#### Title (EN): Domain-Specific NER Adaptation

In the past years, the Named Entity Recognition (NER) technology has been under an active development and enjoy a significant increase in popularity and usage in the academic and industrial sphere. Nevertheless, vast majority of the developed NER systems have been developed as general-purpose systems. While they can perform well on multiple domains (macro level), on specific domains (micro level) their performance quality might be low. The ultimate goal of the thesis is to develop domain-specific NER models. Guidelines:

- Get familiar with the NER technology and available NER frameworks.
- Investigate possible datasets for domain-specific training of NER.
- Develop NER training datasets for several selected domains (e.g. sports, politics, music, etc.).
- Train a domain-specific NER model using existing frameworks, such as DBpedia Spotlight or StanfordNER.
- Validate and evaluate the developed domain-specific NER models.



Master's thesis

## Domain-specific Name Entity Recognition

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# Acknowledgements

I would like to thank my family and friends for support during writing this thesis.

## **Declaration**

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Klíčová slova

# **Abstract**

Keywords

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## Introduction

#### Motivation

### Goals of the thesis

The main goal of the thesis is to show (test) does extracting information from a global domain gives us better results that extracting information from a specific domain, for example politics domain or any other domain.

### Thesis outline

## Background and related work

#### 1.1 Information extraction

Information extraction (IE) is the task of automatically extracting structured information from unstructured and/or semi-structured machine-readable documents. In most of the cases this activity concerns processing human language texts by means of natural language processing (NLP). Recent activities in multimedia document processing like automatic annotation and content extraction out of images/audio/video could be seen as information extraction.

Information extraction, that is, automatically building a relational database from information contained in unstructured text. Unlike linear-chain models, general CRFs can capture long distance dependencies between labels.

PICTURE!!!!

#### 1.2 NER

NER is the problem of identifying and classifying proper names in text, including locations, such as China; people, such as George Bush; and organizations, such as the United Nations. The named-entity recognition task is, given a sentence, first to segment which words are part of entities, and then to classify each entity by type (person, organization, location, and so on). The challenge of this problem is that many named entities are too rare to appear even in a large training set, and therefore the system must identify them based only on context EVALUATION OF NER Precision, recall, F1 measurement The first step in most IE tasks is to find the proper names or named entities mentioned in a text. The task of named entity recognition (NER) is to find each mention of a named entity in the text and label its type. What constitutes a named entity type is application specific; these commonly include people, places, and organizations but also more specific entities from the names of genes and proteins (Cohen and Demner-Fushman, 2014) to the names of college courses (McCallum, 2005).

Named-entity recognition (NER) (also known as entity identification, entity chunking and entity extraction) is a subtask of information extraction that seeks to locate and classify named entities in text into pre-defined categories such as the names of persons, organizations, locations, expressions of times, quantities, monetary values, percentages, etc.

Most research on NER systems has been structured as taking an unannotated block of text, such as this one:

Jim bought 300 shares of Acme Corp. in 2006.

And producing an annotated block of text that highlights the names of entities:

[Jim]Person bought 300 shares of [Acme Corp.]Organization in [2006]Time.

In this example, a person name consisting of one token, a two-token company name and a temporal expression have been detected and classified.

State-of-the-art NER systems for English produce near-human performance. For example, the best system entering MUC-7 scored 93.39% of F-measure while human annotators scored 97.60% and 96.95%. PICTURE FROM Stanford NER GUI!!!!

#### 1.2.1 Stanford NER

Stanford NER 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.)

### 1.3 RDF/NIF

### 1.4 Domain specific NER

#### 1.5 DBpedia ontology

The DBpedia Ontology is a shallow, cross-domain ontology, which has been manually created based on the most commonly used infoboxes within Wikipedia. The ontology currently covers 685 classes which form a subsumption hierarchy and are described by 2,795 different properties.

With the DBpedia 3.2 release, we introduced a new infobox extraction method based on hand-generated mappings of Wikipedia infoboxes to the DBpedia ontology. The mappings defined fine-granular rules on how to parse infobox values. The mappings also addressed weaknesses in the Wikipedia infobox system, like having different infoboxes for the same class, using different property names for the same property, and not having clearly defined datatypes for property values. Therefore, the instance data within the infobox ontology is much cleaner and better structured than the infobox data within the DBpedia infobox dataset which was generated using the old infobox extraction code.

With the DBpedia 3.5 release, we introduced a public wiki for writing infobox mappings, editing existing ones as well as editing the DBpedia ontology. This allows external contributors to define mappings for the infoboxes they are interested in and to extend the existing DBpedia ontology with additional classes and properties.

Since the DBpedia 3.7 release, the ontology is a directed-acyclic graph, not a tree. Classes may have multiple superclasses, which was important for the mappings to schema.org. A taxonomy can still be constructed by ignoring all superclasses except the one that is specified first in the list and is considered the most important.

## 1.6 Evaluation/training datasets

# **Domain specific NER**

There are parameters of the computer used for tests shown in Table ??.

#### 2.1 Data pre-processing

How data are processed? How we choose those domains (Politics, Sport, Transportation)? Coarse grained Fine grained

### 2.2 Types retrieval

At the main file where we write text we retrieve all types that are available for that text. After that, that text is processed with coarse and fine grained types. In coarse grained we have politics, sport and transportation specific domains. In fine grained in politics domain we retrieve in total 26 types (write them all), which we sort in 11 more specific types like for example Ambassador, Mayor, Deputy etc. are fused in one specific domain Politician. We do the same for sport domain where we retrieve in total 171 types, so those types, same as politics domain, are specified in 8 types, like SportClub, SportsLeague, SportsTeam, Athlete, Coach, OrganizationMember, SportsManager, SportsEvent. We also do the same for transportation domain, where we retrieve in total 78 types and minimized in 14 more specific types like Aircraft, Automobile, Locomotive, MilitaryVehicle, Motorcycle, On-SiteTransportation, Rocket, Ship, SpaceShuttle, SpaceStation, Spacecraft, Train, PublicTransitSystem and Infrastructure.

### 2.3 Domain specification

## 2.4 Data transformation/output for Stanford

How we process data to be ready to use on Stanford NER system?

# **Experiments**

We have provide various types of experiments. In next sections we will discuss more about every provided experiment.

#### 3.1 Goals of the experiments

We set a few goals of the experiments. First of all we waned to test does we will get better results if we run the model of all domains in coarse grained, against the model of all domains in fine grained. In this test we run the models also with all domains texts. Then we get those models and we run it with specific domain texts, in both fine and coarse grained. Also we make experiments with specific domain model runned with domain specific texts, for example, politics domain model in coarse grained is runned with politics domain text also annotated in coarse grained, politics domain model in fine grained is runned with politics domain text also annotated in fine grained, and the same for sport and transportation domains.

### 3.2 List of experiments

Make it like experiment - discussion

#### 3.2.1 Top 10 Links

In this experiment we get the model that is trained with all 3 domains together with coarse grained and we make an experiment with the text that is trained, that means text from all 3 domains annotated with coarse grained. Here we have for every domain 10 abstracts, so in total 30 annotated abstracts. This is our smallest model. How we can see from the picture in politics domain F1 value is lower than in sport and transportation. This results with lower F1 value in total, but still that is very satisfying value, because we have only 1 false positive and 2 false negative words.

Table 3.1: TABLE

Entity	P	R	F1
POLITICS	0,9655	0,9333	0,9492
SPORT	1,0000	1,0000	1,0000
TRANSPORTATION	1,0000	1,0000	1,0000
Totals	0,9811	0,9630	0,9720

In this experiment we get the previous trained model and test with politics coarse grained text. Result is not satisfying, because we have a very low recall, so that results with bad F1 value and very big false negative words. We can clearly say that this is not the model that we want to use in annotating. With those results we can say that all 3 domains together with all text perform better results than all 3 domain model tested with specified domain.

Table 3.2: TABLE

Entity	P	R	F1
POLITICS	0,9655	0,3636	0,5283
Totals	0,9655	0,3636	0,5283

Then we get the same model, and like previous, we tested with sport coarse grained text. So how we can see from the picture, we have perfect result, there is no false positive or false negative words, there are only true positive which results with F1 value of 1.000 (no lost words).

Table 3.3: TABLE

Entity	P	R	F1
SPORT	1,0000	1,0000	1,0000
Totals	1,0000	1,0000	1,0000

Finally we tested this model with our last domain, transportation domain with coarse grained text. Because of very small annotated words we have again perfect results without any false positive or false negative words, same as previous test, there are only true positive matches, which is what we want.

Table 3.4: TABLE

Entity	P	$\mathbf{R}$	F1
TRANSPORTATION	1,0000	1,0000	1,0000
Totals	1,0000	1,0000	1,0000

After we finish testing of all 3 domains trained with coarse grained texts, we move on with new type of experiment, model that contains all our domains and is trained with fine grained texts. We run the same experiment like in

coarse grained, but now text is annotated with fine grained. So, in such small trained model is not surprising that we get the same results as in experiment with coarse grained annotated text.

Table 3.5: TABLE

Entity	P	R	F1
Aircraft	1,0000	1,0000	1,0000
Athlete	1,0000	1,0000	1,0000
Coach	1,0000	1,0000	1,0000
PoliticalParty	0,9600	0,9231	0,9412
Politician	1,0000	1,0000	1,0000
PublicTransitSystem	1,0000	1,0000	1,0000
Ship	1,0000	1,0000	1,0000
SportsClub	1,0000	1,0000	1,0000
SportsEvent	1,0000	1,0000	1,0000
SportsLeague	1,0000	1,0000	1,0000
SportsTeam	1,0000	1,0000	1,0000
Totals	0,9811	0,9630	0,9720

We have repeated the same experiments from previous, but now with fine grained annotation. So we tested our model with politics domain annotated in fine grained and we get exactly the same results like in coarse grained. In this case there is no difference if we use coarse or fine grained trained model, because the results are same.

Table 3.6: TABLE

Entity	P	R	F1
Election	0,0000	0,0000	0,0000
PoliticalParty	0,9600	0,9231	0,9412
Politician	1,0000	1,0000	1,0000
Totals	0,9655	0,3636	0,5283

The sport domain text annotated in fine grained provide also same result as coarse grained annotated domain.

Table 3.7: TABLE

Entity	P	R	F1
Athlete	1,0000	1,0000	1,0000
Coach	1,0000	1,0000	1,0000
SportsClub	1,0000	1,0000	1,0000
SportsEvent	1,0000	1,0000	1,0000
SportsLeague	1,0000	1,0000	1,0000
SportsTeam	1,0000	1,0000	1,0000
Totals	1,0000	1,0000	1,0000

Same as sport domain, the transportation domain Figure ?? text annotated with fine grained, provide also same results.

Table 3.8: TABLE

Entity	P	R	$\mathbf{F1}$
Aircraft	1,0000	1,0000	1,0000
PublicTransitSystem	1,0000	1,0000	1,0000
Ship	1,0000	1,0000	1,0000
Totals	1,0000	1,0000	1,0000

After experimenting with models that are trained with all domains together, we move on with experiments where we create specific models, both coarse and fine grained. First we tested the model that is created with politics text annotated in coarse grained. How we can see from Figure ?? we have a better results than that experiment that we provide in all 3 domains. The F1 value is very big which is the results of low false positive and false negative annotated words.

Table 3.9: TABLE

Entity	P	R	F1
POLITICS	0,9737	0,9610	0,9673
Totals	0,9737	0,9610	0,9673

We also provide the same experiment like previous, but now the model is annotated in fine grained. From Figure ?? is clearly that we have improve our model, here the F1 value is bigger that in coarse grained (see Figure ??) and also false positive annotated words are decreased by 1. That means even we have a complete review of our entities and can see the precision of each entity, this domain, in total, is more precise that coarse grained model and all 3 domains in coarse and fine grained.

Table 3.10: TABLE

Entity	P	R	F1
Election	1,0000	0,9333	0,9655
PoliticalParty	0,9600	0,9231	0,9412
Politician	1,0000	1,0000	1,0000
Totals	0,9867	0,9610	0,9737

From here, with this small amount of data we can say that it's better to use a politics specific domain, in fine grained, than a global domain, because in global domain we have 28 words annotated as true positive, but in a politics specific coarse grained domain we have 74 words annotated as true positive, which is very big difference, if we want to be precise.

We repeated the experiment for sport specific domain, but in this case the results are exactly the same in coarse and fine grained (see Figure ?? and Figure ?? as well as in all 3 domains also in coarse and fine grained

Table 3.11: TABLE

Entity	P	R	$\mathbf{F1}$
SPORT	1,0000	1,0000	1,0000
Totals	1,0000	1,0000	1,0000

Table 3.12: TABLE

Entity	P	R	F1
Athlete	1,0000	1,0000	1,0000
Coach	1,0000	1,0000	1,0000
SportsClub	1,0000	1,0000	1,0000
SportsEvent	1,0000	1,0000	1,0000
SportsLeague	1,0000	1,0000	1,0000
SportsTeam	1,0000	1,0000	1,0000
Totals	1,0000	1,0000	1,0000

This model in really small, only 15 annotated words, that's because we cannot make a conclusion which model is better to use. But if we speak about performance, of coarse the better solution is specified domain.

