Named Entity Extraction in RDF/RDFS for Big Tech

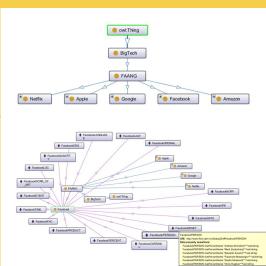
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Topic

Review Named Entity Extraction (NEE) and how NEE can form the taxonomy. Apply one approach of NEE based on one domain and translate it into turtle format of RDF/RDFS data model.

<u>Pipeline</u>



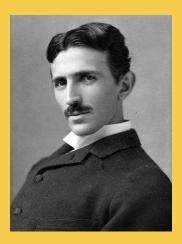


<u>Abstract</u>

The study aims to propose a pipeline that performs Named Entity Extraction using spaCy on raw unstructured Big Tech Wikipedia dataset and convert it to RDF/RDFS format. The simple pipeline was without fine-tuning on the Wikipedia dataset, only fine-tuning done was on the size of the pre-trained model where it ranges from small, medium and big. Competency questions for verification were conducted pre-extraction and SPARQL competency questions were conducted post-extraction for validation. The extracted entities were converted into RDF/RDFS format containing prefixes, classes, properties and individuals where the extracted entities mainly form the RDF part of the Big Tech taxonomy. It was found that the out-off-the-box medium sized spaCy model with Precision, average global Precision, Recall and F-score of 0.83, 0.80 and 0.81 respectively with respect to

1. <u>Introduction</u>

Prior to investing in something, it is a good idea to do some background research, more so if it involves a huge amount risks and money such as in stocks specifically technological company stocks. Nikola is a billion dollar zero emission truck public tech company founded by Trevor Milton and was supposed to rival Tesla. Hindenburg Research (2020) highlighted that using concept truck alone it was worth 20 billion dollars and was built from dozens of lies. Recommended key words or sentences in the form of entities can be obtained by applying pre-trained Named Entity Extraction on publicly available datasets for company of interest to aid background research.

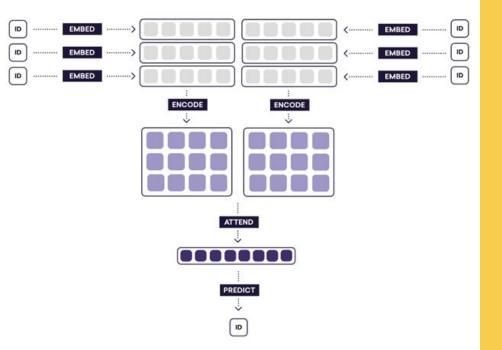




1. Introduction (cont'd)

Named Entity Extraction can be used to extract the hypernym which is a relatively general term such as Facebook and hyponym which is a relatively specific term such as FacebookPERSON, Facebook GPE and others. Relatively, going down the hierarchy, FacebookPERSON is the hypernym while entities extracted such as "Mark Zuckerberg" is the hyponym. Using NEE, a taxonomy or concept hierarchy can be formed as shown in figure on the left

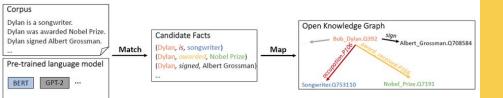
In this study, NEE was used for taxonomy extraction mainly for co-hyponyms or Abox for individual tech companies with highest frequency hypernym extracted from the pipeline. This study employed a modular approach whereby additional input data can be plugged in to further populate the taxonomy.



1. Introduction (cont'd)

The Stanford Natural Language Processing Group (2022) explained that Named Entity Recognition (NER) is used to detect and classify sequences of words in unstructured text into classes of mainly person, organization and location.

In this study, spaCy was employed for NER followed by extraction, the library is neural network based, it is an implementation of embed, encode, attend and predict. Embed is a process where binarization from sparse data into dense vectors happens and then using encode, the data is converted from vector to matrix using CNN in spaCy's case, this is continued by attend where it performs contextual vectorization using attention matrix to compress the data and finally predict where all these data are fed into a multi-layer perceptron neural network for prediction as shown in figure on the left.

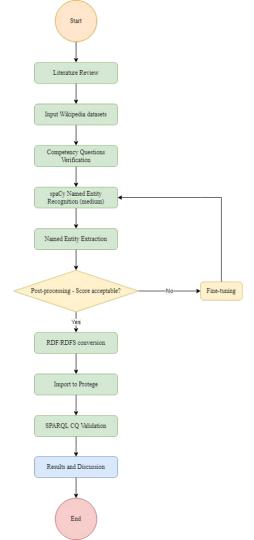


1. Introduction (cont'd)

Shelar et al. (2020) experimented using advance search panel dataset of IBM with multiple libraries for Named Entity Recognition and concluded that spaCy obtains the best score and speed versus the rest i.e Apache OpenNLP and TensorFlow while Chantrapornchai & Tunsakul (2021) used crawled tourism (TripAdvisor, Traveloka and Hotels.com) domain data demonstrated that BERT works slightly better with clean data relative to spaCy.

This study follows the concept of zero-shot learning by Wang et al. (2020) where no fine-tuning was used on the off-the shelf spaCy model since BERT requires extensive cleaning, the concept of zero-shot learning is illustrated in figure on the left.

Mikheev et al. (1999) demonstrated a rule and statistical based hybrid model for Named Entity Recognition, the concept of Partial Match and self-added Exact Match was instead applied as an evaluation technique.



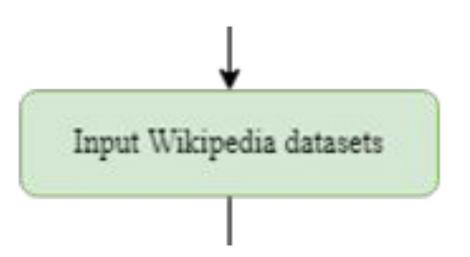
2. Materials and Method

Dataset

• Wikipedia dataset of FAANG.

Flow of the pipeline

- 1. Literature Review.
- 2. Input Wikipedia datasets.
- 3. CQ Verification.
- 4. NER.
- 5. NEE.
- 6. Scoring.
- 7. RDF/RDFS translation.
- 8. Protege import.
- 9. SPARQL CQ Validation.
- 10. Results and Discussion.
 - End.

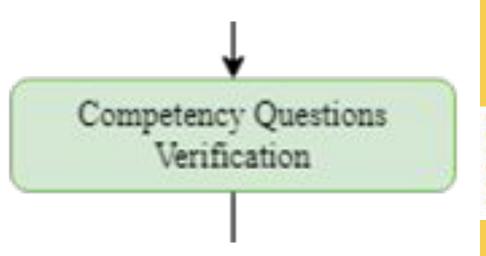


2.1 Input Wikipedia datasets

Figure below shows the code for generating owl type files to facilitate Protégé import, updating the code to .txt works as well.

▼ Open and Load

```
[] 1 #open the file
2 faang_1 = "/content/drive/MyDrive/Colab Notebooks/OKR_NEE_datasets/1_Facebook.txt"
3 file1 = open(faang_1, "r")
4 #read the file
5 Facebook = file1.read()
6 Facebook
```



2.2 CO Verification

Competency questions of 5 numbers were asked to probe the extent of the data.

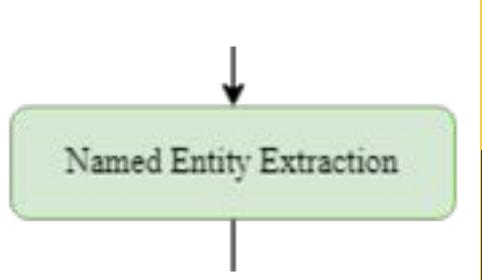
- Q1. Who are the founder(s) of respective FAANG? Q2. Where are they founded?
- Q3. When are they founded?
- Q4. What are their product(s)?
- Q5. What is the nationality of the company?

spaCy Named Entity Recognition (medium)

2.3 spaCy NER

```
[ ] 1 #load spacy
2 NER_1 = spacy.load("en_core_web_md")

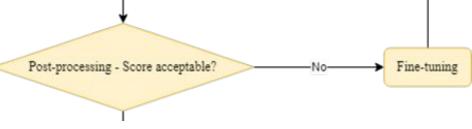
spaCy and displaCy
[ ] 1 #get the labels and entities
2 Facebookdoc = NER_1(Facebook)
```



2.4 spaCy NEE

Entities, labels, start and end positions of the entities can all be extracted using the code as shown in figure below along with highest frequency entities. The extracted entities mainly populates the RDF part of the Big Tech domain taxanomy.

