Comparison of NLP Tools on Named-Entity Recognition of Resumes

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***Abstract*—Named entity recognition (NER) – is an information extraction technique that automatically identifies named entities in a text and classifies them into predefined categories such as person name, organization, location. In this article, I am going to compare open-source APIs SpaCy and NLTK (Stanford NER Tagger) as well as SaaS APIs Google Cloud Natural Language API, Amazon Comprehend Text Analysis API, Microsoft Azure Text Analytics API on Named-Entity Recognition in the text of resumes.**

***Index Terms*—Resume, NER, SpaCy, NLTK, Stanford NER Tagger, Google Cloud Natural Language API, Amazon Comprehend Text Analysis API, Microsoft Azure Text Analytics API**

I. Introduction

This section has short overview of each of the NLP tool with additional details regarding supported languages, named entity types, example of API, support of custom NER model training and additional notes.

A. SpaCy

SpaCy[1] is an open-source software library for advanced natural language processing, written in the programming languages Python and Cython The library is published under the MIT license and its main developers are Matthew Honnibal and Ines Montani, the founders of the software company Explosion.

Unlike NLTK, which is widely used for teaching and research, spaCy focuses on providing software for production usage. As of version 1.0, spaCy also supports deep learning workflows that allow connecting statistical models trained by popular machine learning libraries like TensorFlow, PyTorch or MXNet through its own machine learning library Thinc. Using Thinc as its backend, spaCy features convolutional neural network models for part-of-speech tagging, dependency parsing, text categorization and named entity recognition (NER). Prebuilt statistical neural network models to perform these task are available for English, German, Greek, Spanish, Portuguese, French, Italian, Dutch, Lithuanian and Norwegian, and there is also a multi-language NER model. Additional support for tokenization for more than 50 languages allows users to train custom models on their own datasets as well

Supported NER categories

- CARDINAL
- DATE
- EVENT
- FAC
- GPE
- LANGUAGE
- LAW
- LOC
- MONEY
- NORP
- ORDINAL
- ORG
- PERCENT
- PERSON
- PRODUCT
- QUANTITY
- TIME
- WORK_OF_ ART

Supported Languages

- English
- Chinese
- Danish
- Dutch
- French
- German
- Greek
- Italian
- Japanese
- Lithuanian
- Norwegian Bokmål
- Polish
- Portuguese
- Romanian
- Spanish

Support of custom NER

SpaCy has a step-by-step guide on improving the existing model by adding your data and how to train the model for the new entity type.

Example of API:

```
nlp = spacy.load("en_core_web_lg")tokenized_text =
classified_doc = nlp(doc)
```

Other notes

'O' - outside class automatically filtered. The beginning and end position of a named entity is available.

[1]https://en.wikipedia.org/wiki/SpaCy

B. Stanford NER

Stanford NER[2] is a Java implementation of a Named Entity Recognizer. Named Entity Recognition (NER) labels sequences of words in a text which are the names of things, such as person and company names, or gene and protein names. It comes with well-engineered feature extractors for Named Entity Recognition, and many options for defining feature extractors. Included with the download are good named entity recognizers for English, particularly for the 3 classes (PERSON, ORGANIZATION, LOCATION), and we also make available on this page various other models for different languages and circumstances, including models trained on just the CoNLL 2003 English training data.

Stanford NER is also known as CRFClassifier. The software provides a general implementation of (arbitrary order) linear chain Conditional Random Field (CRF) sequence models. That is, by training your own models on labeled data, you can actually use this code to build sequence models for NER or any other task. (CRF models were pioneered by Lafferty, McCallum, and Pereira (2001); see Sutton and McCallum (2006) or Sutton and McCallum (2010) for more comprehensible introductions.)

Supported NER categories

- Location
- Person
- Organization
- Money
- Percent
- Date
- Time

Supported Languages

- English
- Arabic
- Chinese
- French
- German
- Spanish

Support of custom NER

The documentation for training your classifier is somewhere between bad and non-existent. Nevertheless, everything you need is in the box, and you should look through the Javadoc for at least the classes CRFClassifier and NERFeatureFactory.

Example of API:

```
st = StanfordNERTagger(
        'english.all.3class.distsim.crf.ser.gz',
        'stanford-ner-4.0.0.jar',
        encoding='utf-8')
tokenized_doc = word_tokenize(doc)
classified_doc = st.tag(tokenized_doc)
```

Other notes

The result is a list of tuples for each token without scores. There is no out of the box chunking.

[2]https://nlp.stanford.edu/software/CRF-NER.html

C. Google Cloud Natural Language API

The Cloud Natural Language API[3] provides natural language understanding technologies to developers, including sentiment analysis, entity analysis, entity sentiment analysis, content classification, and syntax analysis. This API is part of the larger Cloud Machine Learning API family.