The transportation model, like a sport domain, is also a very small, only 9 annotated words. We provide the experiments for coarse grained (see Figure ??) and we get same results as in all 3 domains (see Figure ??). Same is happening for the fine grained domain (see Figure ??). In such a small trained domain, we cannot clearly say which model is better to use.

Table 3.13: TABLE

Entity	P	R	F1
TRANSPORTATION	1,0000	1,0000	1,0000
Totals	1,0000	1,0000	1,0000

Table 3.14: TABLE

Entity	P	R	F1
Aircraft	1,0000	1,0000	1,0000
PublicTransitSystem	1,0000	1,0000	1,0000
Ship	1,0000	1,0000	1,0000
Totals	1,0000	1,0000	1,0000

In conclusion of this subsection, we can say that our strategy for creating a specific domain pays off, because in those domains we have a better results that in global domains. But let see in subsection 3.2.2 how domains will behave with a bigger data(text).

#### 3.2.2 Top 20 Links

In subsection 3.2.1 we provide various experiments with different models. Now in this subsection we will repeat those experiments, but now we doubled the number of text to every domain, so we have 20 abstracts for every domain, in total 60 abstract. Those models, like previous, are trained in both coarse and fine grained. The first experiment in Figure ?? is now rerunned with a bigger model and text. From Figure ?? we can see that there are more annotated words and surprisingly better results than in previous domain. Then we tested the model with politics domain text in coarse grained annotation. Again the results are quite better than previous experiment (see Figure ??), also now there is no false positive words, but this is still not satisfying. After that we tested this model with sport domain text in coarse grained annotation (see Figure ??). And like in previous experiment (see Figure ??) we have a perfect results, so we can say that this kind of model with very small domain annotated words is good to use. And finally we tested the model with transportation domain text in coarse grained annotation (see Figure ??). Figure ?? show us that the model annotated some false positive word with SPORT, which even we have a perfect F1 value for transportation domain, in overall calculation, because of that word we have a lower F1 value than experiment in Figure ??.

Table 3.15: TABLE

Entity	P	R	F1
POLITICS	1,0000	0,9615	0,9804
SPORT	1,0000	1,0000	1,0000
TRANSPORTATION	1,0000	1,0000	1,0000
Totals	1,0000	0,9780	0,9889

Table 3.16: TABLE

Entity	P	R	F1
POLITICS	1,0000	0,3906	0,5618
Totals	1,0000	0,3906	0,5618

Table 3.17: TABLE

Entity	P	R	F1
SPORT	1,0000	1,0000	1,0000
Totals	1,0000	1,0000	1,0000

Table 3.18: TABLE

Entity	P	R	F1
SPORT	0,0000	1,0000	0,0000
TRANSPORTATION	1,0000	1,0000	1,0000
Totals	0,9231	1,0000	0,9600

Similarly like experiment with a coarse grained model, we repeated the same experiments, but now, of coarse, with fine grained model. We test the trained model with text from all 3 domains together in fine grained annotation, and how we can see from Figure ?? the results are quite worst that in experiment with coarse grained (see Figure ??), but better that the experiment where we have only 10 abstract (see Figure??). Furthermore we test the model with politics text, and how we can see from Figure?? again results are not even close to previous experiment with all 3 domains together where we have better results like overall also in politics domain. Then we move on with a sport text (see Figure ??) and again we have perfect results like in coarse grained (see Figure ??) and the experiment with 10 abstract (see Figure ??). And final experiment for this model is transportation text. Figure ?? shows us that results are worst that in coarse grained (see Figure??). Now we do not have any false positive word annotated with SPORT domain, but we have a lower number of annotated words which results with a lower F1 value in total.

Table 3.19: TABLE

Entity	P	R	F1
Aircraft	1,0000	0,5000	0,6667
Athlete	1,0000	1,0000	1,0000
Coach	1,0000	1,0000	1,0000
Infrastructure	1,0000	0,5000	0,6667
PoliticalParty	1,0000	0,9512	0,9750
Politician	1,0000	1,0000	1,0000
Ship	1,0000	1,0000	1,0000
SpaceShuttle	1,0000	1,0000	1,0000
SpaceStation	1,0000	1,0000	1,0000
SportsClub	1,0000	1,0000	1,0000
SportsEvent	1,0000	1,0000	1,0000
SportsLeague	1,0000	1,0000	1,0000
SportsTeam	1,0000	1,0000	1,0000
Totals	1,0000	0,9560	0,9775

Table 3.20: TABLE

Entity	P	R	F1
Election	0,0000	0,0000	0,0000
PoliticalParty	1,0000	0,9512	0,9750
Politician	1,0000	0,2000	0,3333
Totals	1,0000	0,3906	0,5618

Table 3.21: TABLE

Entity	P	R	F1
Athlete	1,0000	1,0000	1,0000
Coach	1,0000	1,0000	1,0000
SportsClub	1,0000	1,0000	1,0000
SportsEvent	1,0000	1,0000	1,0000
SportsLeague	1,0000	1,0000	1,0000
SportsTeam	1,0000	1,0000	1,0000
Totals	1,0000	1,0000	1,0000

Table 3.22: TABLE

Entity	P	R	F1
Aircraft	1,0000	0,5000	0,6667
Infrastructure	1,0000	0,5000	0,6667
Ship	1,0000	1,0000	1,0000
SpaceShuttle	1,0000	1,0000	1,0000
SpaceStation	1,0000	1,0000	1,0000
SportsTeam	0,0000	1,0000	0,0000
Totals	0,9091	0,8333	0,8696

After we finish the experiments with models that are trained with texts from every domain, we do tests with models that are trained with texts from a particular domain (politics, sport and transportation). Figure ?? shows the output of politics coarse grain specified domain, where we can see that we have a way more better results than in experiment with a model trained with texts from all 3 domains (see Figure ?? and Figure ??). The politics specific domain finds 125 true positive words unlike the experiments with all 3 domains that gives us only 50 true positive annotated words. However we repeated this experiment, but now with model trained in fine grained. Figure ?? shows the result of experiment, where we can see that there is no false positive annotated word like in previous experiment (see Figure ??), which result with a better F1 value in total.

Table 3.23: TABLE

Entity	P	R	F1
POLITICS	0,9921	0,9766	0,9843
Totals	0,9655	0,3636	0,5283

Table 3.24: TABLE

Entity	P	R	F1
Election	1,0000	0,9688	0,9841
PoliticalParty	1,0000	0,9512	0,9750
Politician	1,0000	1,0000	1,0000
Totals	1,0000	0,9766	0,9881

Sport specific domain do not disappointed us. Figure ?? show the output of experiment in coarse grained and Figure ?? show the output of experiment in fine grained. Both experiment same as experiments with all 3 domains together (see Figure ??, Figure ??, Figure ??, Figure ??) give us perfect results. But if you want to be more precise, we recommend to use the specific model, because is fastest of reading words.

Table 3.25: TABLE

Entity	P	R	<b>F</b> 1
SPORT	1,0000	1,0000	1,0000
Totals	1,0000	1,0000	1,0000

Table 3.26: TABLE

Entity	P	R	F1
Athlete	1,0000	1,0000	1,0000
Coach	1,0000	1,0000	1,0000
SportsClub	1,0000	1,0000	1,0000
SportsEvent	1,0000	1,0000	1,0000
SportsLeague	1,0000	1,0000	1,0000
SportsTeam	1,0000	1,0000	1,0000
Totals	1,0000	1,0000	1,0000

At the end we make experiments with a transportation specific domain. In Figure ?? we can see that our model gives us a worst results that experiment in all 3 domains. For instance experiment in Figure ?? gives us a perfect annotation with 1.0000 value at F1, also experiment in Figure ?? gives the same result like previous experiment, but here because of false positive annotated word in SPORT domain in total we have a lower value in F1. In overall experiments in all 3 domains gives a better result that the experiment in specific domain. Of coarse we make an experiment with model that is trained with fine grained text. How Figure ?? shows that this model even gives worst result that the experiment with coarse grained model, and also worst results than the experiment in Figure ??.

Table 3.27: TABLE

Entity	P	R	F1
TRANSPORTATION	1,0000	0,8333	0,9091
Totals	1,0000	0,8333	0,9091

Table 3.28: TABLE

Entity	P	R	F1
Aircraft	1,0000	0,5000	0,6667
Infrastructure	1,0000	0,5000	0,6667
Ship	1,0000	1,0000	1,0000
SpaceShuttle	1,0000	1,0000	1,0000
SpaceStation	1,0000	1,0000	1,0000
Totals	1,0000	0,7500	0,8571

## **3.2.3** Top 40 Links

Table 3.29: TABLE

Entity	P	$\mathbf{R}$	<b>F</b> 1
POLITICS	0,9890	0,9375	0,9626
SPORT	1,0000	1,0000	1,0000
TRANSPORTATION	1,0000	0,9846	0,9922
Totals	0,9960	0,9724	0,9841

Table 3.30: TABLE

Entity	P	$\mathbf{R}$	$\mathbf{F1}$
POLITICS	0,9890	0,3529	0,5202
Totals	0,9890	0,3529	0,5202

Table 3.31: TABLE

Entity	P	R	F1
SPORT	1,0000	1,0000	1,0000
Totals	1,0000	1,0000	1,0000

Table 3.32: TABLE

Entity	P	R	F1
SPORT	0,0000	1,0000	0,0000
TRANSPORTATION	1,0000	0,9846	0,9922
Totals	0,9697	0,9846	0,9771

Table 3.33: TABLE

Entity	P	R	<b>F</b> 1
Aircraft	1,0000	1,0000	1,0000
Athlete	1,0000	1,0000	1,0000
Coach	1,0000	1,0000	1,0000
Infrastructure	1,0000	1,0000	1,0000
PoliticalParty	0,9863	0,9730	0,9796
Politician	1,0000	0,8182	0,9000
PublicTransitSystem	1,0000	1,0000	1,0000
Ship	1,0000	1,0000	1,0000
SpaceShuttle	1,0000	1,0000	1,0000
SpaceStation	1,0000	1,0000	1,0000
SportsClub	1,0000	1,0000	1,0000
SportsEvent	1,0000	1,0000	1,0000
SportsLeague	1,0000	1,0000	1,0000
SportsTeam	1,0000	1,0000	1,0000
Totals	0,9960	0,9764	0,9861

Table 3.34: TABLE

Entity	P	R	F1
Election	0,0000	0,0000	0,0000
PoliticalParty	0,9863	0,9730	0,9796
Politician	1,0000	$0,\!1565$	0,2707
Totals	0,9890	0,3529	0,5202

Table 3.35: TABLE

Entity	P	R	F1
Athlete	1,0000	1,0000	1,0000
Coach	1,0000	1,0000	1,0000
SportsClub	1,0000	1,0000	1,0000
SportsEvent	1,0000	1,0000	1,0000
SportsLeague	1,0000	1,0000	1,0000
SportsTeam	1,0000	1,0000	1,0000
Totals	1,0000	1,0000	1,0000

Table 3.36: TABLE

Entity	P	R	F1
Aircraft	1,0000	1,0000	1,0000
Infrastructure	1,0000	1,0000	1,0000
PublicTransitSystem	1,0000	1,0000	1,0000
Ship	1,0000	1,0000	1,0000
SpaceShuttle	1,0000	1,0000	1,0000
SpaceStation	1,0000	1,0000	1,0000
SportsTeam	0,0000	1,0000	0,0000
Totals	0,9701	1,0000	0,9848

Table 3.37: TABLE

Entity	P	R	<b>F</b> 1
POLITICS	0,9921	0,9804	0,9862
Totals	0,9921	0,9804	0,9862

Table 3.38: TABLE

Entity	P	R	F1
Election	1,0000	0,9848	0,9924
PoliticalParty	0,9863	0,9730	0,9796
Politician	1,0000	1,0000	1,0000
Totals	0,9960	0,9882	0,9921

Table 3.39: TABLE

Entity	P	R	F1
SPORT	1,0000	1,0000	1,0000
Totals	1,0000	1,0000	1,0000

Table 3.40: TABLE

Entity	P	R	F1
Athlete	1,0000	1,0000	1,0000
Coach	1,0000	1,0000	1,0000
SportsClub	1,0000	0,9474	0,9730
SportsEvent	1,0000	1,0000	1,0000
SportsLeague	1,0000	1,0000	1,0000
SportsTeam	1,0000	1,0000	1,0000
Totals	1,0000	0,9890	0,9945

Table 3.41: TABLE

Entity	P	R	F1
TRANSPORTATION	1,0000	0,9846	0,9922
Totals	1,0000	0,9846	0,9922

Table 3.42: TABLE

Entity	P	R	F1
Aircraft	1,0000	1,0000	1,0000
Infrastructure	1,0000	1,0000	1,0000
PublicTransitSystem	1,0000	0,9630	0,9811
Ship	1,0000	1,0000	1,0000
SpaceShuttle	1,0000	1,0000	1,0000
SpaceStation	1,0000	1,0000	1,0000
SportsTeam	0,0000	1,0000	0,0000
Totals	1,0000	0,9846	0,9922