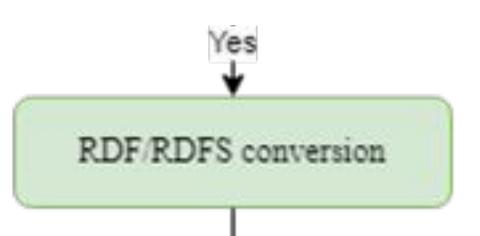
```
spaCy and displaCy
      2 Facebookdoc = NER 1(Facebook)
     4 Facebookentities = []
      5 Facebooklabels = []
     6 Facebookstartpos = []
     7 Facebookendpos = []
     9 for ent in Facebookdoc.ents:
     10 Facebookentities.append(ent)
         Facebooklabels.append(ent.label_)
         Facebookstartpos.append(ent.start char)
         Facebookendpos.append(ent.end char)
    15 Facebookdf = pd.DataFrame({ 'Entities':Facebookentities, 'Labels':Facebooklabels, 'Position_Start':Facebookstartpos, 'Position_End':Facebookendpos})
    17 Facebookdf
     19 Facebookdf.to csv(r'/content/drive/MyDrive/Colab Notebooks/OKR NEE datasets/out.csv', index = False)
      2 items 1 = [x.text for x in Facebookdoc.ents]
     3 y_1 = Counter(items_1).most_common(5) #top 5
[ ] 1 y_1[0][0] #highest frequency
     'Facebook
      2 doc 1 = NER 1(Facebook)
      3 displacy.render(doc_1, style="ent", jupyter=True)
```



2.5 Score

With respect to self-developed gold standard, global and local scores consisting of Precision, Recall and F-score were extracted. Figure below shows the codes necessary for scoring.

```
Score
[] 1 #equate
                2 nlp_1 = NER_1
[ ] 1 #working code
                3 Facebookexamples = []
                5 data_1 = [(Facebook, {"entities": [(0,8,'ORG'), (15,23,'NORP'), (83,97,'ORG'), (109,113,'DATE'), (117,132,'PERSON'),
                6 (145,160, 'ORG'), (184,199, 'PERSON'), (201,216, 'PERSON'), (218,234, 'PERSON'), (240,252, 'PERSON'),
                7 (315,323, 'NORP'), (381,388, 'ORG'), (428,442, 'NORP'), (467,471, 'DATE'), (480,497, 'DATE'),
                8 (505,509, 'DATE'), (511,519, 'ORG'), (528,539, 'CARDINAL'), (540,547, 'DATE'), (573,580, 'ORDINAL'),
                9 (648,657, 'DATE'), (659,667, 'ORG'), (1085,1103, 'PRODUCT'), (1187,1195, 'ORG'), (1266,1274, 'ORG'),
              10 (1347,1366,'ORG'), (1418,1422,'DATE'), (1423,1427,'GPE'), (1639,1647,'ORG')]})]
              12 for text_1, annots_1 in data_1:
                              doc_1 = nlp_1.make_doc(text_1)
                              Facebookexamples.append(Example.from_dict(doc_1, annots_1))
              16 #output to txt
              17 f = sys.stdout
              18 f = open('score_output.txt', 'a') #append to opened common file
              20 print("#Facebook score .", file=f)
              21 print(nlp_1.evaluate(Facebookexamples), file=f) #Global and local entity metrics
              22 f.close() #close file
[ ] 1 print(nlp_1.evaluate(Facebookexamples))
              {'token acc': 1.0, 'token p': 1.0, 'token r': 1.0, 'token f': 1.0, 'tag acc': None, 'sents p': None, 'sents r': None, 'sents p': None, 'sents
```



2.6 RDF/RDFS conversion

Basically, the general idea is to transform for individual 18 numbers of spaCy labels and extracted entities to be RDF/RDFS compatible.

```
4 f = sys.stdout
 5 f = open('p107443 output.owl', 'a') #append to opened common file
 7 PropLabel 1 = y 1[0][0]
 9 #General Prefixes
10 print("#Prefixes", file=f)
11 print("@prefix faang: <http://www.ftsm.ukm.my/faangOnt#> .", file=f)
12 print("@prefix rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#> .", file=f)
13 print("@prefix rdfs: <a href="http://www.w3.org/2000/01/rdf-schema#">http://www.w3.org/2000/01/rdf-schema#</a> .", file=f)
14 print("@prefix xsd: <a href="http://www.w3.org/2001/XMLSchema#">http://www.w3.org/2001/XMLSchema#</a> .", file=f)
16 #General Class and SubClass
17 print("\n#Classes and SubClasses", file=f)
18 print("faang:BigTech rdf:type rdfs:Class .", file=f) #Class
19 print("faang:FAANG rdf:type rdfs:Class .", file=f) #Class
20 print("faang:FAANG rdfs:subClassOf faang:BigTech .", file=f) #SubClass
21 print("faang:{proplab_1} rdf:type rdfs:Class .".format(proplab_1=PropLabel_1), file=f) #Class
22 print("faang:{proplab_1} rdfs:subClassOf faang:FAANG .".format(proplab_1=PropLabel_1), file=f) #Facebook SubClass
24 #Facebook Individuals
25 print("\n#Facebook Individuals", file=f)
26 print("faang:{proplab_1}PERSON rdf:type faang:{proplab_1} .".format(proplab_1=PropLabel_1), file=f)
27 print("faang:{proplab 1}NORP rdf:type faang:{proplab 1} .".format(proplab 1=Proplabel 1), file=f)
28 print("faang:{proplab_1}FAC rdf:type faang:{proplab_1} .".format(proplab_1=PropLabel_1), file=f)
29 print("faang:{proplab_1}ORG rdf:type faang:{proplab_1} .".format(proplab_1=Proplabel 1), file=f)
30 print("faang:{proplab_1}GPE rdf:type faang:{proplab_1} .".format(proplab_1=PropLabel_1), file=f)
31 print("faang:{proplab_1}LOC rdf:type faang:{proplab_1} .".format(proplab_1=PropLabel_1), file=f)
32 print("faang:{proplab 1}PRODUCT rdf:type faang:{proplab 1} .".format(proplab 1=Proplabel 1), file=f)
```

```
52 LOC = "hasLocation" #6
                                                          108 if FacebooklistLabels[i]=='PERSON':
53 PRODUCT = "hasProduct" #7
                                                          110 elif FacebooklistLabels[i]=='NORP':
54 EVENT = "hasEvent" #8
                                                          112 elif FacebooklistLabels[i]=='FAC':
55 WORK OF ART = "hasWorkOfArt" #9
                                                          114 elif FacebooklistLabels[i]=='ORG':
56 LAW = "hasLaw" #10
57 LANGUAGE = "hasLanguage" #11
                                                          116 elif FacebooklistLabels[i]=='GPE':
58 DATE = "hasDate" #12
                                                          118 elif FacebooklistLabels[i]=='LOC':
59 TIME = "hasTime" #13
                                                          120 elif FacebooklistLabels[i]=='PRODUCT':
60 PERCENT = "hasPercent" #14
                                                          122 elif FacebooklistLabels[i]=='EVENT':
61 MONEY = "hasMoney" #15
                                                          124 elif FacebooklistLabels[i]=='WORK OF ART':
62 QUANTITY = "hasQuantity" #16
                                                          126 elif FacebooklistLabels[i]=='LAW':
63 ORDINAL = "hasOrdinal" #17
64 CARDINAL = "hasCardinal" #18
                                                          128 elif FacebooklistLabels[i]=='LANGUAGE':
                                                          130 elif FacebooklistLabels[i]=='DATE':
66 #General Data Properties
                                                          132 elif FacebooklistLabels[i]=='TIME':
                                                               print('faang:{proplab_1}TIME faang:{lab} "{ent}"^^xsd:string .' .format(proplab_1=Proplabel_1, lab='hasTime', ent=FacebooklistEntities[i]), file=f),
67 print("\n#Data Properties", file=f)
68 print("faang:{} rdf:type rdf:Property ." .format(PERSON), file=f) #1
69 print("faang:{} rdfs:range xsd:string ." .format(PERSON), file=f) #1a
70 print("faang:{} rdf:type rdf:Property ." .format(NORP), file=f) #2
71 print("faang:{} rdfs:range xsd:string ." .format(NORP), file=f) #2a
72 print("faang:{} rdf:type rdf:Property ." .format(FAC), file=f) #3
73 print("faang:{} rdfs:range xsd:string ." .format(FAC), file=f) #3a
74 print("faang:{} rdf:type rdf:Property ." .format(ORG), file=f) #4
```