Supported NER categories

- UNKNOWN
- PERSON
- LOCATION
- ORGANIZATION
- EVENT
- WORK_OF_ART
- CONSUMER_GOOD
- OTHER
- PHONE_NUMBER
- Phone
- ADDRESS
- DATE
- NUMBER
- PRICE

Supported Languages

- English
- Chinese (Simplified)
- Chinese (Traditional)
- French
- German
- Italian
- Japanese
- Korean
- Portuguese (Brazilian & Continental)
- Russian
- Spanish

Support of custom NER

Google has AutoML Natural Language, which allows the end-user to train the custom NER model.

Example of API:

```
client = language.LanguageServiceClient
    .from_service_account_json('services.json')
doc = types.Document(content=text,
    type=language.enums.Document.Type.PLAIN_TEXT)
features = {'extract_syntax': False,
    'extract_entities': True,
    'extract_document_sentiment': False,
    'extract_entity_sentiment': False,
    'classify_text': False}
response = client.annotate_text(doc, features)
entities = response.entities
```

Other notes

Credentials can be easily exported from the web interface and imported to the client using a JSON file. There is a limitation on the request size.

[3]https://cloud.google.com/natural-language/docs

D. Amazon Comprehend Text Analysis API

Amazon Comprehend[4] uses natural language processing (NLP) to extract insights about the content of documents. Amazon Comprehend processes any text file in UTF-8 format. It develops insights by recognizing the entities, key phrases, language, sentiments, and other common elements in a document. Use Amazon Comprehend to create new products based on understanding the structure of documents. For example, using Amazon Comprehend you can search social networking feeds for mentions of products or scan an entire document repository for key phrases.

Supported NER categories

- COMMERCIAL_ITEM
- DATE
- EVENT
- LOCATION
- ORGANIZATION
- OTHER
- PERSON
- QUANTITY
- TITLE

Supported Languages

- English
- German
- Spanish
- Italian
- Portuguese
- French
- Japanese
- Korean
- Hindi
- Arabic
- Chinese (simplified)
- Chinese (traditional)

Support of custom NER

Amazon has Comprehend's custom entity recognition service to train the custom NER model. The service automatically tests for the best algorithm and parameters while training the model to use, looking for the most accurate combination of these components.

Example of API:

```
comprehend = boto3.client(
    service_name='comprehend')
comprehend.detect_entities(Text=documents,
    LanguageCode='en')
```

Other notes

Comprehend the client is automatically looking for credentials in the environment variables. There is a 5000 bytes limitation on the request size. API supports both single document and batch modes.

[4]https://docs.aws.amazon.com/comprehend/latest/dg/what-is.html

E. Microsoft Azure Text Analytics API

The Text Analytics API[5] is a cloud-based service that provides Natural Language Processing (NLP) features for text mining and text analysis, including: sentiment analysis, opinion mining, key phrase extraction, language detection, and named entity recognition. The API is a part of Azure Cognitive Services, a collection of machine learning and AI algorithms in the cloud for your development projects. You can use these features with the REST API, or the client library.

Supported NER categories

- Person
- PersonType
- Location
- Organization
- Event
- Product
- Skill
- Address
- PhoneNumber
- Email
- URL
- IP
- DateTime
- Quantity

Supported Languages

- English
- Arabic
- Czech
- Chinese-Simplified
- Chinese-Traditional
- Danish
- Dutch
- Finnish
- French
- German
- Hebrew
- Hungarian
- Italian
- Japanese
- Korean
- Norwegian (Bokmål)
- Polish
- Portuguese (Portugal)
- Portuguese (Brazil)
- Russian
- Spanish
- Swedish
- Turkish

Support of custom NER

Custom NER model training can be done through Azure Language Understanding (LUIS) service. This service is mostly designed for chatbots.

[5]https://docs.microsoft.com/en-us/azure/cognitive-services/text-analytics/overview

Example of API:

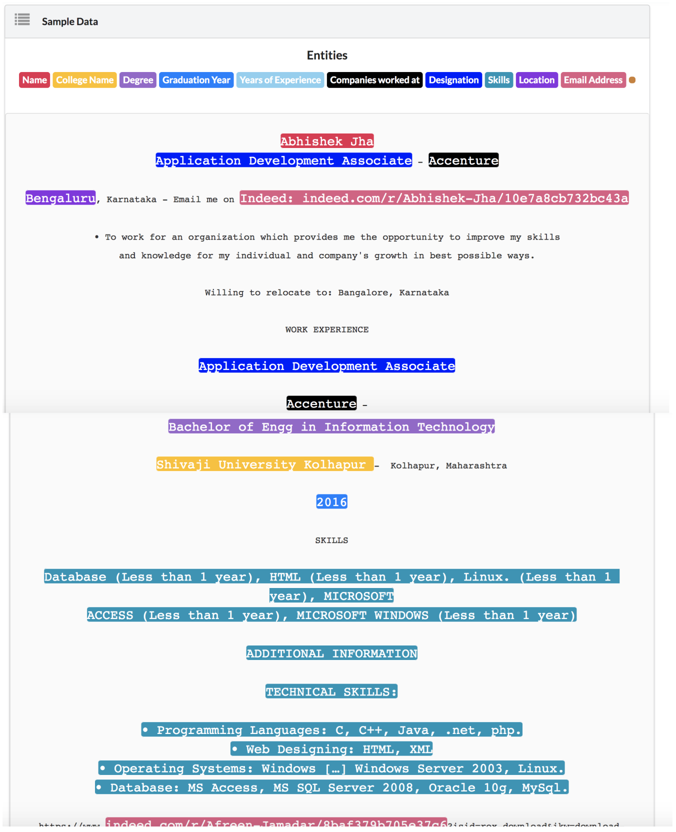
```
credential = AzureKeyCredential(api_key)
client = TextAnalyticsClient(endpoint,
    credential)
client.recognize_entities(documents,
     language="en")
```

Other notes

To run any of the Azure Text Analytics containers, you must have the host computer and container environments. There is a 5120 character limitation on the request size. API supports both single document and batch modes.

II. Dataset and Analysis Methodology

This dataset is a document annotation dataset used to perform NER on resumes from indeed.com, which was obtained from https://www.kaggle.com/dataturks/resume-entities-for-ner/home.



Sample Data

Entities

Name | College Name | Degree | Graduation Year | Years of Experience | Companies worked at | Designation | Skills | Location | Email Address ●

```
Abhishek Jha
Application Development Associate - Accenture

Bengaluru, Karnataka - Email me on Indeed: indeed.com/r/Abhishek-Jha/10e7a8cb732bc43a

• To work for an organization which provides me the opportunity to improve my skills
and knowledge for my individual and company's growth in best possible ways.

Willing to relocate to: Bangalore, Karnataka

WORK EXPERIENCE

Application Development Associate

Accenture -
Bachelor of Engg in Information Technology

Shivaji University Kolhapur - Kolhapur, Maharashtra

2016

SKILLS

Database (Less than 1 year), HTML (Less than 1 year), Linux. (Less than 1
year), MICROSOFT
ACCESS (Less than 1 year), MICROSOFT WINDOWS (Less than 1 year)

ADDITIONAL INFORMATION

TECHNICAL SKILLS:

• Programming Languages: C, C++, Java, .net, php.
• Web Designing: HTML, XML
• Operating Systems: Windows […] Windows Server 2003, Linux.
• Database: MS Access, MS SQL Server 2008, Oracle 10g, MySql.

https://www.indeed.com/r/Afreen-Jamadar/8baf379b705e37c6?isid=rex-download&ikw=download-
```

Fig. 1. Example of a tagged resume.

I used the 'Name' tag as PERSON class, both 'College Name' and ' Companies worked at' as ORGANIZATION class and 'Location' as LOCATION class.

III. Results

Examples of TP

Examples of FP

Examples of FN

Benefits of each of the tool

TABLE I
Results (Person)

NLP Tool	**Person**					
	TP	***FP***	***FN***	***Precision***	***Recall***	***F1 Score***
SpaCy	184	470	34	0.281	0.844	0.422
Stanford	57	268	161	0.175	0.261	0.210
Google	69	2058	149	0.032	0.317	0.059
Amazon	180	168	38	**0.517**	**0.826**	**0.636**
Microsoft	68	122	150	0.358	0.312	0.333

TABLE II
Results (Organization)

NLP Tool	**Organization**					
	TP	***FP***	***FN***	***Precision***	***Recall***	***F1 Score***
SpaCy	157	6030	375	0.025	0.295	0.047
Stanford	84	2169	448	0.037	0.158	0.060
Google	165	3335	367	0.047	0.310	0.082
Amazon	195	1979	337	**0.090**	**0.367**	**0.144**
Microsoft	27	772	505	0.034	0.051	0.041

TABLE III
Results (Location)

NLP Tool	**Location**					
	TP	***FP***	***FN***	***Precision***	***Recall***	***F1 Score***
SpaCy	143	795	60	**0.152**	**0.704**	**0.251**
Stanford	27	851	176	0.031	0.133	0.050
Google	133	1478	70	0.083	0.655	0.147
Amazon	44	978	159	0.043	0.217	0.072
Microsoft	98	737	105	0.117	0.483	0.189