## **3.2.4** Top 100 Links

Table 3.43: TABLE

Entity	P	R	F1
POLITICS	0,9920	0,9612	0,9764
SPORT	0,9963	0,9926	0,9944
TRANSPORTATION	1,0000	0,9735	0,9865
Totals	0,9952	0,9766	0,9856

Table 3.44: TABLE

Entity	P	R	F1
POLITICS	0,9920	0,3615	0,5299
Totals	0,9920	0,3615	0,5299

Table 3.45: TABLE

Entity	P	R	F1
SPORT	0,9962	0,9888	0,9925
Totals	0,9962	0,9888	0,9925

Table 3.46: TABLE

Entity	P	R	F1
SPORT	0,0000	1,0000	0,0000
TRANSPORTATION	1,0000	0,9735	0,9865
Totals	0,9821	0,9735	0,9778

Table 3.47: TABLE

Entity	P	R	F1
Aircraft	1,0000	0,6957	0,8205
Athlete	1,0000	0,4167	0,5882
Automobile	1,0000	1,0000	1,0000
Coach	1,0000	0,6667	0,8000
Infrastructure	1,0000	1,0000	1,0000
PoliticalParty	0,8774	0,6700	0,7598
Politician	1,0000	0,7455	0,8542
PublicTransitSystem	0,9744	0,7308	0,8352
Ship	1,0000	0,6000	0,7500
SpaceShuttle	1,0000	1,0000	1,0000
SpaceStation	1,0000	1,0000	1,0000
SportsClub	0,9512	0,9398	0,9455
SportsEvent	0,9737	0,8605	0,9136
SportsLeague	0,9500	0,8636	0,9048
SportsManager	1,0000	1,0000	1,0000
SportsTeam	1,0000	0,6364	0,7778
Train	1,0000	1,0000	1,0000
Totals	0,9452	0,7535	0,8385

Table 3.48: TABLE

Entity	P	R	F1
Election	0,0000	0,0000	0,0000
PoliticalParty	0,8774	0,6700	0,7598
Politician	1,0000	0,1285	0,2278
SportsEvent	0,0000	1,0000	0,0000
Totals	0,8985	0,2580	0,4009

Table 3.49: TABLE

Entity	P	R	F1
Athlete	1,0000	0,4167	0,5882
Coach	1,0000	0,6667	0,8000
SportsClub	0,9506	0,9390	0,9448
SportsEvent	1,0000	0,8605	0,9250
SportsLeague	0,9500	0,8636	0,9048
SportsManager	1,0000	1,0000	1,0000
SportsTeam	1,0000	0,6250	0,7692
Totals	0,9683	0,7985	0,8753

Table 3.50: TABLE

Entity	P	R	F1
Aircraft	1,0000	0,6957	0,8205
Automobile	1,0000	1,0000	1,0000
Infrastructure	1,0000	1,0000	1,0000
PublicTransitSystem	0,9744	0,7308	0,8352
Ship	1,0000	0,6000	0,7500
SpaceShuttle	1,0000	1,0000	1,0000
SpaceStation	1,0000	1,0000	1,0000
SportsClub	0,0000	1,0000	0,0000
SportsTeam	0,0000	1,0000	0,0000
Train	1,0000	1,0000	1,0000
Totals	0,9677	0,7965	0,8738

Table 3.51: TABLE

Entity	P	R	F1
POLITICS	0,9956	0,9898	0,9927
Totals	0,9956	0,9898	0,9927

Table 3.52: TABLE

Entity	P	R	F1
Election	1,0000	0,9878	0,9939
PoliticalParty	0,9950	0,9852	0,9901
Politician	0,9937	0,9906	0,9922
Totals	0,9956	0,9883	0,9920

Table 3.53: TABLE

Entity	P	R	F1
SPORT	0,9963	0,9963	0,9963
Totals	0,9963	0,9963	0,9963

Table 3.54: TABLE

Entity	P	R	F1
Athlete	1,0000	0,9722	0,9859
Coach	1,0000	1,0000	1,0000
SportsClub	1,0000	0,9878	0,9939
SportsEvent	1,0000	0,9767	0,9882
SportsLeague	1,0000	1,0000	1,0000
SportsManager	1,0000	1,0000	1,0000
SportsTeam	1,0000	1,0000	1,0000
Totals	1,0000	0,9888	0,9944

Table 3.55: TABLE

Entity	P	$\mathbf{R}$	<b>F</b> 1
TRANSPORTATION	1,0000	0,9912	0,9956
Totals	1,0000	0,9912	0,9956

Table 3.56: TABLE

Entity	P	R	F1
Aircraft	1,0000	1,0000	1,0000
Automobile	1,0000	1,0000	1,0000
Infrastructure	1,0000	1,0000	1,0000
PublicTransitSystem	1,0000	0,9808	0,9903
Ship	1,0000	1,0000	1,0000
SpaceShuttle	1,0000	0,6667	0,8000
SpaceStation	1,0000	1,0000	1,0000
Train	1,0000	1,0000	1,0000
Totals	1,0000	0,9735	0,9865

## 3.2.5 Top 300 Links

MAIN EXPERIMENT This is our main experiment where other experiments will be compared with this one. This model is trained with top 300 Wikipedia abstracts based on PageRank. The text is annotated in coarse grained and has around 2300 annotated words in total. First experiment that we do with this model is that we run it with the same text that model is

created. Results are not bad at all, we are above 95%, which is great number for such middle weight model.

Table 3.57: All 3 domain model with top 300 abstracts, tested with all 3 domain texts

Entity	P	R	F1
POLITICS	0,9872	0,9462	0,9662
SPORT	0,9846	0,9629	0,9736
TRANSPORTATION	0,9940	0,9823	0,9881
Totals	0,9875	0,9625	0,9748

Table 3.58: TABLE

Entity	P	R	F1
POLITICS	0,9839	0,4025	0,5713
TRANSPORTATION	0,0000	1,0000	0,0000
Totals	0,9792	0,4025	0,5705

Table 3.59: TABLE

Entity	P	$\mathbf{R}$	<b>F</b> 1
POLITICS	0,0000	1,0000	0,0000
SPORT	0,9846	0,9628	0,9736
TRANSPORTATION	0,0000	1,0000	0,0000
Totals	0,9819	0,9628	0,9722

Table 3.60: TABLE

Entity	P	R	F1
SPORT	0,0000	1,0000	0,0000
TRANSPORTATION	0,9940	0,9822	0,9880
Totals	0,9861	0,9822	0,9841

Table 3.61: TABLE

Entity	P	R	F1
Aircraft	1,0000	1,0000	1,0000
Athlete	1,0000	0,9802	0,9900
Automobile	1,0000	1,0000	1,0000
Coach	1,0000	1,0000	1,0000
Infrastructure	1,0000	0,9820	0,9909
PoliticalParty	0,9860	0,9628	0,9743
Politician	1,0000	0,9353	0,9665
PublicTransitSystem	0,9919	0,9839	0,9879
Ship	1,0000	1,0000	1,0000
SpaceShuttle	1,0000	1,0000	1,0000
SpaceStation	1,0000	1,0000	1,0000
SportsClub	0,9796	0,9683	0,9739
SportsEvent	1,0000	0,9242	0,9606
SportsLeague	0,9647	0,9805	0,9725
SportsManager	1,0000	0,9423	0,9703
SportsTeam	1,0000	0,9805	0,9902
Train	1,0000	1,0000	1,0000
Totals	0,9880	0,9712	0,9795

Table 3.62: TABLE

Entity	P	R	F1
Election	0,0000	0,0000	0,0000
PoliticalParty	0,9860	0,9628	0,9743
Politician	1,0000	0,1849	0,3120
PublicTransitSystem	0,0000	1,0000	0,0000
Ship	0,0000	1,0000	0,0000
SportsLeague	0,0000	1,0000	0,0000
Totals	0,9825	0,4072	0,5758

Table 3.63: TABLE

Entity	P	R	F1
Athlete	1,0000	0,9802	0,9900
Coach	1,0000	1,0000	1,0000
Politician	0,0000	1,0000	0,0000
SportsClub	0,9794	0,9680	0,9737
SportsEvent	1,0000	0,9242	0,9606
SportsLeague	0,9678	0,9805	0,9741
SportsManager	1,0000	0,9423	0,9703
SportsTeam	1,0000	0,9804	0,9901
Train	0,0000	1,0000	0,0000
Totals	0,9821	0,9716	0,9768

Table 3.64: TABLE

Entity	P	R	F1
Aircraft	1,0000	1,0000	1,0000
Automobile	1,0000	1,0000	1,0000
Infrastructure	1,0000	0,9820	0,9909
Politician	0,0000	1,0000	0,0000
PublicTransitSystem	0,9918	0,9837	0,9878
Ship	1,0000	1,0000	1,0000
SpaceShuttle	1,0000	1,0000	1,0000
SpaceStation	1,0000	1,0000	1,0000
SportsClub	0,0000	1,0000	0,0000
SportsTeam	0,0000	1,0000	0,0000
Train	1,0000	1,0000	1,0000
Totals	0,9862	0,9881	0,9871

Table 3.65: TABLE

Entity	P	$\mathbf{R}$	$\mathbf{F1}$
POLITICS	0,8039	0,6779	0,7355
Totals	0,8039	0,6779	0,7355

Table 3.66: TABLE

Entity	P	R	F1
Election	0,8240	0,6398	0,7203
PoliticalParty	0,8100	0,7006	0,7513
Politician	0,8599	0,7234	0,7858
Totals	0,8354	0,6980	0,7606

Table 3.67: TABLE

Entity	P	R	F1
SPORT	0,9432	0,8839	0,9126
Totals	0,9432	0,8839	0,9126

Table 3.68: TABLE

Entity	P	R	F1
Athlete	0,9713	0,8366	0,8989
Coach	1,0000	0,7500	0,8571
SportsClub	0,9453	0,9041	0,9242
SportsEvent	1,0000	0,7879	0,8814
SportsLeague	0,9418	0,8958	0,9182
SportsManager	1,0000	0,9615	0,9804
SportsTeam	0,9845	0,8301	0,9007
Totals	0,9592	0,8750	0,9152

Table 3.69: TABLE

Entity	P	R	F1
TRANSPORTATION	0,9583	0,9109	0,9340
Totals	0,9583	0,9109	0,9340

Table 3.70: TABLE

Entity	P	R	F1
Aircraft	0,9659	0,8333	0,8947
Automobile	1,0000	0,8000	0,8889
Infrastructure	0,9550	0,9550	0,9550
PublicTransitSystem	0,9662	0,9309	0,9482
Ship	1,0000	0,6429	0,7826
SpaceShuttle	1,0000	0,8333	0,9091
SpaceStation	0,0000	1,0000	0,0000
Train	1,0000	1,0000	1,0000
Totals	0,9660	0,9010	0,9324

## $3.2.6\quad Top\ 400\ Links$

Table 3.71: TABLE

Entity	P	R	F1
POLITICS	0,9804	0,9434	0,9615
SPORT	0,9832	0,9590	0,9709
TRANSPORTATION	0,9941	0,9754	0,9847
Totals	0,9849	0,9584	0,9714

Table 3.72: TABLE

Entity	P	$\mathbf{R}$	$\mathbf{F1}$
POLITICS	0,9754	0,4082	0,5756
SPORT	0,0000	1,0000	0,0000
TRANSPORTATION	0,0000	1,0000	0,0000
Totals	0,9531	0,4082	0,5716

Table 3.73: TABLE

Entity	P	R	F1
POLITICS	0,0000	1,0000	0,0000
SPORT	0,9837	0,9588	0,9711
TRANSPORTATION	0,0000	1,0000	0,0000
Totals	0,9805	0,9588	0,9695

Table 3.74: TABLE

Entity	P	R	F1
POLITICS	0,0000	1,0000	0,0000
SPORT	0,0000	1,0000	0,0000
TRANSPORTATION	0,9939	0,9762	0,9806
Totals	0,9861	0,9822	0,9841

Table 3.75: TABLE

Entity	P	R	<b>F</b> 1
Aircraft	1,0000	1,0000	1,0000
Athlete	1,0000	0,9899	0,9949
Automobile	1,0000	1,0000	1,0000
Coach	1,0000	1,0000	1,0000
Infrastructure	1,0000	0,9896	0,9948
PoliticalParty	0,9766	0,9486	0,9624
Politician	1,0000	0,9893	0,9946
PublicTransitSystem	0,9935	0,9776	0,9855
Ship	1,0000	0,9231	0,9600
SpaceShuttle	1,0000	1,0000	1,0000
SpaceStation	1,0000	1,0000	1,0000
SportsClub	0,9796	0,9658	0,9726
SportsEvent	1,0000	0,8636	0,9268
SportsLeague	0,9698	0,9835	0,9766
SportsManager	1,0000	0,9726	0,9861
SportsTeam	1,0000	0,9851	0,9925
Train	1,0000	1,0000	1,0000
Totals	0,9870	0,9709	0,9789