105 #Specific Facebook Triples

106 print("\n#Facebook Triples", file=f)

45 #General spaCy labels to Data Properties

48 NORP = "hasNationalityReligiousPolitical" #2 49 FAC = "hasBuildingsAirportsHighwaysBridges" #3 50 ORG = "hasCompaniesAgenciesInstitutions" #4

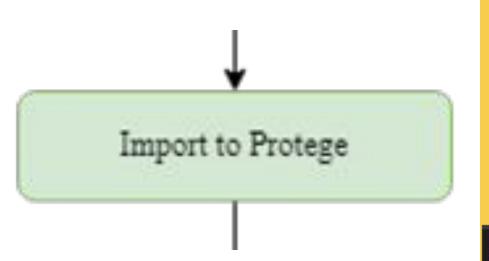
46 print("\n#spaCy labels", file=f)

51 GPE = "hasCountriesCitiesState" #5

47 PERSON = "hasPersonName" #1

2.6 RDF/RDFS conversion (cont'd)

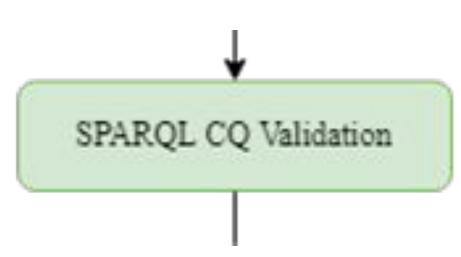
```
107 for i in range(len(FacebooklistEntities)):
       print('faang:{proplab_1}PERSON faang:{lab} "{ent}"^^xsd:string .' .format(proplab_1=Proplabel_1, lab='hasPersonName', ent=FacebooklistEntities[i]), file=f)
       print('faang:{proplab 1}NORP faang:{lab} "fent}"^^xsd:string .' .format(proplab 1=Proplabel 1, lab='hasNationalityReligiousPolitical', ent=FacebooklistEntities[i])
       print('faang:{proplab_1}FAC faang:{lab} "{ent}"^^xsd:string .' .format(proplab_1=PropLabel_1, lab='hasBuildingsAirportsHighwaysBridges', ent=FacebooklistEntities[i
       print('faang:{proplab 1}ORG faang:{lab} "{ent}"^^xsd:string .' .format(proplab_1=Proplabel_1, lab='hasCompaniesAgenciesInstitutions', ent=FacebooklistEntities[i])
       print('faang:{proplab_1}GPE faang:{lab} "{ent}"^^xsd:string .' .format(proplab_1=PropLabel_1, lab='hasCountriesCitiesState', ent=FacebooklistEntities[i]), file=f)
       print('faang:{proplab 1}LOC faang:{lab} "{ent}"^^xxd:string .' .format(proplab 1=Proplabel 1, lab='haslocation', ent=FacebooklistEntities[i]), file=f)
       print('faang:{proplab_1}PRODUCT faang:{lab} "{ent}"^xsd:string .' .format(proplab_1=Proplabel_1, lab='hasProduct', ent=FacebooklistEntities[i]), file=f)
       print('faang:{proplab 1}EVENT faang:{lab} "fent}"^^xsd:string .' .format(proplab 1=PropLabel 1, lab='hasEvent', ent=FacebooklistEntities[i]), file=f)
       print('faang:{proplab 1}WORK OF ART faang:{lab} "(ent)"^^xsd:string .' .format(proplab 1=Proplabel 1, lab='hasWorkOfArt', ent=FacebooklistEntities[i]), file=f)
       print('faang:{proplab 1}LAW faang:{lab} "{ent}"^^xsd:string .' .format(proplab 1=Proplabel 1, lab='hasLaw', ent=FacebooklistEntities[i]), file=f)
       print('faang:{proplab_1}LANGUAGE faang:{lab} "(ent)"^^xsd:string .' .format(proplab_1=Proplabel_1, lab='hasLanguage', ent=FacebooklistEntities[i]), file=f)
       print('faang:{proplab 1}DATE faang:{lab} "fent}"^^xsd:string .' .format(proplab 1=PropLabel 1, lab='hasDate', ent=FacebooklistEntities[i]), file=f)
```



2.7 Import to Protégé

Figure below shows the code for generating owl type files to facilitate Protégé import, updating the code to .txt works as well.

```
1 #For Facebook
2
3 #output to owl
4 f = sys.stdout
5 f = open('p107443_output.owl', 'a') #append to opened common file
```



2.8 SPARQL queries CQ Validation

```
#Fixed
PREFIX faang: <a href="mailto:rhttp://www.ftsm.ukm.my/faangOnt#">http://www.ftsm.ukm.my/faangOnt#>
PREFIX rdf: <a href="http://www.w3.org/1999/02/22-rdf-syntax-ns#">http://www.w3.org/1999/02/22-rdf-syntax-ns#</a>
PREFIX owl: <a href="mailto:right">http://www.w3.org/2002/07/owl#>
PREFIX rdfs: <a href="http://www.w3.org/2000/01/rdf-schema#">http://www.w3.org/2000/01/rdf-schema#>
PREFIX xsd: <a href="http://www.w3.org/2001/XMLSchema#">http://www.w3.org/2001/XMLSchema#></a>
SELECT ?subject ?object
Q1. Who are the founder(s) of respective FAANG?
#Variable
WHERE
?subject rdf:type faang:Facebook . #swap "Facebook" for subsequent {F}AANGs
?subject faang:hasPersonName ?object .
Q2. Where are they founded?
#Variable
WHERE
?subject rdf:type faang:Facebook . #swap "Facebook" for subsequent {F}AANGs
?subject faang:hasCountriesCitiesState ?object .
Q3. When are they founded?
#Variable
WHERE
?subject rdf:type faang:Facebook . #swap "Facebook" for subsequent {F}AANGs
?subject faang:hasDate ?object .
Q4. What are their product(s)?
#Variable
WHERE
?subject rdf:type faang:Facebook . #swap "Facebook" for subsequent {F}AANGs
?subject faang:hasCompaniesAgenciesInstitutions ?object . #for all FAANGs
#include hasPersonName for Amazon
#include hasProduct for Apple
#include hasPersonName for Google
#include hasBuildingsAirportsHighwaysBridges for Google
Q5. What is the nationality of the company?
#Variable
WHERE
?subject faang:hasNationalityReligiousPolitical ?object .
```

Table 2. Out-of-the-box Precision, Recall and F-score

Size	ENTS_P	ENTS_R	ENTS_F
Small	0.85	0.84	0.84
Medium	0.85	0.84	0.85
Large	0.86	0.85	0.85

Reference: spaCy, 2022

Table 3. Overall Precision, Recall and F-score

	Tel Cliff (1974) 1974 (1974) 1974 (1974) 1974 (1974) 1974 (1974) 1974 (1974) 1974 (1974) 1974 (1974) 1974 (1		
FAANG	Precision	Recall	F-score
Facebook	0.846154	0.758621	0.800000
Amazon	0.836735	0.803922	0.820000
Apple	0.875000	0.851351	0.863014
Netflix	0.882353	0.923077	0.902256
Google	0.730159	0.638889	0.681481
Average	0.8340802	0.795172	0.8133502

Table 4. Facebook Precision. Recall and F-score

Labels	Precision	Recall	F-score
NORP	1.000000	1.000000	1.000000
ORG	0.833333	0.500000	0.625000
DATE	0.857143	0.857143	0.857143
PERSON	0.833333	1.000000	0.909091
CARDINAL	1.000000	1.000000	1.000000
ORDINAL	1.000000	1.000000	1.000000
GPE	0.500000	1.000000	0.666667
PRODUCT	0.000000	0.000000	0.000000

3. Results and Discussion

Table 2 shows that the model has an off-the-shelf Precision, Recall and F-score of 0.85, 0.84 and 0.85 respectively. Based on my observation, the values shown are ceiling values as average scores obtained did not exceed the values shown for Medium size models.

