 0
    elif len(weight)==1:
        r1, r2, r3 = weight[0][0], 0, 0
        pmi = weight[0][1]['weight']
    elif len(weight)==2:
        r1, r2, r3 = weight[0][0], weight[1][0], 0
        pmi = weight[0][1]['weight']
    else:
        r1, r2, r3 = weight[0][0], weight[1][0], weight[2][0]
        pmi = weight[0][1]['weight']

    result.append((q, r1, r2, r3, pmi))

result.sort(key=lambda x: x[4], reverse=True)

for q, r1, r2, r3, _ in result[:10]:
    print("query: {}".format(q))
    print("result: {0}, {1}, {2}\n".format(r1, r2, r3))
```

```
query: spastic
result: hypertonia, reflex, muscle

query: hypertonia
result: spastic, reflex, muscle

query: jatropha
result: endophyte, colonization, crop

query: endophyte
result: jatropha, colonization, crop

query: thrombopoietin
result: thrombopoiesis, megakaryocyte, platelet

query: thrombopoiesis
result: thrombopoietin, megakaryocyte, platelet

query: megakaryocyte
result: thrombopoietin, thrombopoiesis, platelet

query: mamluk
result: terracotta, mesopotamia, lustre

query: terracotta
result: mamluk, mesopotamia, lustre

query: colonialism
result: patriarchy, solidarity, meter
```

Visualization

- The final plot shows that related words form a group of cluster

In [26]:
```
samples = ["spastic", "hypertonia", "reflex", "muscle", "endophyte", "jatropha", "colonization", "crop", "colonialism", "patriarchy", "solidarity", "meter"]
```

In [27]:

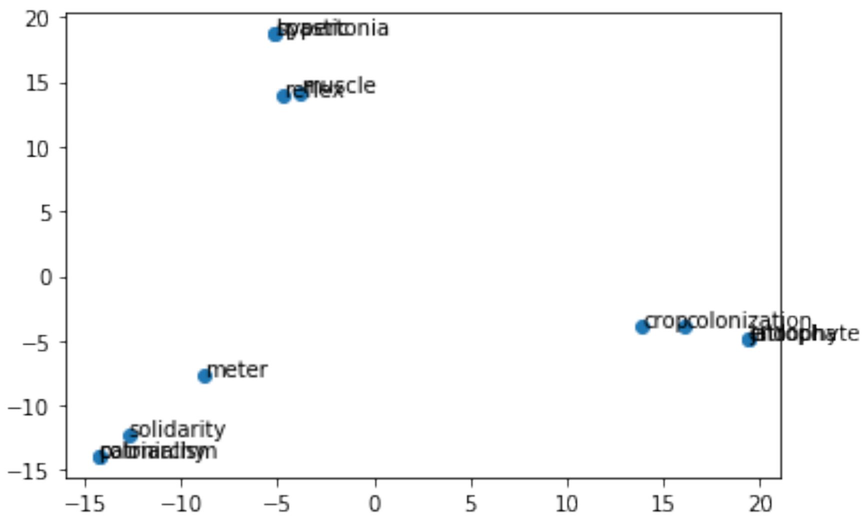
```
matrix = list()
for i, row in enumerate(samples):
    row_temp = list()
    for j, col in enumerate(samples):
        w1, w2 = samples[i], samples[j]
        if G.adj.get(w1, 0) and G.adj[w1].get(w2, 0) and G.adj[w1][w2]
.get("weight", 0):
            row_temp.append(G.adj[w1][w2]["weight"])
        else:
            row_temp.append(0)
    matrix.append(row_temp)
```

In [28]:

```
from sklearn.decomposition import PCA

pca = PCA(n_components=2)
result = pca.fit_transform(matrix)
```

In [30]:

```
from matplotlib import pyplot

pyplot.scatter(result[:, 0], result[:, 1])
for i, word in enumerate(samples):
    pyplot.annotate(word, xy=(result[i, 0], result[i, 1]))

pyplot.figure(figsize=(15,15))
pyplot.show()
```




```
<Figure size 1080x1080 with 0 Axes>
```

Future Directions

- Tokenization
  - Include `n-gram` (2,3,4,...) extractor to extract longer keywords.
  - e.g.) keyword: computer science
  - `Phrase mining` or `Named Entity Recogntition` can be used during the process

- Embedding
  - Use cooccurence matrix to train word embeddings (Glove)
  - Or, load word embedding from Glove or Word2Vec and proejct to 2D plot.
  - Evalutate the similarity of two words by using `l1 distance`, `l2 distance`, or `cosine similiarity`.

- Metric
  - We may investigate `NPMI`

References

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- Useful tutorials
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- Word embeddings and visualization
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