Table 3.76: TABLE

Entity	P	R	F1
Aircraft	0,0000	1,0000	0,0000
Election	0,0000	0,0000	0,0000
PoliticalParty	0,9766	0,9484	0,9623
Politician	1,0000	0,2092	0,3460
PublicTransitSystem	0,0000	1,0000	0,0000
Ship	0,0000	1,0000	0,0000
SportsClub	0,0000	1,0000	0,0000
SportsLeague	0,0000	1,0000	0,0000
Totals	0,9619	0,4151	0,5799

Table 3.77: TABLE

Entity	P	R	F1
Aircraft	0,0000	1,0000	0,0000
Athlete	1,0000	0,9899	0,9949
Coach	1,0000	1,0000	1,0000
PoliticalParty	0,0000	1,0000	0,0000
Politician	0,0000	1,0000	0,0000
SportsClub	0,9794	0,9654	0,9724
SportsEvent	1,0000	0,8636	0,9268
SportsLeague	0,9696	0,9834	0,9765
SportsManager	1,0000	0,9726	0,9861
SportsTeam	1,0000	0,9850	0,9924
Train	0,0000	1,0000	0,0000
Totals	0,9821	0,9721	0,9770

Table 3.78: TABLE

Entity	P	R	F1
Aircraft	1,0000	1,0000	1,0000
Automobile	1,0000	1,0000	1,0000
Infrastructure	1,0000	0,9896	0,9948
PoliticalParty	0,0000	1,0000	0,0000
Politician	0,0000	1,0000	0,0000
PublicTransitSystem	0,9934	0,9773	0,9853
Ship	1,0000	1,0000	1,0000
SpaceShuttle	1,0000	1,0000	1,0000
SpaceStation	1,0000	1,0000	1,0000
SportsClub	0,0000	1,0000	0,0000
SportsTeam	0,0000	1,0000	0,0000
Train	1,0000	1,0000	1,0000
Totals	0,9866	0,9866	0,9866

Table 3.79: TABLE

Entity	P	R	F1
POLITICS	0,9866	0,9479	0,9669
Totals	0,9866	0,9479	0,9669

Table 3.80: TABLE

Entity	P	R	F1
Election	0,9975	0,9590	0,9779
PoliticalParty	0,9767	0,9530	0,9647
Politician	0,9977	0,9920	0,9948
Totals	0,9906	0,9717	0,9810

Table 3.81: TABLE

Enti	ty	P	${f R}$	F1
SPO	RT	0,9858	0,9676	0,9766
Tota	als	0,9858	0,8676	0,9766

Table 3.82: TABLE

Entity	P	R	F1
Athlete	1,0000	0,9731	0,9863
Coach	1,0000	1,0000	1,0000
SportsClub	0,9815	0,9715	0,9765
SportsEvent	1,0000	0,9091	0,9524
SportsLeague	0,9718	0,9787	0,9752
SportsManager	1,0000	0,9726	0,9850
SportsTeam	1,0000	0,9900	0,9796
Totals	0,9865	0,9727	0,9796

Table 3.83: TABLE

Entity	P	R	F1
TRANSPORTATION	0,9954	0,9747	0,9850
Totals	0,9954	0,9747	0,9850

Table 3.84: TABLE

Entity	P	R	F1
Aircraft	1,0000	0,9835	0,9917
Automobile	1,0000	0,9583	0,9787
Infrastructure	1,0000	0,9948	0,9974
PublicTransitSystem	0,9934	0,9773	0,9853
Ship	1,0000	1,0000	1,0000
SpaceShuttle	1,0000	0,6667	0,8000
SpaceStation	1,0000	1,0000	1,0000
Train	1,0000	1,0000	1,0000
Totals	0,9970	0,9807	0,9888

## 3.2.7 Top 500 Links

Table 3.85: TABLE

Entity	P	R	F1
POLITICS	0,9788	0,9444	0,9613
SPORT	0,9850	0,9596	0,9721
TRANSPORTATION	0,9962	0,9750	0,9855
Totals	0,9857	0,9587	0,9720

Table 3.86: TABLE

Entity	P	$\mathbf{R}$	<b>F</b> 1
POLITICS	0,9734	0,4095	0,5765
SPORT	0,0000	1,0000	0,0000
TRANSPORTATION	0,0000	1,0000	0,0000
Totals	0,9549	0,4095	$0,\!5732$

Table 3.87: TABLE

Entity	P	R	F1
POLITICS	0,0000	1,0000	0,0000
SPORT	0,9849	0,9594	0,9720
TRANSPORTATION	0,0000	1,0000	0,0000
Totals	0,9788	0,9594	0,9690

Table 3.88: TABLE

Entity	P	R	F1
POLITICS	0,0000	1,0000	0,0000
SPORT	0,0000	1,0000	0,0000
TRANSPORTATION	0,9961	0,9769	0,9864
Totals	0,9870	0,9769	0,9819

Table 3.89: TABLE

Entity	P	R	F1
Aircraft	1,0000	0,9929	0,9964
Athlete	1,0000	0,9896	0,9948
Automobile	1,0000	1,0000	1,0000
Coach	1,0000	1,0000	1,0000
Infrastructure	1,0000	0,9783	0,9890
PoliticalParty	0,9775	0,9403	0,9585
Politician	1,0000	0,9874	0,9937
PublicTransitSystem	0,9944	0,9807	0,9875
Ship	1,0000	0,9259	0,9615
SpaceShuttle	1,0000	1,0000	1,0000
SpaceStation	1,0000	1,0000	1,0000
SportsClub	0,9756	0,9553	0,9654
SportsEvent	1,0000	0,8796	0,9360
SportsLeague	0,9700	0,9810	0,9755
SportsManager	1,0000	0,9780	0,9889
SportsTeam	1,0000	0,9831	0,9915
Train	1,0000	1,0000	1,0000
Totals	0,9866	0,9669	0,9766

Table 3.90: TABLE

Entity	P	R	F1
Aircraft	0,0000	1,0000	0,0000
Election	0,0000	0,0000	0,0000
PoliticalParty	0,9774	0,9400	0,9583
Politician	1,0000	0,2171	0,3567
PublicTransitSystem	0,0000	1,0000	0,0000
Ship	0,0000	1,0000	0,0000
SportsClub	0,0000	1,0000	0,0000
SportsLeague	0,0000	1,0000	0,0000
Totals	0,9631	0,4138	0,5789

Table 3.91: TABLE

Entity	P	R	F1
Aircraft	0,0000	1,0000	0,0000
Athlete	1,0000	0,9896	0,9948
Coach	1,0000	1,0000	1,0000
PoliticalParty	0,0000	1,0000	0,0000
Politician	0,0000	1,0000	0,0000
SportsClub	0,9753	0,9549	0,9650
SportsEvent	1,0000	0,8796	0,9360
SportsLeague	0,9717	0,9810	0,9763
SportsManager	1,0000	0,9780	0,9889
SportsTeam	1,0000	0,9831	0,9915
Train	0,0000	1,0000	0,0000
Totals	0,9785	0,9690	0,9737

Table 3.92: TABLE

Entity	P	R	F1
Aircraft	1,0000	0,9927	0,9963
Automobile	1,0000	1,0000	1,0000
Infrastructure	1,0000	0,9783	0,9890
PoliticalParty	0,0000	1,0000	0,0000
Politician	0,0000	1,0000	0,0000
PublicTransitSystem	0,9943	0,9804	0,9873
Ship	1,0000	1,0000	1,0000
SpaceShuttle	1,0000	1,0000	1,0000
SpaceStation	1,0000	1,0000	1,0000
SportsClub	0,0000	1,0000	0,0000
SportsTeam	0,0000	1,0000	0,0000
Train	1,0000	1,0000	1,0000
Totals	0,9884	0,9833	0,9858

Table 3.93: TABLE

Entity	P	R	F1
POLITICS	0,9808	0,9450	0,9626
Totals	0,9808	0,9450	0,9626

Table 3.94: TABLE

Entity	P	R	F1
Election	0,9915	0,9393	0,9647
PoliticalParty	0,9777	0,9502	0,9637
Politician	0,9962	0,9877	0,9919
Totals	0,9890	0,9648	0,9768

Table 3.95: TABLE

Entity	P	R	F1
SPORT	0,9856	0,9706	0,9780
Totals	0,9856	0,9706	0,9780

Table 3.96: TABLE

Entity	P	R	F1
Athlete	1,0000	0,9791	0,9894
Coach	1,0000	1,0000	1,0000
SportsClub	0,9771	0,9630	0,9700
SportsEvent	1,0000	0,9074	0,9515
SportsLeague	0,9755	0,9848	0,9801
SportsManager	1,0000	0,9780	0,9889
SportsTeam	1,0000	0,9915	0,9957
Totals	0,9861	0,9731	0,9796

Table 3.97: TABLE

Entity	P	R	F1
TRANSPORTATION	0,9974	0,9756	0,9864
Totals	0,9974	0,9756	0,9864

Table 3.98: TABLE

Entity	P	R	F1
Aircraft	1,0000	0,9781	0,9889
Automobile	1,0000	0,8800	0,9362
Infrastructure	1,0000	0,9870	0,9934
PublicTransitSystem	0,9915	0,9804	0,9860
Ship	1,0000	1,0000	1,0000
SpaceShuttle	1,0000	0,6667	0,8000
SpaceStation	1,0000	1,0000	1,0000
Train	1,0000	1,0000	1,0000
Totals	0,9961	0,9769	0,9864

Figure 3.2: All 3 Domains Fine Grained Top 500 Links With All 3 Domains Fine Grained Top 500 Links And All 3 Domains Fine Grained Top 500 Links With Lower Page Rank

## 3.2.8 MIXED

Figure 3.1: All 3 Domains Fine Grained Top 300 With All 3 Domains Fine Grained Top 500 Links And All 3 Domains Fine Grained Top 500 Links With Lower PageRank

```
CRFCLassifier tagged 336613 words in 1 documents at 2685,15 words per second.

Entity P R F1 TP FP FN

Aircraft 0,6667 0,1111 0,1905 8 4 64

Athlete 0,4675 0,1268 0,1994 36 41 248

Automobile 0,0000 0,0000 0,0000 0 0 0 36

Coach 0,0000 0,0000 0,0000 0 0 0 14

Infrastructure 0,5352 0,1387 0,2203 38 33 236

Locomotive 0,0000 0,0000 0,0000 0 0 0 1

OrganisationMember 0,0000 0,0000 0,0000 0 0 1

PoliticalParty 0,5462 0,4097 0,4682 195 162 281

Politician 0,5962 0,1867 0,2844 31 21 135

PublicTransitSystem 0,6943 0,4098 0,5154 109 48 157

Rocket 0,0000 0,0000 0,0000 0 0 5

Ship 0,0000 0,0000 0,0000 0 0 5

ShaceShuttle 0,0000 0,0000 0,0000 0 0 5

SpaceShuttle 0,0000 0,0000 0,0000 0 0 0 1

SportsClub 0,6370 0,2675 0,3768 172 98 471

SportsEvent 0,2667 0,0412 0,0714 4 11 93

SportsEvent 0,2667 0,0412 0,0714 4 11 93

SportsEvent 0,2667 0,0412 0,0714 4 11 93

SportsLeague 0,6395 0,4125 0,5915 165 93 235

SportsManager 0,6000 0,0000 0,0000 0 0 5

Train 0,0000 0,0000 0,0000 0 0 5

Train 0,0000 0,0000 0,0000 0 0 5

Train 0,0000 0,0000 0,0000 0 0 5

CC.\Dev\stanford-ner-2017-06-09>java xmxx11g -cp stanford-ner.jar edu.stanford.nlp.ie.crf.CRFClassifier loadClassifier modelsWithOneAnnotation\Top500LinksTextWithSameProcessedLinksOnabbrractFineGrainedSpecifiedWithLowerpageRank.tsv
```