Table 3 shows the global scores of respective FAANG where the highest F-score peaks at 0.90 for Netflix and bottoms at 0.68 for Google. These scores are computed with respect to the gold standard.

Tables 4 shows the individual labels local scores for Facebook. It has issue with "PRODUCT", "GPE" and "ORG" labels.

Table 5. Amazon Precision, Recall and F-score Labels Precision Recall F-score ORG 0.827586 0.800000 0.813559 NORP 1.000000 1.000000 1.000000 CARDINAL 0.333333 1.000000 0.500000

1 000000

1 0000000

PRODUCT	0.000000	0.000000	0.000000
ORDINAL	1.000000	1.000000	1.000000
MONEY	1.000000	1.000000	1.000000
DATE	1.000000	1.000000	1.000000
PERSON	0.500000	1.000000	0.666667
CONTRACTOR OF THE PARTY OF THE	1.000000		

1 000000

GPE

Table 6 Apple Precision Recall and F-score

Table	Apple Precision, Re	ecall and F-score	
Labels	Precision	Recall	F-score
ORG	0.785714	0.916667	0.846154
NORP	1.000000	1.000000	1.000000
MONEY	0.666667	0.666667	0.666667
DATE	1.000000	1.000000	1.000000
ORDINAL	1.000000	1.000000	1.000000
CARDINAL	0.500000	1.000000	0.666667
PERSON	0.900000	0.692308	0.782609
PRODUCT	1.000000	0.333333	0.500000
GPE	1.000000	1.000000	1.000000

3. Results and Discussion (cont'd)

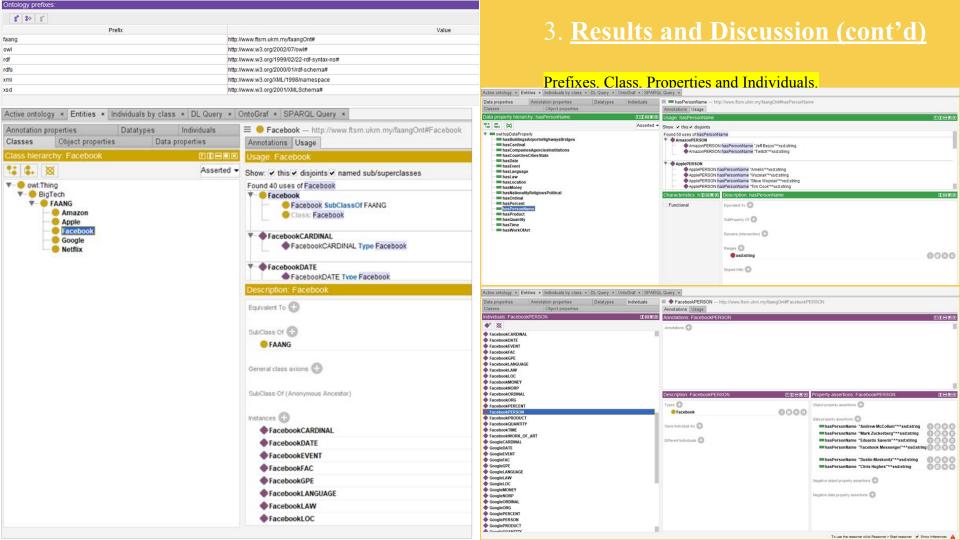
Tables 5 and 6 shows the individual labels local scores for Amazon and Apple. Both of them have similar issues with "PRODUCT" and "CARDINAL" labels.

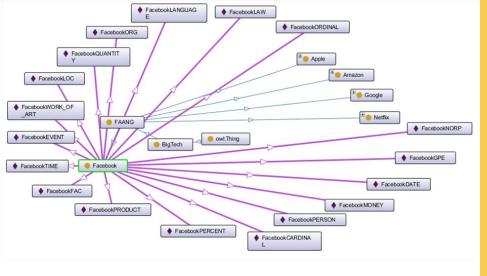
Labels	Precision	Recall	F-score
ORG	0.823529	0.875000	0.848485
NORP	1.000000	1.000000	1.000000
GPE	1.000000	1.000000	1.000000
DATE	1.000000	1.000000	1.000000
PERSON	0.666667	1.000000	0.800000
CARDINAL	0.750000	0.750000	0.750000
LOC	1.000000	1.000000	1.000000
ORDINAL	1.000000	0.750000	0.857143
WORK_OF_ART	0.000000	0.000000	0.000000
MONEY	1.000000	1.000000	1.000000
PRODUCT	0.000000	0.000000	0.000000
PERCENT	1.000000	1 000000	1 000000
PERCENT	1.000000	1.000000	1.000000
Table 8. C	Google Precision, R	ecall and F-score	
Table 8. C	Google Precision, R Precision	ecall and F-score	e F-score
Table 8. C Labels ORG	Google Precision, R Precision 0.729730	ecall and F-score Recall 0.794118	F-score 0.760563
Table 8. C	Google Precision, R Precision 0.729730 1.000000	ecall and F-score Recall 0.794118 1.000000	F-score 0.760563 1.000000
Table 8. C Labels ORG NORP	Google Precision, R Precision 0.729730	ecall and F-score Recall 0.794118	F-score 0.760563 1.000000 0.00000 0
Table 8. C Labels ORG NORP CARDINAL	Precision R Precision 0.729730 1.000000 0.000000	ecall and F-score Recall 0.794118 1.000000 0.000000	F-score 0.760563 1.000000 0.00000 1.000000
Table 8. C Labels ORG NORP CARDINAL DATE	Precision, R Precision 0.729730 1.000000 0.000000 1.000000	Recall and F-score Recall 0.794118 1.000000 0.000000 1.000000	F-score 0.760563 1.000000 0.000000 1.000000
Table 8. C Labels ORG NORP CARDINAL DATE PERSON	Google Precision, R Precision 0.729730 1.000000 0.000000 1.000000 0.571429	Recall and F-score Recall 0.794118 1.000000 0.000000 1.000000 0.800000	F-score 0.760563 1.000000 0.000000 1.000000 0.666667 0.000000
Table 8. C Labels ORG NORP CARDINAL DATE PERSON WORK_OF_ART	Foogle Precision, R Precision 0.729730 1.000000 0.000000 1.000000 0.571429 0.000000	Recall and F-score Recall 0.794118 1.000000 0.000000 1.000000 0.800000 0.000000	
Table 8. C Labels ORG NORP CARDINAL DATE PERSON WORK_OF_ART GPE	Foogle Precision, R Precision 0.729730 1.000000 0.000000 1.000000 0.571429 0.000000 0.500000	ecall and F-score Recall 0.794118 1.000000 0.000000 1.000000 0.800000 0.0000000 1.0000000	F-score 0.760563 1.000000 0.000000 1.000000 0.666667 0.000000
Table 8. C Labels ORG NORP CARDINAL DATE PERSON WORK_OF_ART GPE PERCENT	Google Precision, R Precision 0.729730 1.000000 0.000000 1.000000 0.571429 0.000000 0.500000 1.000000	Recall and F-score Recall 0.794118 1.000000 0.000000 1.000000 0.800000 0.000000 1.000000 1.000000	F-score 0.760563 1.000000 0.000000 1.000000 0.666667 0.000000 0.666667

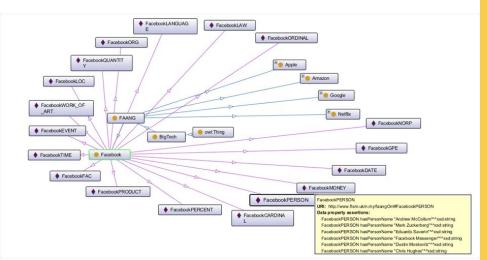
3. Results and Discussion (cont'd)

Tables 7 and 8 shows the individual labels local scores for Netflix and Google. Both of them have similar issues with "PRODUCT" label.