Figure 3.3: All 3 Domains Fine Grained Top 500 Links With All 3 Domains Fine Grained Top 500 Links With Lower PageRank

```
CRFClassifier tagged 344007 words in 2 documents at 4801,01 words per second.

Entity P R F T TP FP FN

Aircraft 0,9950 0,9766 0,9826 198 1 6

Athlete 0,0000 0,0000 0,0000 0,0000 0 0 202

Automobile 1,0000 0,8500 0,9189 34 0 6

Coach 0,0000 0,0000 0,0000 0 0 4

Infrastructure 1,0000 0,9820 0,9909 218 0 4

PoliticalParty 0,0000 0,0000 0,0000 0 0 0 511

Politician 0,0000 0,0000 0,0000 0 0 0 139

PublicTransitystem 0,9835 0,9876 0,9755 478 8 16

Ship 1,0000 0,0657 0,9825 28 0 1

SpaceShuttle 1,0000 0,0667 0,8000 8 0 4

SpaceStation 1,0000 1,0000 1,0000 2 0 0

SportsClub 0,0000 0,0000 0,0000 0,0000 0 0 347

SportsEvent 0,0000 0,0000 0,0000 0 0 0 347

SportsEvent 0,0000 0,0000 0,0000 0 0 0 347

SportsEvent 0,0000 0,0000 0,0000 0 0 0 307

SportsEvent 0,0000 0,0000 0,0000 0 0 0 0 307

SportsEvent 0,0000 0,0000 0,0000 0 0 0 0 0 154

Train 1,0000 0,0001 0,0000 0,0000 0 0 0 0 52

SportsTeam 0,0000 0,0000 0,0000 0 0 0 0 154

Train 1,0000 0,0001 0,5510 0 1 0 0 1

Totals 0,9000 0,0001 0,5524 10 0 1

Totals 0,9000 0,0001 0,5524 10 0 1

Totals 0,9000 0,0001 0,5524 10 0 1

Totals 0,9000 0,0001 0,5504 10 0 1

Totals 0,9000 1,5163 976 9 1820

C:\Dev\stanford-ner-2017-06-09\symbolis x -xmx11g -cp stanford-ner.jar edu.stanford.nlp.ie.crf.CRFClassifier -loadclassifier modelsWithOneAnnotation\Top300Links\landshithOneAnnotation\Top300Links\landshithOneAnnotation\Top300Links\landshithOneAnnotation\Top300Links\landshithOneAnnotation\Top300Links\landshithOneAnnotation\Top300Links\landshithOneAnnotation\Top300Links\landshithOneAnnotation\Top300Links\landshithOneAnnotation\Top300Links\landshithOneAnnotation\Top300Links\landshithOneAnnotation\Top300Links\landshithOneAnnotation\Top300Links\landshithOneAnnotation\Top300Links\landshithOneAnnotation\Top300Links\landshithOneAnnotation\Top300Links\landshithOneAnnotation\Top300Links\landshithOneAnnotation\Top300Links\landshithOneAnnotation\Top300Links\landshithOneAnnotation\Top300Links\landshithOneAnnotation\Top300Links\landshithOneAnnotation\Top300Links\landshithOneAnnotation\Top300Links\landshi
```

Figure 3.4: Transportation Fine Grained Top 500 Links Runned With All 3 Domains Fine Grained Top 300 Links And Transportation Fine Grained Top 300 Links

#### 3.2.9 With lower links on model

```
CRFClassifier tagged 97089 words in 1 documents at 2905,12 words per second.

Entity P
Aircraft 1,0000 0,0435 0,0833 1 0 22
Athlete 1,0000 0,0278 0,0541 1 0 35
Automobile 0,0000 0,0000 0 0 0 3
Coach 1,0000 0,3333 0,5000 1 0 2
PoliticalParty 0,6458 0,3054 0,4147 62 34 141
Politician 1,0000 0,0727 0,1356 4 0 51
PublicTransitSystem 0,8750 0,1346 0,2333 7 1 45
Ship 1,0000 0,2000 0,0000 0 0 0 6
SpaceShuttle 0,0000 0,0000 0,0000 0 0 6
SpaceStation 0,0000 0,0000 0,0000 0 0 0 6
SpaceStation 0,0000 0,0000 0,0000 0 0 0 0 0
SportsEvent 1,0000 0,023 0,0455 1 0 42
SportsLeague 0,6667 0,2121 0,3218 14 7 52
SportsLeague 0,6667 0,2121 0,3218 14 7 52
SportsLeague 0,6667 0,2121 0,3218 14 7 52
SportsLeague 0,0000 0,0000 0,0000 0 0 0 0
SportsTeam 1,0000 0,0000 0,0000 0 0 0 0
C:\Dev\stanford-ner-2017-06-09\sjava -cp stanford-ner-jar edu.stanford.nlp.ie.crf.CRFClassifier -loadClassifier modelsWithOneAnnotation\Top100Links\All
BDomainsTop100Links\TextWithSameProcessedLinks\SunAbstractFineGrainedSpecified.tsv
```

Figure 3.5: All 3 Domains Fine Grained Top 10 Links Runned With All 3 Domains Fine Grained Top 100 Links

```
CRFClassifier tagged 270361 words in 1 documents at 3542,70 words per second.

Entity P R F 1

Aircraft 1,0000 0,0098 0,0094 1 0 101

Athlete 1,0000 0,0050 0,0099 1 0 201

Automobile 0,0000 0,0050 0,0090 1 0 3

Infrastructure 0,0000 0,0000 0,0000 0 0 11

PoliticalParty 0,557 0,2192 0,3137 112 91 399

Politician 0,8000 0,0288 0,0556 4 1 135

PublicTransitSystem 0,6364 0,0282 0,0556 4 1 135

PublicTransitSystem 0,6364 0,0282 0,0556 4 1 35

Ship 1,0000 0,0000 0,0000 0,0000 0 0 0 0 0

SpaceShuttle 0,0000 0,0000 0,0000 0 0 0 0 0

SpaceStation 0,0000 0,0000 0,0000 0 0 0 0

SpaceStation 0,0000 0,0000 0,0000 0 0 0 0

SportsEvent 1,0000 0,0452 0,0299 1 0 65

SportsEvent 1,0000 0,0152 0,0299 1 0 65

SportsLeague 0,6102 0,1173 0,1967 36 23 271

SportsLeague 0,6102 0,1173 0,1967 36 23 271

SportsEvam 1,0000 0,0000 0,0000 0 0 0 0 0

SportsTeam 1,0000 0,0000 0,0000 0 0 0 52

Comparison 0,0000 0,0000 0,0000 0 0 0 0 0 0

Totals 0,5967 0,0781 0,1382 179 121 2112

C:\Dev\stanford-ner-2017-06-09\sylaw -cp stanford-ner-jar edu.stanford.nlp.ie.crf.CRFClassifier -loadClassifier modelsWithOneAnnotation\Top10links\ner-All3DomainsTop10linksFineGrained.ser.gz -testfile domainsWithOneAnnotation\Top300Links\All3DomainsTop10LinksFineGrained.ser.gz -testfile domainsWithOneAnnotation\Top300Links\All3DomainsTop10LinksFineGrained.ser.gz -testfile domainsWithOneAnnotation\Top300Links\All3DomainsTop10LinksFineGrained.ser.gz -testfile domainsWithOneAnnotation\Top300Links\All3DomainsTop300Links\Comparison 0.5000 0.5000 0.5000 0.5000 0.5000 0.5000 0.5000 0.5000 0.5000 0.5000 0.5000 0.5000 0.5000 0.5000 0.5000 0.5000 0.5000 0.5000 0.5000 0.5000 0.5000 0.5000 0.5000 0.5000 0.5000 0.5000 0.5000 0.5000 0.5000 0.5000 0.5000 0.5000 0.5000 0.5000 0.5000 0.5000 0.5000 0.5000 0.5000 0.5000 0.5000 0.5000 0.5000 0.5000 0.5000 0.5000 0.5000 0.5000 0.5000 0.5000 0.5000 0.5000 0.5000 0.5000 0.5000
```

Figure 3.6: All 3 Domains Fine Grained Top 10 Links Runned With All 3 Domains Fine Grained Top 300 Links

Figure 3.7: All 3 Domains Fine Grained Top 10 Links Runned With All 3 Domains Fine Grained Top 500 Links

Figure 3.8: All 3 Domains Fine Grained Top 10 Links Runned With All 3 Domains Fine Grained Top 500 Links With Lower PageRank

```
CRFClassifier tagged 423454 words in 1 documents at 2649,15 words per second.

Entity P R F1 TP FP FN

Aircraft 0,9677 0,2143 0,3509 30 1 110

Athlete 1,0000 0,0392 0,0754 15 0 368

Automobile 1,0000 0,3600 0,2759 4 0 21

Coach 1,0000 0,3333 0,5000 2 0 4

Infrastructure 0,8065 0,1087 0,1916 25 6 205

Political Party 0,7288 0,4473 0,5543 352 131 435

Politician 0,8851 0,3222 0,4724 77 10 162

PublicTransitSystem 0,8217 0,3564 0,4971 129 28 233

Ship 1,0000 0,1111 0,2000 3 0 24

SpaceShuttle 1,0000 0,8571 0,921 6 0 1

SportsCtub 0,8193 0,3254 0,4658 204 45 423

SportsExtion 1,0000 0,5000 0,6667 1 0 1

SportsCtub 0,8193 0,3254 0,4658 204 45 423

SportsLeague 0,8392 0,4953 0,6229 261 50 266

SportsManager 1,0000 0,9769 0,1429 7 0 84

SportsTeam 1,0000 0,5000 0,6667 3 0 3

Totals 0,8136 0,3155 0,4546 1200 275 2664

C:\Dev\stanford-ner-2017-06-09>java -Xmx11g -cp stanford-ner.jar edu.stanford.nlp.ie.crf.CRFClassifier -loadClassifier modelsWithOneAnnotation\Top500Links\All3DomainsTop500Links\Nerverlandshord-nrocessedLinksOnAbstractFineGrained.ser.gz -testFile domainsWithOneAnnotation\Top500Links\Nerverlandshord-nrocessedLinksOnAbstractFineGrained.ser.gz -testFile domainsWithOneAnnotation\Top500Links\Nerverlandshord-nrocessedLinksOnAbstractFineGrained.ser.gz -testFile domainsWithOneAnnotation\Top500LinksTextwitthSameProcessedLinksOnAbstractFineGrained.ser.gz -testFile domainsWithOneAnnotation\Top500LinksTextwitthSameProcessedLinksOnAbstractFineGrained.ser.gz -testFile domainsWithOneAnnotation\Top500LinksTextwitthSameProcessedLinksOnAbstractFineGrained.ser.gz -testFile domainsWithOneAnnotation\Top500LinksTextwitthSameProcessedLinksOnAbstractFineGrained.ser.gz -testFile domainsWithOneAnnotation\Top500LinksTextwitthSameProcessedLinksOnAbstractFineGrained.ser.gz -testFile domainsWithOneAnnotation\Top500LinksTextwithSameProcessedLinksOnAbstractFineGrained.ser.gz -testFile domainsWithOneAnnotation\Top500LinksTextwithSameProcessedLinksOnAbstractFineGrained.ser.gz -testFile domainsWithOneAnnotation\Top500LinksTextwithSameProce
```

Figure 3.9: All 3 Domains Fine Grained Top 100 Links Runned With All 3 Domains Fine Grained Top 500 Links

```
CRFCLassifier tagged 336613 words in 1 documents at 3519,92 words per second.
Entity P R F1 TP FP FN
Aircraft 0,0000 0,0000 0,0000 0 0 0 284
Automobile 0,0000 0,0000 0,0000 0 0 0 36
Coach 0,0000 0,0000 0,0000 0 0 14
Infrastructure 0,0000 0,0000 0,0000 0 0 14
Locomotive 0,0000 0,0000 0,0000 0 0 0 1
Motorcycle 0,0000 0,0000 0,0000 0 0 0 1
OrganisationNember 0,0000 0,0000 0,0000 0 0 1
OrganisationNember 0,0000 0,0000 0,0000 0 0 1
PoliticalParty 0,5022 0,2374 0,3224 113 112 363
Politician 0,5517 0,0064 0,1604 116 13 150
PublicTransitSystem 0,7255 0,1391 0,2334 37 14 229
Rocket 0,0000 0,0000 0,0000 0 0 5
SpaceShuttle 0,0000 0,0000 0,0000 0 0 1
SpaceShuttle 0,0000 0,0000 0,0000 0 0 1
SpaceStation 0,0000 0,0000 0,0000 0 0 1
SportsClub 0,6093 0,1431 0,2317 92 59 551
SportsEague 0,000 0,0000 0,0000 0 0 1
SportsClub 0,6093 0,1431 0,2317 92 59 551
SportsEague 0,000 0,0000 0,0000 0 0 1
SportsClaugue 0,000 0,0000 0,0000 0 0 1
SportsClaugue 0,000 0,0000 0,0000 0 0 1
SportsClaugue 0,000 0,0000 0,0000 0 0 0 1
SportsClaugue 0,000 0,0000 0,0000 0 0 0 1
SportsClaugue 0,000 0,0000 0,0000 0 0 0 5
SportsEague 0,8509 0,2650 0,3693 166 68 294
SportsEague 0,8509 0,8550 0,3693 166 68 294
SportsEague 0,8509 0,8000 0,0000 0 0 0 5
Totals 0,5090 0,1243 0,2040 371 281 2614

C:\Dev\stanford-ner-2017-06-09>java -Xmx11g -cp stanford-ner-jar edu.stanford.nlp.ie.crf.CRFClassifier -loadClassifier modelsWithDoeAnnotation\Top500LinksWithDoeAnnotation\Top500LinksWithDoeAnnotation\Top500LinksWithLowerPageRank\All3DomainsTop500LinksTextWithSameProcessedLinksOnAbstractFineGrainedSpecifiedWithLowerPageRank\tsv
```

Figure 3.10: All 3 Domains Fine Grained Top 100 Links Runned With All 3 Domains Fine Grained Top 500 Links With Lower PageRank

```
CRFClassifier tagged 164960 words in 1 documents at 3254,58 words per second.
Entity P R F1 TP FP N
Election 0,0000 0,0000 0,0000 0 0 494

PoliticalParty 0,7282 0,4483 0,5549 351 131 432

Politician 0,9398 0,0739 0,1371 78 5 977

SportsEvent 0,0000 1,0000 0,0000 0 1 0
SportsLeague 0,0000 1,0000 0,0000 0 5 0
Totals 0,7513 0,1840 0,2956 429 142 1903

C:\Dev\stanford-ner-2017-06-09\java -Xmx11g -cp stanford-ner.jar edu.stanford.nlp.ie.crf.CRFClassifier -loadClassifier modelsWithOneAnnotation\Top100Links\ner-All3DomainsTop100LinksFineGrained.ser.gz -testFile domainsWithOneAnnotation\Top500Links\politicsFineGrained.ser.gz -testFile domai
```