2 doc_1 = NER_1(Facebook) displacy.render(doc 1, style="ent", jupyter=True) Facebook is an American NORP online social media and social networking service owned by Facebook, ORO Inc. Founded in 2004 CATE by Mark Zuckerberg PERSON with follow Harvard College ORO students and roommates Eduardo Saverir PERSON , Andrew McCollum PERSON , Dustin Moskovitz PERSON , and Chris Hughes PERSON , its name comes from the face book directories often given to American NORP university students. Membership was initially limited to Harvard ORO tudents, gradually expanding to other North American NORP universities and, since 2006 DATE anyone over 13 years old DATE As of 2020 DATE Facebook ORG claimed 2.6 billion CARDINAL monthly DATE active users, and ranked seventh CRDINAL in global internet usage. It was the most downloaded mobile app of the 2010s DATE . Facebook can be accessed from devices with Internet connectivity, such as personal con as user privacy (as with the Cambridge Analytica GPE data scandal), political manipulation (as with the 2016 DATE U.S. GPE elections), mass surveillance, psychological effects such as addiction and low self-esteem, and content such as fake news 3. Results and Discussion (cont'd) displaCy visualization. doc_4 = NER_4(Netflix) 2 doc_2 = NER_2(Amazon) spacy.displacy.render(doc_4, style="ent", jupyter=True) spacy,displacy,render(doc 2, style="ent", jupyter=True) Netflix, Inc. ORG is an American NORP over-the-top content platform and production company headquartered in Los Gatos GPE subscribers, including 72 million CARDINAL in the United States OPE and Canada OPE . It is available worklowide except in mainland China OPE (due to local restrictions). Syria OPE Washington GPE on July 5, 1994 DATE . It started as an online r US GPE sanctions). The company has offices in Canada GPE , France GPE , Brazil GPE , the Netherlands GPE Amazon ORG surpassed Walmart ORG as the most valuable retailer in the United States GPE by market capitalization. In 2017 DATE Netfix: ORG is a member of the Motion Picture Association ORG (MPA ORG)) producing and distributing content from countries all over the globe. Netfix: ORG 's initial business model included DVD sales and rental by mail, but Hastings: PERSON which substantially increased its footprint as a physical retailer. In 2015 DATE i, its two-day DATE delivery service, Amazon Prime ORG i, surpassed 100 million CARDMAL subscribers workwide. Amazon ORG is known for abandoned the sales about a year DATE after the company's founding to focus on the initial DVD rental business. Nettic CRG expanded its business in 2007 DATE with the introduction of streaming media while retaining the DVD and Blu-ray ORG expanded its business in 2007 DATE. ical innovation and mass scale. It is the world's largest online marketplace, AI ORG assistant provider, live-streaming platform and cloud computing distiform as measured by revenue and market business. The company expanded internationally in 2018 DATE with streaming available in Canada OPE , followed by Latin America LOC and the Caribbean LOC . Netfix ORG entered the content-production industry in 2013 DATE , debuting its et company by revenue in the world. It is the second ORDINAL largest private employer in the United States GPE and one CARDINAL of the world's most valuable companies. As of 2020 DATE Since 2012 DATE Netflix ORG has taken more of an active role as producer and distributor for both film and television series, and to that end, offers a variety of Netflix Original WORK_OF_ART *content Netflix ORG services operated in more than 190 CARDINAL countries. Netflix ORG released an estimated 126 CARDINAL original series and films in 2016 DATE, more than any other network or cable channel. As of December 31, 2020 DATE , the company had \$16 billion MONEY in long term debt, which if accumulated to fund its growth. The company is ranked 164th ORDINAL on the Fortune 500 and PRODUCT 204th on the Fortune 500 a Echo ORG devices. Its acquisitions over the years DATE include Ring ORG , Twilich, Whole Foods Market, and IMOb. Amazon ORG is currently in the process of purchasing film and television studio, Netflix ORG was ranked as the 8th ORDINAL most trusted brand globally by Morning Consult WORK_OF_ART mayon Q89 has been criticized for practices including technological surveillance overreach, a hyper-competitive and demanding work culture, tax avoidance, and anti-competitive behavior Netflix ORG was the top-performing stock in the S&P 500 stock market index, with a total return of 3,693% PERCENT 2 doc_5 = NER_5(Google) spacy.displacy.render(doc_5, style="ent", jupyter=True) 3 spacy.displacy.render(doc 3, style="ent", jupyter=True) 2020 DATE) and, since January 2021 DATE , the world's most valuable company. As of 2021 DATE , Apple ORD is the world's fourth ORDNAL -largest PC vendor by unit sales, and fourth ORDNAL -largest PC vendor by unit sales, and fourth ORDNAL -largest smartphone manufacturer. It is one of Page PERSON and Seggey Brin PERSON while they were Ph.D. WORK_OF_ART students at Stanford University ORG in California GPE Together they own about 14% PERCENT of its publicly-listed shares and control. 56% PERCENT of the tockholder voting power through super-voting stock. The company went public via an initial public offering (IPO) in 2004 DATE , in 2015 DATE , Google ORG was reorganized as a wholly owned subsidiary of Alphabet Inc ORG ... Google is Alphabet and Ronald Wayne PERSON in 1976 DATE to develop and sell Wozniak PERSON is Apple Computer, It was incorporated by Jobs and Wozniak PERSON as Apple Computer, Inc. ORG in 1977 DATE and sales of its computer. chading the Apple II ORG grew quickly. They went public in 1900 DATE to instant financial success. Over the next few years DATE Apple ORG shipped new computers featuring innovative graphical user interfaces, such as the original Macintosh ORG 's largest subsidiary and is a holding company for Alphabet ORG 's internet properties and interests. Sundar Pichai PERSON was appointed CEO of Google ORG on October 24, 2015 DATE replacing Larry Page PERSON , who became the ORG announced with the critically acclaimed advert 1984 DATE . However, the high price of its products and limited application library caused problems, as did power struggles between executives. In 1985 DATE . Wozniak FERSON departed Apple CEO of Alphabet ORG On December 3, 2019 DATE Pichal OPE also became the CEO of Alphabet ORG In 2021 DATE the Alphabet Workers Union ORG was founded, mainly composed of Google ORG employees. The company's rapid growth since incorporation has included products, acquisitions, and partnerships beyond Google ORG 's core search engine, (Google Search ORG). It offers services designed for work and productivity (Google Docs, Google Sheets ORG , and Google Windows PRODUCT on Intel ORG PC clones. The board recruited CEO Gil Amelio PERSON , who prepared the struggling company for eventual success with extensive reforms, product focus and layoffs in his 500 day Sides FERSON), email (Gmail ORG), scheduling and time management (Google Catendar), cloud storage (Google Drive), instant messaging and video chat (Google Duo, Google Chat ORG , and Google Meet), language translation (Google Translation) GII ORG bought NeXT ORG to resolve Apple ORG 's unsuccessful OS strategy and bring back. Steve Jobs PERSON who replaced Amelio PERSON as CEO later that year DATE. Apple ORG returned to mapping and navigation (Google Maps, Waze PERSON , Google Earth, and Street View FAC), podcast hosting (Google Podcasts CRG), video sharing (YouTube CRG), blog publishing (Blogger), note-taking (Google Keep and Jamboard PERSON vitakzing "Think different" campaign, launching the Mac ORO and Pod ORO opening a retail chain of Apple Stores ORO in 2001 DATE, and acquiring numerous companies to broaden their software portfolio. In 2007 DATE and photo organizing and editing (Google Photos). The company leads the development of the Android DRB mobile operating system, the Google Chrome web browser, and Chrome OS (a lightweight, proprietary operating system based on the free and open-source company launched the Phone PRODUCT to critical acclaim and financial success. In 2011 DATE, Jobs resigned as CEO due to health complications, and died two months later DATE. He was succeeded by Tim Cook PERSON. In August 2018. Chromium ORG OS operating system). Google ORG has moved increasingly into hardware, from 2010 to 2015 DATE, it partnered with major electronics manufacturers in the production of its Google Nexus ORG devices, and it released multiple DATE Apple ORG Decame the first ORDINAL publicly traded U.S. GPE company to be valued at over \$1 trillion MONEY and the first ORDINAL valued over \$2 trillion MONEY two years later DATE. It has a high level of brand loyalty and is hardware products in 2016 DATE , including the Google Pixel line of smartphones, Google Home ORG smart speaker, Google Wifi mesh wireless router ORG Google ORG has also experimented with becoming an Internet carrier (Google Fiber OR ranked as the world's most valuable brand, as of January 2021 DATE , there are 1.65 billion CARDINAL Apple ORG products in use worldwide. However, the company receives significant criticism regarding the labor practices of its contractors, its and Google FI) Google.com ORG as the most visited website worldwide. Several other Google ORG -owned websites also are on the list of most popular websites, including YouTube ORG and Blogger. On the list of most valuable brands, Google ORG ironmental practices, and business ethics, including anti-competitive behavior, and materials sourcing ranked second ORDINAL by Forbes ORG and fourth ORDINAL by Interbrand ORG its monopoly position







3. Results and Discussion (cont'd)

Radial hierarchy.