Figure 3.11: All 3 Domains Fine Grained Top 100 Links Runned With Politics Fine Grained Top 500 Links

```
CRFClassifier tagged 117053 words in 1 documents at 3034,66 words per second.

Entity P R F1 TP FP N

Election 0,0000 0,0000 0,0000 0 0 0 197

Infrastructure 0,0000 1,0000 0,0000 0 2 0

PoliticalParty 0,5045 0,2379 0,3233 113 111 362

Politician 0,6667 0,0245 0,0473 16 8 636

PublicTransitSystem 0,0000 1,0000 0,0000 0 3 0

SportsEvent 0,0000 1,0000 0,0000 0 2 0

SportsEvent 0,0000 1,0000 0,0000 0 3 0

Totals 0,5000 0,0974 0,1631 129 129 1195

C:\Dev\stanford-ner-2017-06-09\java -Xmx11g -cp stanford-ner.jar edu.stanford.nlp.ie.crf.CRFClassifier -loadClassifier mo delsWithOwenPageRank\PoliticsFineGrainedTop500LinksWithLowerPageRank.tsv
```

Figure 3.12: All 3 Domains Fine Grained Top 100 Links Runned With Politics Fine Grained Top 500 Links With Lower PageRank

```
CRFClassifier tagged 142322 words in 1 documents at 3035,30 words per second.

Entity P R F1 TP FP FN

Athlete 1,0000 0,0392 0,0754 15 0 368

Coach 1,0000 0,3332 0,5000 2 0 4

Infrastructure 0,0000 1,0000 0,0000 0 1 0

PoliticalParty 0,0000 1,0000 0,0000 0 1 0

PoliticalParty 0,0000 1,0000 0,0000 0 1 0

PoliticalParty 0,0000 1,0000 0,0000 0 1 0

SportsClub 0,8185 0,3269 0,4672 203 45 418

SportsClub 0,8185 0,3519 0,5101 38 3 70

SportsLeague 0,8497 0,4952 0,6258 260 46 265

SportsManager 1,0000 0,0769 0,1429 7 0 84

SportsTeam 1,0000 0,0769 0,1429 7 0 84

SportsTeam 1,0000 0,0769 0,1429 7 0 84

C:\Dev\stanford-ner-2017-06-09\java -Xmx11g -cp stanford-ner.jar edu.stanford.nlp.ie.crf.CRFClassifier -loadClassifier modelsWithOneAnnotation\Top500Links\SportFineGrainedTop500Links\Star
```

Figure 3.13: All 3 Domains Fine Grained Top 100 Links Runned With Sport Fine Grained Top 500 Links

```
CRFClassifier tagged 118469 words in 1 documents at 3761,28 words per second.

Entity P R F1 TP FP FN

Athlete 0,0000 0,0000 0,0000 0 0 0 271

Coach 0,0000 0,0000 0,0000 0 0 14

Infrastruture 0,0000 1,0000 0,0000 0 0 1 0

OrganisationNember 0,0000 0,0000 0,0000 0 0 1

Politician 0,0000 1,0000 0,0000 0 0 0 0 1

Politician 0,0000 1,0000 0,0000 0 0 0 0 1

Sportsclub 0,6216 0,1467 0,2374 92 56 535

SportsEvent 0,2500 0,0104 0,0200 1 3 95

SportsLeague 0,0082 0,0200 0,3602 104 67 293

SportsLeague 0,0082 0,0200 0,3602 104 67 293

SportsTeam 0,851 0,0504 0,0952 6 1 113

Totals 0,6042 0,1258 0,2082 203 133 1411

C:\Dev\stanford-ner-2017-06-09>java -Xmx11g -cp stanford-ner-jar edu.stanford.nlp.ie.crf.CRFClassifier -loadClassifier modelsWithOneAnnotation\Top500L inksWithLowerPageRank.tsv
```

Figure 3.14: All 3 Domains Fine Grained Top 100 Links Runned With Sport Fine Grained Top 500 Links With Lower PageRank

```
CRFClassifier tagged 117072 words in 1 documents at 3791,68 words per second.

Entity P R F1 TP FP FN

Aircraft 0,9677 0,2190 0,3571 30 1 107

Automobile 1,0000 0,1600 0,2759 4 0 21

Infrastruture 0,8333 0,1087 0,1292 25 5 205

Politician 0,0000 1,0000 0,0000 0 3 0

Public ransitystem 0,8217 0,3003 0,5010 129 28 229

Ship 1,0000 0,1875 0,3158 3 0 13

SpaceShuttle 1,0000 1,0000 1,0000 0,6667 1 0 1

SportsClub 0,0000 1,0000 0,6667 1 0 1

SportsClub 0,0000 1,0000 0,0000 0 1

Frain 1,0000 0,0000 0,0000 0 1 0

Train 1,0000 0,5000 0,7500 3 0 2

Totals 0,8375 0,2580 0,3945 201 39 578

C:\Dev\stanford-ner-2017-06-09>java -xmx11g -cp stanford-ner.jar edu.stanford.nlp.ie.crf.CRFClassifier -loadClassifier mc
delsWithOneAnnotation\Top100Links\text{NernasportationFineGrainedTop500Links.tsv}
```

Figure 3.15: All 3 Domains Fine Grained Top 100 Links Runned With Transportation Fine Grained Top 500 Links

```
CRFClassifier tagged 101091 words in 1 documents at 3831,82 words per second.

Entity P R F1 TP FP FN

Aircraft 0,0000 0,0000 0,0000 0 1 72

Automobile 0,0000 0,0000 0,0000 0 0 36

Infrastructure 0,0000 0,0000 0,0000 0 0 2

Locomotive 0,0000 0,0000 0,0000 0 0 2

Motorcycle 0,0000 0,0000 0,0000 0 0 1

Politician 0,000 1,0000 0,0000 0 1 0

Politician 0,000 1,0000 0,0000 0 1 0

PublicTransitSystem 0,7083 0,1399 0,2337 34 14 209

Rocket 0,0000 0,0000 0,0000 0 0 5

Ship 0,0000 0,0000 0,0000 0 0 1 2

SpaceShutile 0,0000 0,0000 0,0000 0 0 1 2

SpaceShutile 0,0000 0,0000 0,0000 0 0 1 2

SpaceStutile 0,0000 0,0000 0,0000 0 0 0 1

SportsClub 0,0000 1,0000 0,0000 0 0 0 1

SportsClub 0,0000 1,0000 0,0000 0,0000 0 0 0 1

SportsClub 0,0000 1,0000 0,0000 0 0 0 0 0

Train 0,0000 0,0000 0,0000 0 0 0 0

Train 0,0000 0,0000 0,0000 0 0 0 5

C:\Dev\stanford-ner-2017-06-09>java -Xmxilg -cp stanford-ner.jar edu.stanford.nlp.ie.crf.CRFClassifier -loadClassifier modelsWithOneAnnotation\Top100Links\ner-All3DomainsTop100Links\ner-All3DomainsTop100Links\ner-All3DomainsTop100Links\ner-All3DomainsTop100Links\ner-All3DomainsTop100Links\ner-All3DomainsTop100Links\ner-All3DomainsTop100Links\ner-All3DomainsTop100Links\ner-All3DomainsTop100Links\ner-All3DomainsTop100Links\ner-All3DomainsTop100Links\ner-All3DomainsTop100Links\ner-All3DomainsTop100Links\ner-All3DomainsTop100Links\ner-All3DomainsTop100Links\ner-All3DomainsTop100Links\ner-All3DomainsTop100Links\ner-All3DomainsTop100Links\ner-All3DomainsTop100Links\ner-All3DomainsTop100Links\ner-All3DomainsTop100Links\ner-All3DomainsTop100Links\ner-All3DomainsTop100Links\ner-All3DomainsTop100Links\ner-All3DomainsTop100Links\ner-All3DomainsTop100Links\ner-All3DomainsTop100Links\ner-All3DomainsTop100Links\ner-All3DomainsTop100Links\ner-All3DomainsTop100Links\ner-All3DomainsTop100Links\ner-All3DomainsTop100Links\ner-All3DomainsTop100Links\ner-All3DomainsTop100Links\ner-All3DomainsTop100Links\ner-All3DomainsTop100Links\ner-All3DomainsTop100Links\ner-All3DomainsTop100Links\ner-All3DomainsTop100Links\ner-A
```

Figure 3.16: All 3 Domains Fine Grained Top 100 Links Runned With Transportation Fine Grained Top 500 Links With Lower PageRank

```
CRFClassifier tagged 423454 words in 1 documents at 2349,18 words per second.

Entity P R F1 TP FP FN

Aircraft 0,9573 0,8000 0,8716 112 5 28

Athlete 0,8889 0,5849 0,9055 224 28 159

Automobile 0,9555 0,8800 0,9167 22 1 3

Coach 1,0000 0,6667 0,8000 4 0 2

Infrastructure 0,9034 0,5569 6,9097 131 14 99

PoliticalParty 0,8854 0,7268 0,7983 572 74 215

Politician 0,9664 0,6025 0,7423 144 5 95

PublicTransitSystem 0,8966 0,7961 0,8399 286 33 76

Ship 1,0000 0,5556 0,7143 15 0 12

SpaceStutie 1,0000 0,8557 0,9231 6 0 1

SpaceStutie 1,0000 0,8577 0,9231 6 0 1

SportsClub 0,918 0,6443 0,7516 404 44 223

SportsLeague 0,9079 0,7850 0,8423 414 42 113

SportsLeague 0,9079 0,7850 0,8423 414 42 113

SportsTeam 0,9784 0,7637 0,8578 181 4 56

Train 1,0000 1,0000 1,0000 0,6877 2636 253 1168

C:\Dev\stanford-ner-2017-06-09\java -Xmx11g -cp stanford-ner.jar edu.stanford.nlp.ie.crf.CRFClassifier -loadClassifier modelsWithOneAnnotation\Top500L inks\slights\substantiant\slights\substantiant\slights\substantiant\slights\substantiant\slights\substantiant\slights\substantiant\slights\substantiant\slights\substantiant\slights\substantiant\slights\substantiant\slights\substantiant\slights\substantiant\slights\substantiant\slights\substantiant\slights\substantiant\slights\substantiant\slights\substantiant\slights\substantiant\slights\substantiant\slights\substantiant\slights\substantiant\slights\substantiant\slights\substantiant\slights\substantiant\slights\substantiant\slights\substantiant\slights\substantiant\slights\slights\substantiant\slights\substantiant\slights\substantiant\slights\substantiant\slights\slights\slights\slights\slights\slights\slights\slights\slights\slights\slights\slights\slights\slights\slights\slights\slights\slights\slights\slights\slights\slights\slights\slights\slights\slights\slights\slights\slights\slights\slights\slights\slights\slights\slights\slights\slights\slights\slights\slights\slights\slights\slights\slights\slights\slights\slights\slights\slights\slights\slights\slights\slights\slights\slights\sli
```

Figure 3.17: All 3 Domains Fine Grained Top 300 Links Runned With All 3 Domains Fine Grained Top 500 Links

```
CRFClassifier tagged 336613 words in 1 documents at 3545,42 words per second.

Entity P R F1 TP FP FN

Aircraft 0,6667 0,1389 0,2299 10 5 62

Athlete 0,5000 0,0000 0,0000 0,0000 0 0 0 36

Coach 0,0000 0,0000 0,0000 0 0 14

Infrastructure 0,5667 0,0620 0,0118 17 13 257

Locomotive 0,0000 0,0000 0,0000 0 0 0 0 1

OrganisationMember 0,0000 0,0000 0,0000 0 0 0 1

OrganisationMember 0,0000 0,0000 0,0000 0 0 0 1

PoliticalParty 0,5191 0,3424 0,4127 163 151 313

Politician 0,594 0,1325 0,2167 22 15 144

PublicTransitSystem 0,6846 0,3835 0,4916 102 47 164

Rocket 0,0000 0,0000 0,0000 0 0 0 5

Ship 0,0000 0,0000 0,0000 0 1 1

SpaceShuttle 0,0000 0,0000 0,0000 0 0 0 5

SpaceStation 0,0000 0,0000 0,0000 0 0 0 1

SportsClub 0,6043 0,2162 0,3184 139 91 504

SportsLeague 0,6000 0,0300 0,0594 3 1 94

SportsLeague 0,6000 0,0300 0,0594 3 1 94

SportsLeague 0,6000 0,0300 0,0300 0 0 0 0 0 0 0

SportsRanager 0,6667 0,0211 0,0408 2 1 93

SportsLeague 0,6000 0,0000 0,0000 0 0 0 0 0

C:\Dev\stanford-ner-2017-06-09>java -Xmx11g -cp stanford-ner.jar edu.stanford.nlp.ie.crf.CRFClassifier -loadClassifier modelsWithOneAnnotation\Top300LinksWithLowerPageRank\All 3DomainsTop500LinksTextWithSameProcessedLinksOnAbstractFineGrainedSpecifiedWithLowerPageRank.tsv
```

Figure 3.18: All 3 Domains Fine Grained Top 300 Links Runned With All 3 Domains Fine Grained Top 500 Links With Lower PageRank

Figure 3.19: All 3 Domains Fine Grained Top 300 Links Runned With Politics Fine Grained Top 500 Links

```
CRFClassifier tagged 117053 words in 1 documents at 4211,90 words per second.

Entity P R F I TP FP FN

Athlete 0,0000 1,0000 0,0000 0 6 0

Election 0,0000 0,0000 0,0000 0 0 197

Infrastructure 0,0000 1,0000 0,0000 0 0 1 0

PoliticalParty 0,5209 0,3411 0,4122 162 149 313

Politician 0,5882 0,0307 0,0583 20 14 632

PublicTransitSystem 0,0000 1,0000 0,0000 0 9 0

SportsLeague 0,0001 1,0000 0,0000 0 2 0

SportsTeam 0,0000 1,0000 0,0000 0 1 0

Totals 0,5000 0,1375 0,2156 182 182 1142

C:\Dev\stanford-ner-2017-66-09\java -Xmx11g -cp stanford-ner.jar edu.stanford.nlp.ie.crf.CRFClassifier -loadClassifier modelsWithOuerPageRank\PoliticsFineGrained.ser.gz -testFile domainsWithOneAnnotation\Top500LinksWithLowerPageRank\PoliticsFineGrainedTop500LinksWithLowerPageRank\PoliticsFineGrainedTop500LinksWithLowerPageRank\tsv
```

Figure 3.20: All 3 Domains Fine Grained Top 300 Links Runned With Politics Fine Grained Top 500 Links With Lower PageRank

```
CRFClassifier tagged 142322 words in 1 documents at 4466,12 words per second.

Entity P
Aircraft 0,0000 1,0000 0,0000 0 1 0
Athlete 0,9218 0,5849 0,7157 224 19 159
Automobile 0,0000 1,0000 0,0000 0 1 0
Coach 1,0000 0,0000 0 1 0
Coach 1,0000 0,0000 0 1 0
Coach 1,0000 0,0000 0 1 0
Politicial 0,0000 1,0000 0,0000 0 3 0
SportsClub 0,9000 1,0000 0,0000 0 3 0
SportsClub 0,9000 0,6441 0,7512 400 44 221
SportsEvent 0,9688 0,741 0,7209 62 2 46
SportsLeague 0,9097 0,7867 0,8437 413 41 112
SportsManager 1,0000 0,5714 0,7273 52 0 39
SportsTeam 0,9783 0,7627 0,8571 180 4 56
Train 0,0000 1,0000 0,0000 0 1 0
Totals 0,9194 0,6777 0,7802 1335 117 635

C:\Dev\stanford-ner-2017-06-09>java -Xmx11g -cp stanford-ner.jar edu.stanford.nlp.ie.crf.CRFClassifier -loadClassifier mcdelsWithOneAnnotation\Top300Links\nervalue links\SportfineGrainedTop500Links\nervalue links\SportfineGrainedTop500Links\nervalue links\SportfineGrainedTop500Links\text{tsy}
```

Figure 3.21: All 3 Domains Fine Grained Top 300 Links Runned With Sport Fine Grained Top 500 Links

```
CRFClassifier tagged 118469 words in 1 documents at 4461,27 words per second.

Entity P R F T TP FP FN

Athlete 0,5833 0,1933 0,1755 28 20 243

Coach 0,0000 0,0000 0,0000 0 0 14

OrganisationNember 0,0000 0,0000 0,0000 0 0 1

PoliticalParty 0,0000 1,0000 0,0000 0 0 0 1

Politician 0,0000 1,0000 0,0000 0 3 0

PoliticalParty 0,0000 1,0000 0,0000 0 3 0

SportsClub 0,6006 0,2217 0,3251 139 89 488

SportsEvent 0,7500 0,0313 0,0600 3 1 93

SportsLeague 0,6000 0,3325 0,4279 132 88 265

SportsManager 0,6667 0,0225 0,4325 2 1 87

SportsTeam 0,5833 0,2533 0,3353 28 20 91

Totals 0,5961 0,2057 0,3058 332 225 1282

C:\Dev\stanford-ner-2017-06-09\java -Xmx11g -cp stanford-ner.jar edu.stanford.nlp.ie.crf.CRFClassifier -loadClassifier modelsWithOneAnnotation\Top500Links\Inequal inks\Information\Top500Links\Inequal inks\Information\Top500Links\Inequal inks\Information\Top500Links\Inequal inks\Information\Top500Links\Inequal inks\Information\Top500Links\Inequal inks\Information\Top500Links\Information\Top500Links\Information\Top500Links\Information\Top500Links\Information\Top500Links\Information\Top500Links\Information\Top500Links\Information\Top500Links\Information\Top500Links\Information\Top500Links\Information\Top500Links\Information\Top500Links\Information\Top500Links\Information\Top500Links\Information\Top500Links\Information\Top500Links\Information\Top500Links\Information\Top500Links\Information\Top500Links\Information\Top500Links\Information\Top500Links\Information\Top500Links\Information\Top500Links\Information\Top500Links\Information\Top500Links\Information\Top500Links\Information\Top500Links\Information\Top500Links\Information\Top500Links\Information\Top500Links\Information\Top500Links\Information\Top500Links\Information\Top500Links\Information\Top500Links\Information\Top500Links\Information\Top500Links\Information\Top500Links\Information\Top500Links\Information\Top500Links\Information\Top500Links\Information\Top500Links\Information\Top500Links\Information\Top500Links\Information\Top500Links\Information\Top500Links\In
```

Figure 3.22: All 3 Domains Fine Grained Top 300 Links Runned With Sport Fine Grained Top 500 Links With Lower PageRank

```
CRFClassifier tagged 117072 words in 1 documents at 4190,42 words per second.

Entity P R F1 TP FP FN

Aircraft 0,9569 0,8102 0,8775 111 5 26

Automobile 1,0000 0,8000 0,9362 22 0 3

Infrastructure 0,9034 0,5696 0,6987 131 14 99

Politician 0,0000 1,0000 0,0000 0 2 0

PublicTransitSystem 0,8959 0,7933 0,8415 284 33 74

Ship 1,0000 0,8750 0,9333 14 0 2

SpaceShuttle 1,0000 1,0000 1,0000 6 0 0 0

SpaceShuttle 1,0000 1,0000 0,0000 1 0 1

SportsClub 0,0000 1,0000 0,0000 0 3 0

SportsClub 0,0000 1,0000 0,0000 0 3 0

SportsTeam 0,0000 1,0000 0,0000 0 1 0 0

Train 1,0000 1,0000 1,0000 0,0000 5 0 0

Totals 0,9082 0,7368 0,8136 574 58 205

C:\Dev\stanford-ner-2017-66-09\java -Xmx11g -cp stanford-ner.jar edu.stanford.nlp.ie.crf.CRFClassifier -loadClassifier modelsWithOneAnnotation\Top500Links\TransportationFineGrainedTop500Links\text{ster}
```

Figure 3.23: All 3 Domains Fine Grained Top 300 Links Runned With Transportation Fine Grained Top 500 Links

```
CRFClassifier tagged 101091 words in 1 documents at 3283,24 words per second.

Entity P R F1 TP FP N

Aircraft 0,6667 0,1389 0,2299 10 5 62

Athlete 0,0000 1,0000 0,0000 0 2 0

Automobile 0,0000 0,0000 0,0000 0 0 36

Infrastructure 0,5862 0,6625 0,1130 17 12 255

Locomotive 0,0000 0,0000 0,0000 0 0 0 2

Motorcycle 0,0000 0,0000 0,0000 0 0 1

PublicTransitSystem 0,6714 0,3868 0,4909 94 46 149

Rocket 0,0000 0,0000 0,0000 0 0 5

Ship 0,0000 0,0000 0,0000 0 0 5

Ship 0,0000 0,0000 0,0000 0 0 1 12

SpaceShuttle 0,0000 0,0000 0,0000 0 0 9

SpaceStation 0,0000 0,0000 0,0000 0 0 9

SportsClub 0,0000 1,0000 0,0000 0 0 0 0

SportsClub 0,0000 1,0000 0,0000 0 0 0 2

SportsLeague 0,0000 1,0000 0,0000 0 0 0 2

Train 0,0000 0,0000 0,0000 0 0 5

Totals 0,6302 0,8339 0,2847 121 71 537

C:\Dev\stanford-ner-2017-66-09\java -Xmx11g -cp stanford-ner.jar edu.stanford.nlp.ie.crf.CRFClassifier -loadClassifier mo delsWithOneAnnotation\Top300Links\Ine-All3DomainsTop300LinksWithLowerPageRank.tsv
```

Figure 3.24: All 3 Domains Fine Grained Top 300 Links Runned With Transportation Fine Grained Top 500 Links With Lower PageRank

```
CRFClassifier tagged 10336 words in 1 documents at 2532,71 words per second.

Entity P R F1 TP FP FN

Aircraft 1,0000 1,0000 1,0000 1 0 0 0

Athlete 1,0000 1,0000 1,0000 1 0 0 0

Coach 1,0000 1,0000 1,0000 1 0 0 0

PoliticalParty 0,9545 0,8077 0,8750 21 1 5

Politician 1,0000 1,0000 1,0000 4 0 0

PublicTransitSystem 1,0000 0,8571 0,9231 6 0 1

Ship 1,0000 1,0000 1,0000 1 0 0 0

SportsClub 1,0000 1,0000 1,0000 1 0 0 0

SportsEvent 1,0000 1,0000 1,0000 1 0 0 0

SportsEvent 1,0000 1,0000 1,0000 1 0 0 0

SportsEvent 1,0000 0,7500 0,8571 3 0 1

SportsTeam 1,0000 1,0000 1,0000 1 0 0

Totals 0,9792 0,8704 0,9216 47 1 7

C:\Dev\stanford-ner-2017-06-09\java -Xmx11g -cp stanford-ner.jar edu.stanford.nlp.ie.crf.CRFClassifier -loadClassifier mc delsWithOneAnnotation\Top300Links\ner-All3DomainsTop300LinksFineGrained.ser.gz -testFile domainsWithOneAnnotation\Top10Links\statisticners
```

Figure 3.25: All 3 Domains Fine Grained Top 300 Links Runned With All 3 Domains Fine Grained Top 10 Links

## 3.2.10 With higher links on model

```
CRFCLassifier tagged 97089 words in 1 documents at 4145,56 words per second.

Entity P R F1 TP FP FN

Aircraft 1,0000 1,0000 1,0000 23 0 0

Athlet 1,0000 1,0000 1,0000 36 0 0

Automobile 1,0000 1,0000 1,0000 3 0 0

Coach 1,0000 1,0000 1,0000 2 0 0

Infrastructure 1,0000 1,0000 1,0000 22 0 0

PoliticalParty 0,9848 0,9606 0,9726 195 3 8

Politician 1,0000 0,8909 0,9423 49 0 6

PublicTransitSystem 0,980 0,9423 0,9608 49 1 3

Ship 1,0000 1,0000 1,0000 5 0 0

SpaceStation 1,0000 1,0000 1,0000 6 0 0

SpaceStation 1,0000 1,0000 1,0000 6 0 0

SportsClub 0,0630 0,9639 0,9639 80 3 3 3

SportsEvent 1,0000 0,9767 0,9882 42 0 1

SportsLeague 0,9403 0,9539 0,9639 80 3 3 3

SportsLeague 0,9403 0,9539 0,9639 80 3 3

SportsTeam 1,0000 0,8333 0,9091 5 0 1

SportsIeague 0,9400 1,0000 1,0000 1 0 0

Train 1,0000 1,0000 1,0000 1 0 0

Totals 0,9825 0,9610 0,9716 616 11 25

C:\Dev\stanford-ner-2017-06-09y-java xmx11g -cp stanford-ner-jar edu stanford.nlp.ie.crf.CRFClassifier -loadClassifier modelsWithOneAnnotation\Top300Links\ner-All3DomainsTop300LinksFineGrained.ser.gz -testFile domainsWithOneAnnotation\Top100LinksIner-All3DomainsTop300LinksFineGrained.ser.gz -testFile domainsWithOneAnnotation\Top100LinksIner-All3DomainsTop300LinksFineGrained.ser.gz -testFile domainsWithOneAnnotation\Top100LinksIner-All3DomainsTop300LinksFineGrained.ser.gz -testFile domainsWithOneAnnotation\Top100LinksIner-All3DomainsTop300LinksFineGrained.ser.gz -testFile domainsWithOneAnnotation\Top100LinksIner-All3DomainsTop300LinksIner-All3DomainsTop300LinksIner-All3DomainsTop300LinksIner-Iner-All3DomainsTop300LinksIner-Iner-All3DomainsTop300LinksIner-Iner-All3DomainsTop300LinksIner-Iner-All3DomainsTop300LinksIner-Iner-All3DomainsTop300LinksIner-Iner-All3DomainsTop300LinksIner-Iner-All3DomainsTop300LinksIner-Iner-All3DomainsTop300LinksIner-Iner-All3DomainsTop300LinksIner-Iner-All3DomainsTop300LinksIner-Iner-All3DomainsTop300LinksIner-Iner-All3DomainsTop300LinksIner-Iner-All3DomainsTop300LinksIner-Iner-All3DomainsTop300LinksIner-Iner-All3DomainsTop300LinksIner-Ine
```