SPARQL query: PREFIX faang: http://www.fism.ukm.my/faangOnt#">http://www.fism.ukm.my/faangOnt#">http://www.fism.ukm.my/faangOnt#">http://www.fism.ukm.my/faangOnt#">http://www.fism.ukm.my/faangOnt#">http://www.mg/figegoogle/fism.ms#">http://www.mg/figegoogle/fism.ms#">http://www.mg/figegoogle/fism.ms#">http://www.mg/figegoogle/fism.ms#">http://www.mg/fism.ukm.ms#

Google
Apple

Amazon Netflix

Facebook

3. Results and Discussion (cont'd)

FAANG types.

Q1. Who are the founder(s) of respective FAANG? 1. Mark Zuckerberg, Eduardo Saverin, Andrew McCollum, Dustin Moskovitz and Chris Hughes

- 2. Jeff Bezos
- 3. Steve Jobs, Steve Wozniak and Ronald Wayne

SPARQL query

AmazonPERSON

AmazonPERSON

4. Reed Hastings and Mark Randolph 5. Larry Page and Sergey Brin Q1 (Facebook, Amazon, Apple and Netflix).

PREFIX faang: http://www.ftsm.ukm.my/faangOnt#> PREFIX rdf: http://www.w3.org/1999/02/22-rdf-syntax-ns#> PREFIX rdfs: http://www.w3.org/2000/01/rdf-schema#> PREFIX xsd: http://www.w3.org/2001/XMLSchema#> SELECT ?subject ?object WHERE ?subject rdf.type faang:Facebook ?subject faang:hasPersonName ?object

subject	object
FacebookPERSON	"Dustin Moskovitz"^^ <http: 2001="" www.w3.org="" xmlschema#string=""></http:>
FacebookPERSON	"Eduardo Saverin"^^ http://www.w3.org/2001/XMLSchema#string>
FacebookPERSON	"Mark Zuckerberg"^^ <http: 2001="" www.w3.org="" xmlschema#string=""></http:>
F	F

1 decoon Errout	Eddardo Carcini International Control of Con
FacebookPERSON	"Mark Zuckerberg"^^ http://www.w3.org/2001/XMLSchema#string
FacebookPERSON	"Facebook Messenger"^^ <http: 2001="" th="" www.w3.org="" xmlschema#string<=""></http:>
FacebookPERSON	"Chris Hughes"^^ http://www.w3.org/2001/XMLSchema#string>
FacebookPERSON	"Andrew McCollum"^^ http://www.w3.org/2001/XMLSchema#string>
SPARQL query:	
PREFIX faang: http://www.ftsm.ukm.my/faangOnt#>	

PREFIX rdf: http://www.w3.org/1999/02/22-rdf-syntax-ns#> PREFIX owl: PREFIX rdfs: http://www.w3.org/2000/01/rdf-schema#> PREFIX xsd: http://www.w3.org/2001/XMLSchema# SELECT ?subject ?object WHERE ?subject rdf:type faang:Amazon

?subject faang:hasPersonName ?object

3. Results and Discussion (cont'd)

"Steve Wozniak"^^http://www.w3.org/2001/XMLSchema#string

"Hastings"^^<http://www.w3.org/2001/XMLSchema#string>

"Reed Hastings"^^http://www.w3.org/2001/XMLSchema#string>

"Marc Randolph"^^http://www.w3.org/2001/XMLSchema#string>

SPARQL query PREFIX faang: http://www.ftsm.ukm.mv/faangOnt#> PREFIX rdf: http://www.w3.org/1999/02/22-rdf-syntax-ns#> PREFIX owl: http://www.w3.org/2002/07/owl#>

PREFIX rdfs: http://www.w3.org/2000/01/rdf-schema#> PREFIX xsd: http://www.w3.org/2001/XMLSchema#> SELECT ?subject ?object WHERE ?subject rdf:type faang:Apple ?subject faang:hasPersonName ?object

ApplePERSON

ApplePERSO

ApplePERSO

SPARQL (PREFIX faar PREFIX rdf:

NetflixPERSON

NetflixPERSON

NetflixPERSON

object

"Twitch"*^http://www.w3.org/2001/XMLSchema#string>

"Jeff Bezos"^^http://www.w3.org/2001/XMLSchema#string>

ApplePERSON "Amelio"^^http://www.w3.org/2001/XMLSchema#string> ApplePERSON "Ronald Wayne"^^http://www.w3.org/2001/XMLSchema#string> ApplePERSON "Wozniak"^^http://www.w3.org/2001/XMLSchema#string ApplePERSON "Gil Amelio"^^http://www.w3.org/2001/XMLSchema#string>

SON SON	"Tim Cook"^^ " jobs"^^<a="" steve="">http://www.w3.org/2001/XMLSchema#string>"Steve Jobs"^^">http://www.w3.org/2001/XMLSchema#string>>http://www.w3.org/2001/XMLSchema#string>>http://www.w3.org/2001/XMLSchema#string>>http://www.w
query:	
ang: ">http://www.tlsm.ukm.myflaangOnt#>">http://www.w3.org/199900222-df-syntax-ns#>"/- ">http://www.w3.org/2002/07/owt#>">http://www.w3.org/2000/07/owt#>">http://www.w3.org/2000/07/owt#>"> ">http://www.w3.org/2001/owt#>"> http://www.w3.org/2001/owt.schema#"> http://www.w3.org/2001/owt.schema#"> http://www.w3.org/2001/owt.schema#"> http://www.w3.org/2001/owt.schema#"> http://www.w3.org/2001/owt.schema# <a href<="" td=""><td></td>	

PREFIX owl PREFIX rdfs PREFIX xsd: SELECT ?sul WHERE ?subject rdf.type faang:Netflix ?subject faang:hasPersonName ?object .

PREFIX faang: http://www.ftsm.ukm.my/faangOnt#> PREFIX rdf: http://www.w3.org/1999/02/22-rdf-syntax-ns# PREFIX owl: PREFIX owl: http://www.w3.org/2002/07/owl# PREFIX rdfs: http://www.w3.org/2000/01/rdf-schema#> PREFIX xsd: http://www.w3.org/2001/XMLSchema#> SELECT ?subject ?object WHERE ?subject rdf:type faang:Google ?subject faang:hasPersonName ?object . subject object GooglePERSON "Jamboard"^^http://www.w3.org/2001/XMLSchema#string GooglePERSON "Sundar Pichai"^^http://www.w3.org/2001/XMLSchema#string> GooglePERSON "Waze"^^<http://www.w3.org/2001/XMLSchema#string> GooglePERSON "Larry Page"^^http://www.w3.org/2001/XMLSchema#string> GooglePERSON "Google Slides"^^http://www.w3.org/2001/XMLSchema#string> GooglePERSON "Sergey Brin"^^http://www.w3.org/2001/XMLSchema#string>

SPARQL query:

3. Results and Discussion (cont'd)

Q1 (Google).

Q2. Where are they founded? 1. US 2. Bellevue, Washington 3. US 4. Los Gatos, California 5. California SPARQL query: PREFIX faang: http://www.ftsm.ukm.mv/faangOnt#> PREFIX rdf: http://www.w3.org/1999/02/22-rdf-syntax-ns#> PREFIX owl: PREFIX owl: http://www.w3.org/2002/07/owl# PREFIX rdfs: http://www.w3.org/2000/01/rdf-schema#> PREFIX xsd: http://www.w3.org/2001/XMLSchema#> SELECT ?subject ?object PREFIX faang: <http://www.ftsm.ukm.my/faangOnt#> PREFIX rdf: http://www.w3.org/1999/02/22-rdf-syntax-ns# ?subject rdf:type faang:Facebook. PREFIX owl: "> PREFIX owl: PREFIX owl: <a href="http://www.w3.org/2002/07/ ?subject faang:hasCountriesCitiesState ?object . PREFIX rdfs: http://www.w3.org/2000/01/rdf-schema#>

"Washington"^^<http://www.w3.org/2001/XMLSchema#string> "U.S."AAhttp://www.w3.org/2001/XMLSchema#string

"Bellevue"^^http://www.w3.org/2001/XMLSchema#string

"the United States"^^http://www.w3.org/2001/XMLSchema#string>

"Cambridge Analytica"^^http://www.w3.org/2001/XMLSchema#string "U.S."^^http://www.w3.org/2001/XMLSchema#string>

?subject rdf.type faang:Amazon. ?subject faang:hasCountriesCitiesState ?object .

AmazonGPE

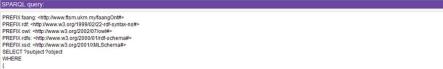
AmazonGPE AmazonGPE

AmazonGPE

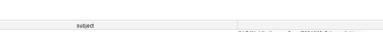
?subject rdf.type faang:Apple ?subject faang:hasCountriesCitiesState ?object . FacebookGPE FacebookGPE AppleGPE PREFIX faang: http://www.ftsm.ukm.mv/faangOnt#> PREFIX rdf: http://www.w3.org/1999/02/22-rdf-syntax-ns# PREFIX owl: "> PREFIX owl: PREFIX owl: PREFIX owl: <a href="http://www.wa.org/2002/07/ PREFIX rdfs: http://www.w3.org/2000/01/rdf-schema#> PREFIX xsd: http://www.w3.org/2001/XMLSchema#> SELECT ?subject ?object WHERE



(Facebook, Amazon and Appi	e).	







"U.S."^^<http://www.w3.org/2001/XMLSchema#string>

SPARCIL query: PREFIX faang: -http://www.wilsm.ukm.my/faangOnt#> PREFIX faang: -http://www.wilsm.ukm.my/faangOnt#> PREFIX fow: -http://www.wilsm.goz/2002/07/out#> PREFIX fow: -http://www.wilsm.goz/2002/07/out#> PREFIX fow: -http://www.wilsm.goz/2002/07/out#> PREFIX fow: -http://www.wilsm.goz/2001/out#> PREFIX fow: -http://www.goz/2001/out#> P

NetflixGPE	"Los Gatos"^^ http://www.w3.org/2001/XMLSchema#string>
NetflixGPE	"Japan"^^ <http: 2001="" www.w3.org="" xmlschema#string=""></http:>
NetflixGPE	"Canada"^^ <http: 2001="" www.w3.org="" xmlschema#string=""></http:>
NetflixGPE	"California" ^{AA.} http://www.w3.org/2001/XMLSchema#string
NetflixGPE	"Crimea"^^ http://www.w3.org/2001/XMLSchema#string>
NetflixGPE	"South Korea"^^ <http: 2001="" www.w3.org="" xmlschema#string=""></http:>
NetflixGPE	"North Korea"^^ http://www.w3.org/2001/XMLSchema#string
NetflixGPE	"India"^^ <http: 2001="" www.w3.org="" xmlschema#string=""></http:>
NetflixGPE	"the United Kingdom"^^ http://www.w3.org/2001/XMLSchema#string>
NetflixGPE	"Syria"^^ <http: 2001="" www.w3.org="" xmlschema#string=""></http:>
NetflixGPE	"China"^^ <http: 2001="" www.w3.org="" xmlschema#string=""></http:>
NetflixGPE	"Netherlands"^^ <http: 2001="" www.w3.org="" xmlschema#string=""></http:>
NetflixGPE	"Brazil"^^. <http: 2001="" www.w3.org="" xmlschema#string=""></http:>
NetflixGPE	"Scotts Valley"^^ http://www.w3.org/2001/XMLSchema#string>
NetflixGPE	"the United States"^^. http://www.w3.org/2001/xMLSchema#string
NetflixGPF	"France"^ <http: 2001="" www.w3.org="" xmi.schema#string=""></http:>

Execute

SPARQL query PREFIX faang: -thtp://www.flsm.ukm.myflaangont#> PREFIX faang: -thtp://www.do.org/1999/02/22-dd-syntax-ns#> PREFIX rds -thtp://www.w3.org/2002/07/owl#> PREFIX rds -thtp://www.w3.org/2002/07/owl#> PREFIX rds -thtp://www.w3.org/200001 rds-dchema#> PREFIX sd -thtp://www.w3.org/2001/MLSchema#> SELECT 7subject 7object 7obje

 Subject
 object

 GoogleGPE
 "Pichai**-http://www.w3.org/2001/xMLSchema#string>

 GoogleGPE
 "California**-http://www.w3.org/2001/xMLSchema#string>

3. Results and Discussion (cont'd)

Q2 (Netflix and Google).

object

Q3. When are they founded? 1.2004 2. July 5, 1994 Q3 (Facebook, Amazon and Apple). 4. 1997 5. September 4, 1998 SPARQL query SPARQL query PREFIX faang: http://www.ftsm.ukm.mv/faangOnt#> PREFIX rdf: http://www.w3.org/1999/02/22-rdf-syntax-ns#> PREFIX faang: http://www.ftsm.ukm.my/faangOnt#> PREFIX owl; PREFIX owl; PREFIX owled. PREFIX rdf: http://www.w3.org/1999/02/22-rdf-syntax-ns# PREFIX rdfs: http://www.w3.org/2000/01/rdf-schema#> PREFIX owl: "> PREFIX owl: http://www.w3.org/2002/07/owl#> PREFIX xsd: http://www.w3.org/2001/XMLSchema#> PREFIX rdfs: http://www.w3.org/2000/01/rdf-schema#>

SELECT ?subject ?object WHERE ?subject rdf.type faang:Facebook ?subject faang:hasDate ?object subject object FacebookDATE "2006"^Ahttp://www.w3.org/2001/XMLSchema#string> FacebookDATE "13 years old"^^http://www.w3.org/2001/XMLSchema#string> "2016"^^http://www.w3.org/2001/XMLSchema#string> FacebookDATE FacebookDATE "2004"^^http://www.w3.org/2001/XMLSchema#string> Encahani/DATE manth /// http://www.scamonathatrings SPARQL query PREFIX faang: http://www.ftsm.ukm.mv/faangOnt#> PREFIX rdf: http://www.w3.org/1999/02/22-rdf-syntax-ns# PREFIX owl: http://www.w3.org/2002/07/owl#> PREFIX rdfs: http://www.w3.org/2000/01/rdf-schema#> PREFIX xsd: http://www.w3.org/2001/XMLSchema#> SELECT ?subject ?object ?subject rdf:type faang:Amazon ?subject faang:hasDate ?object subject AmazonDATE "July 5, 1994"^^http://www.w3.org/2001/XMLSchema#string AmazonDATE "2018"^^http://www.w3.org/2001/XMLSchema#string>

AmazonDATE

AmazonDATE

AmazonDATE

AmazonDATE

AmazonDATE

3. Results and Discussion (cont'd)

WHERE

AppleDATE

"2017"^^http://www.w3.org/2001/XMLSchema#string>

"2015"^^http://www.w3.org/2001/XMLSchema#string>

"2020"^^http://www.w3.org/2001/XMLSchema#string>

"two-day"^^http://www.w3.org/2001/XMLSchema#string

"the years"^^<http://www.w3.org/2001/XMLSchema#string>



"August 2018"^^http://www.w3.org/2001/XMLSchema#string

"later that year"^^http://www.w3.org/2001/XMLSchema#string>

"1985"^^http://www.w3.org/2001/XMLSchema#string

"1997"^^<http://www.w3.org/2001/XMLSchema#string>

"1980"^^<http://www.w3.org/2001/XMI.Schema#string>

SPARQL query: PREFIX faang: *http://www.fis.m.ukm.my/faangOnt#> PREFIX rot: *http://www.w3.org/199902/22-dd-syntax-ns#> PREFIX rot: *http://www.w3.org/2000/02/10/rot#> PREFIX rot: *http://www.w3.org/2000/01/rot#-schema#> PREFIX rot: *http://www.w3.org/2001/rotf-schema#> PREFIX rot: *http://www.

subject	object
VetflixDATE	"July 2021"^^. http://www.w3.org/2001/XMLSchema#string
VetflixDATE	"2010" ^{M.} http://www.w3.org/2001/XMLSchema#string
VetflixDATE	"2021"^^ <http: 2001="" www.w3.org="" xmlschema#string=""></http:>
NetflixDATE	"July 10, 2020"^^- http://www.w3.org/2001/kMLSchema#string
NetflixDATE	"2013"^^ <http: 2001="" www.w3.org="" xmlschema#string=""></http:>
VetflixDATE	"2012"^^ <http: 2001="" www.w3.org="" xmlschema#string=""></http:>
NetflixDATE	"1997"^^ <http: 2001="" www.w3.org="" xmlschema#string=""></http:>
NetflixDATE	"2016"^^ <http: 2001="" www.w3.org="" xmlschema#string=""></http:>
NetflixDATE	"about a year"^^ <http: 2001="" www.w3.org="" xmlschema#string=""></http:>
NetflixDATE	"December 31, 2020"^A http://www.w3.org/2001/XMLSchema#string>
NetflixDATE	"the 2010s decade"^/ <http: 2001="" jmlschema#string="" www.w3.org=""></http:>
NetflixDATE	"January 2016"^^ http://www.w3.org/2001/XMLSchema#string
NetflixDATE	"2007"^^. http://www.w3.org/2001/XMLSchema#string>

3. Results and Discussion (cont'd)

Q3 (Netflix and Google).

SPARQL query: PREFIX faang -thtp://www.fism.ukm.myfaangOnt#> PREFIX rd.-thtp://www.wi.sm.ukm.myfaangOnt#> PREFIX rd.-thtp://www.wi.sm.gorg/10990/2/22-dd-syntax-ns#> PREFIX rds.-thtp://www.wi.sm.gorg/2002/07/out#> PREFIX rds.-thtp://www.wi.sm.gorg/2002/07/out#> PREFIX rds.-thtp://www.wi.sm.gorg/2000/01/trds.chema#> PREFIX rds.-thtp://www.wi.sm.gorg/2001/out#.Schema#> SELECT 7 subject 7 object WHERE { { 7 subject rdttype faang Google . 7 subject rdttype faang Google . 7 subject rdttype faang Soogle .

subject	object
GoogleDATE	"2015"^^http://www.w3.org/2001/XMLSchema#string>
GoogleDATE	"2010 to 2015"^^ <http: 2001="" www.w3.org="" xmlschema#string=""></http:>
GoogleDATE	"2004"^^ http://www.w3.org/2001/XMLSchema#string>
GoogleDATE	"2016"^^ http://www.w3.org/2001/XMLSchema#string>
GoogleDATE	"2021"^^ http://www.w3.org/2001/XMLSchema#string>
GoogleDATE	"October 24, 2015"^^ http://www.w3.org/2001/XMLSchema#string
GoogleDATE	"December 3, 2019"^^ http://www.w3.org/2001/XMLSchema#string>
GoogleDATE	"September 4, 1998"^^ http://www.w3.org/2001/XMLSchema#string>

Q4 is the competency question where there are 3 scenarios namely exact match, partial match and no match, exact match refers to queries that requires only a single predicate for matching respective FAANG's competency question while partial match refers to queries that requires multiple predicates for matching respective FAANG's competency question.

For Facebook and Netflix as shown in Table 9 and 12 respectively, the SPARQL query returns an exact match where it only requires predicate to match Q4's answers while for Apple the SPARQL query returns a partial match 2 different predicates. Amazon and Google both contains a mixture of partial match and no match.

It can be seen that fine-tuning is required for better identification of "PRODUCT" because "hasProduct" if used as the predicate will only return an iPhone as can be seen in Table 11, most of the predicate that returns answers matching the competency questions comes from "hasCompaniesAgenciesInstitutions" which identifies as an "ORG" or company. Some comes from "hasPersonName" that identifies as a "PERSON" in the case of Amazon and Google as can be seen in Table 10 and 13 respectively. In the case of Google as well, "hasBuildingsAirportsHighwaysBridges" that identifies as "FAC" or facility was observed. For companies with many products such as Amazon and Google, there are numerous no matches "-NA-".

Table 9. Q4 Answer versus SPARQL for Facebook

Q4 Answer No.		SPARQL	
ESCHALL STANCE		(hasCompaniesAgenciesInstitutions)	
Facebook	1	Facebook	

3. Results and Discussion (cont'd)

OA (Eggabook and Amazon)

Table 10. Q4 Answer versus SPARQL for Amazon

Q4 Answer	No.	SPARQL
		(hasCompaniesAgenciesInstitutions)
Amazon	1	Amazon
Whole Foods Market	2	Whole Foods Market
Amazon Prime Video	3	Amazon Prime Video
Amazon Music	4	Amazon Music
Twitch	5	(hasPersonName)
7 (1 (1 (1 (1 (1 (1 (1 (1 (1 (Twitch
Audible	6	Audible
Amazon Publishing	7	Amazon Publishing
Amazon Studios	8	Amazon Studios
Amazon Web Services	9	Amazon Web Services
Kindle	10	-NA-
Fire tablets	11	-NA-
Fire TV	12	Fire TV
Echo	13	Echo
Ring	14	Ring
IMDb	15	-NA-
15	Count	12

Table 11. Q4 Answer versus SPARQL for Apple

Q4 Answer	No.	SPARQL	
630 1 11 11 11 11 11		(hasCompaniesAgenciesInstitutions)	
iMac	1	iMac	
iPod	2	iPod	
iPhone	3	(hasProduct) iPhone	

Table 12. Q4 Answer versus SPARQL for Netflix

Q4 Answer	No.	SPARQL
AND THE PROPERTY OF THE PARTY O		(hasCompaniesAgenciesInstitutions)
Netflix	1	Netflix

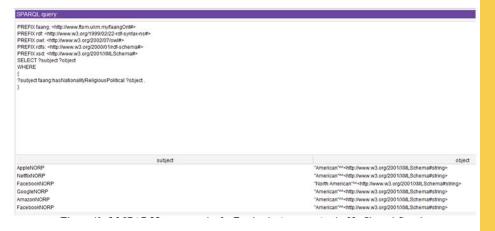
3. Results and Discussion (cont'd)

Q4 (Apple Netflix and Goodle)

O4 Answer	No.	r versus SPARQL for Google SPARQL
Q4 Allswei	140.	(hasCompaniesAgenciesInstitutions)
Google Search	1	Google Search
Google Docs	2	-NA-
Google Sheets	3	Google Sheets
Google Slides	4	(hasPersonName)
Google ondes	7	Google Slides
Gmail	5	Gmail
Google Calendar	6	-NA-
Google Drive	7	-NA-
Google Duo	8	-NA-
Google Chat	9	Google Chat
Google Meet	10	-NA-
Google Translate	11	-NA-
Google Maps	12	-NA-
Waze	13	(hasPersonName)
		Waze
Google Earth	14	-NA-
Street View	15	(hasBuildingsAirportsHighwaysBridges Street View
Google Podcasts	16	Google Podcasts
YouTube	17	YouTube
Blogger	18	-NA-
Google Keep	19	-NA-
Jamboard	20	(hasPersonName)
		Jamboard
Google Photos	21	-NA-
Google Chrome	22	-NA-
Android	23	Android
Chromium OS	24	Chromium
Google Nexus	25	Nexus
Google Pixel	26	-NA-
Google Home	27	Google Home
Google Wifi	28	Google Wifi mesh wireless router
Google Fiber	29	Google Fiber
Google Fi	30	-NA-
30	Count	16

Q5. What is the nationality of the company? (NORP)

- 1. American
- 2. American
- 3. American
- 4. American
- 5. American



3. Results and Discussion (cont'd)

Q5 (Facebook, Amazon, Apple, Netflix and Google).

4. Conclusion

In conclusion, an out-of-the-box pre-trained model can be used for general Named Entity Extraction as demonstrated and further transformed into RDF/RDFS format for visualization in Protégé. This was done for Big Tech data consisting of FAANG companies and can be considered a general domain, as such also shows that it can be applied to other domains as well without fine-tuning to suit that domain. Future works, should be done using an ensemble of SOTA NER before NEE for better scores with micro fine-tuning and experiment with k-shot learning as experimented by Van Hoang et al. (2021).



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