Figure 3.26: All 3 Domains Fine Grained Top 300 Links Runned With All 3 Domains Fine Grained Top 100 Links

```
CRFClassifier tagged 4504 words in 1 documents at 2969,02 words per second.

Entity P R F1 TP FP FN

Election 0,0000 0,0000 0,0000 0 0 05

PoliticalParty 0,9545 0,8077 0,8750 21 1 5

Politician 1,0000 0,1111 0,2000 4 0 32

Totals 0,9615 0,3247 0,4854 25 1 52

C:\Dev\stanford-ner-2017-06-09>java -Xmx11g -cp stanford-ner.jar edu.stanford.nlp.ie.crf.CRFClassifier -loadClassifier mcdelsWithOneAnnotation\Top300Links\ner-All3DomainsTop300LinksFineGrained.ser.gz -testFile domainsWithOneAnnotation\Top10Links.tsv
```

Figure 3.27: All 3 Domains Fine Grained Top 300 Links Runned With Politics Fine Grained Top 10 Links

```
CRFClassifier tagged 40673 words in 1 documents at 4019,47 words per second.

Entity P R F1 TP FP FN
Election 0,0000 0,0000 0,0000 0 0 0 164

PoliticalParty 0,9848 0,9606 0,9726 195 3 8

Politician 1,0000 0,1536 0,2663 49 0 270

Totals 0,9879 0,3557 0,5230 244 3 442

C:\Dev\stanford-ner-2017-06-09\java -Xmx11g -cp stanford-ner.jar edu.stanford.nlp.ie.crf.CRFClassifier -loadClassifier modelsWithOneAnnotation\Top300Links\ner.all3DomainsTop300LinksFineGrained.ser.gz -testFile domainsWithOneAnnotation\Top100Links.tsv
```

Figure 3.28: All 3 Domains Fine Grained Top 300 Links Runned With Politics Fine Grained Top 100 Links

```
CRFClassifier tagged 2854 words in 1 documents at 2994,75 words per second.

Entity P R I TP FP FN

Athlete 1,0000 1,0000 1,0000 1 0 0

Coach 1,0000 1,0000 1,0000 1 0 0

SportsClub 1,0000 1,0000 1,0000 7 0 0

SportsEvent 1,0000 1,0000 1,0000 1 0 0

SportsEvent 1,0000 0,7500 0,8571 3 0 1

SportsTeam 1,0000 1,0000 1,0000 1 0 0

Totals 1,0000 0,9333 0,9655 14 0 1

C:\Dev\stanford-ner-2017-06-09>java -Xmx11g -cp stanford-ner.jar edu.stanford.nlp.ie.crf.CRFClassifier -loadClassifier modelsWithOneAnnotation\Top1001inks\SportFineGrainedTop10Links.tsv
```

Figure 3.29: All 3 Domains Fine Grained Top 300 Links Runned With Sport Fine Grained Top 10 Links

```
CRFClassifier tagged 31872 words in 1 documents at 3691,88 words per second.

Entity P R F1 TP FP FN
Athlete 1,0000 1,0000 1,0000 36 0 0
Coach 1,0000 1,0000 1,0000 3 0 0
SportsClub 0,9634 0,9634 0,9634 79 3 3
SportsEvent 1,0000 0,9767 0,9882 42 0 1
SportsEvent 1,0000 0,9767 0,9882 42 0 1
SportsHanager 1,0000 0,9833 0,901 5 0 1
SportsTeam 1,0000 1,0000 1,0000 32 0 0
Totals 0,9738 0,9701 0,9720 260 7 8

C:\Dev\stanford-ner-2017-06-09>java -Xmx11g -cp stanford-ner.jar edu.stanford.nlp.ie.crf.CRFClassifier -loadClassifier modelsWithOneAnnotation\Top300Links\ner-All3DomainsTop300LinksFineGrained.ser.gz -testFile domainsWithOneAnnotation\Top100Links\starty
```

Figure 3.30: All 3 Domains Fine Grained Top 300 Links Runned With Sport Fine Grained Top 100 Links

Figure 3.31: All 3 Domains Fine Grained Top 300 Links Runned With Transportation Fine Grained Top 10 Links

Figure 3.32: All 3 Domains Fine Grained Top 300 Links Runned With Transportation Fine Grained Top 100 Links

```
CRFClassifier tagged 10336 words in 1 documents at 3459,17 words per second.

Entity P R 1 FP FN

Aircraft 1,0000 1,0000 1,0000 1 0 0

Athlete 1,0000 1,0000 1,0000 1 0 0

Coach 1,0000 1,0000 1,0000 1 0 0

PoliticalParty 0,9545 0,8077 0,8750 21 1 5

Politician 1,0000 1,0000 1,0000 4 0 0

PublicransitSystem 0,8333 0,7143 0,7692 5 1 2

Ship 1,0000 1,0000 0,0000 1 0 0 0

SportsClub 0,8750 1,0000 0,0000 1 0 0 0

SportsClub 0,8750 1,0000 0,0000 1 0 0 0

SportsEvent 1,0000 1,0000 1,0000 1 0 0 0

CC:\Dev\stanford-ner-2017-06-09>java -Xmx11g -cp stanford-ner.jar edu.stanford.nlp.ie.crf.CRFClassifier -loadClassifier modelsWithOneAnnotation\Top500LinksTextWithSameProcessedLinksOnAbstractFineGrainedSpecified.tsy
```

Figure 3.33: All 3 Domains Fine Grained Top 500 Links Runned With All 3 Domains Fine Grained Top 10 Links

```
CRFClassifier tagged 97089 words in 1 documents at 3675,94 words per second.

Entity P R F1 TP FP FN

Aircraft 1,0000 1,0000 1,0000 23 0 0

Athlete 1,0000 1,0000 1,0000 36 0 0

Automobile 1,0000 1,0000 1,0000 3 0 0

Coach 1,0000 1,0000 1,0000 3 0 0

Infrastructure 1,0000 0,9755 0,9767 21 0 1

PoliticalParty 0,9799 0,9606 0,9701 195 4 8

Politician 1,0000 1,0000 1,0000 55 0 0

PublicTransitSystem 0,9796 0,9231 0,9505 48 1 4

Ship 1,0000 1,0000 1,0000 5 0 0 0

SpaceShuttle 1,0000 1,0000 1,0000 5 0 0

SpaceShuttle 1,0000 1,0000 1,0000 1 0 0

SportsClub 0,9529 0,9759 0,9643 81 4 2

SportsEvent 1,0000 0,8837 0,9383 38 0 5

SportsEvent 1,0000 1,0000 1,0000 1 0 0

SportsTeam 1,0000 1,0000 1,0000 1 0 0

SportsTeam 1,0000 1,0000 1,0000 1 0 0

SportsTeam 1,0000 1,0000 1,0000 1 0 0

Train 1,000 1,0000 1,0000 1 0 0

Train 1,0000 1,0000 1,0000 1 0 0

Totals 0,9779 0,9657 0,9717 619 14 22

C:\Dev\stanford-ner-2017-06-09\java -Xmx11g -cp stanford-ner.jar edu.stanford.nlp.ie.crf.CRFClassifier -loadClassifier modelsWithOneAnnotation\Top1001

Inks\All 2000mainsTop100Links\TextStarkThismeProcessedLinksOnAbstractFineGrained.ser.gz -testFile domainswithOneAnnotation\Top1001

Inks\All 2000mainsTop100Links\TextStarkThismeProcessedLinksOnAbstractFineGrained.ser.gz -testFile domainswithOneAnnotation\Top1001
```

Figure 3.34: All 3 Domains Fine Grained Top 500 Links Runned With All 3 Domains Fine Grained Top 100 Links

Figure 3.35: All 3 Domains Fine Grained Top 500 Links Runned With All 3 Domains Fine Grained Top 300 Links

Figure 3.36: All 3 Domains Fine Grained Top 500 Links Runned With Politics Fine Grained Top 10 Links

```
CRFClassifier tagged 40673 words in 1 documents at 4212,64 words per second.

Entity P R F1 TP FP FN

Election 0,0000 0,0000 0,0000 0 0 164

PoliticalParty 0,9799 0,9606 0,9701 195 4 8

Politician 1,0000 0,1724 0,2941 55 0 264

Totals 0,9843 0,3644 0,5319 250 4 436

C:\Dev\stanford-ner-2017-06-09>java -Xmx11g -cp stanford-ner.jar edu.stanford.nlp.ie.crf.CRFClassifier -loadClassifier modelsWithOneAnnotation\Top500Links\ner-All3DomainsTop500LinksFineGrained.ser.gz -testFile domainsWithOneAnnotation\Top100Links.ter
```

Figure 3.37: All 3 Domains Fine Grained Top 500 Links Runned With Politics Fine Grained Top 100 Links

Figure 3.38: All 3 Domains Fine Grained Top 500 Links Runned With Politics Fine Grained Top 300 Links

```
CRFClassifier tagged 2854 words in 1 documents at 2679,81 words per second.

Entity P R F1 TP FP FN

Athlete 1,0000 1,0000 1,0000 1 0 0

Coach 1,0000 1,0000 1,0000 1 0 0

SportsClub 0,8750 1,0000 0,9333 7 1 0

SportsEvent 1,0000 1,0000 1,0000 1 0 0 0

SportsLeague 1,0000 1,0000 1,0000 1 0 0 0

SportsLeague 1,0000 1,0000 1,0000 1 0 0 0

SportsTeam 1,0000 1,0000 1,0000 1 0 0 0

Totals 0,9375 1,0000 0,9677 15 1 0

C:\Dev\stanford-ner-2017-06-09\java -Xmx11g -cp stanford-ner.jar edu.stanford.nlp.ie.crf.CRFClassifier -loadClassifier mo delsWithOneAnnotation\Top500Links\ner-All3DomainsTop500LinksFineGrained.ser.gz -testFile domainsWithOneAnnotation\Top10Links\SportFineGrainedTop10Links.tsv
```

Figure 3.39: All 3 Domains Fine Grained Top 500 Links Runned With Sport Fine Grained Top 10 Links

```
CRFClassifier tagged 31872 words in 1 documents at 4022,72 words per second.

Entity P R F1 TP FP FN

Athlete 1,0000 1,0000 1,0000 36 0 0

Coach 1,0000 1,0000 1,0000 36 0 0

SportsClub 0,9524 0,9756 0,9639 80 4 2

SportsEvent 1,0000 0,8837 0,9383 38 0 5

SportsLeague 0,9275 0,9697 0,9481 64 5 2

SportsLeague 0,9275 0,9600 1,0000 6 0 0

SportsTeam 1,0000 1,0000 1,0000 6 0 0

SportsTeam 1,0000 1,0000 1,0000 32 0 0

Totals 0,9664 0,9664 0,9664 259 9 9

C:\Dev\stanford-ner-2017-06-09>java -Xmx11g -cp stanford-ner.jar edu.stanford.nlp.ie.crf.CRFClassifier -loadClassifier modelsWithOneAnnotation\Top500Links\ner-All3DomainsTop500LinksFineGrained.ser.gz -testFile domainsWithOneAnnotation\Top100Links\SportFineGrainedTop100Links.tsv
```

Figure 3.40: All 3 Domains Fine Grained Top 500 Links Runned With Sport Fine Grained Top 100 Links

```
CRFClassifier tagged 89224 words in 1 documents at 3135,95 words per second.

Entity P R F T TP FP FN

Athlete 1,0000 0,9802 0,9900 198 0 4

Coach 1,0000 1,0000 1,0000 0 2 0

SportsClub 0,9707 0,9622 0,9664 331 10 13

SportsEvent 1,0000 0,8333 0,9091 55 0 11

SportsLeague 0,9582 0,9707 0,9642 4298 13 9

SportsLeague 0,9582 0,9707 0,9644 298 13 9

SportsTeague 0,9600 0,9615 0,9804 50 0 2

SportsTeam 1,0000 0,9804 0,9901 150 0 3

Train 0,0000 1,0000 0,9804 0,9901 150 0 3

Totals 0,9766 0,9628 0,9696 1086 26 42

C:\Dev\stanford-ner-2017-06-09\java -Xmx11g -cp stanford-ner.jar edu.stanford.nlp.ie.crf.CRFClassifier -loadClassifier mc delsWithOneAnnotation\Top500tlinks\text{inks\toptfineGrained.ser.gz -testFile domainsWithOneAnnotation\Top300tlinks\text{inks\toptfineGrained.ser.gz -testFile domainsWithOneAnnotation\Top300tlinks\toptfineGrained.ser.gz -testFile domainsWithOneAnnotation\Top300tlinks\toptfineGrained.ser.gz -testFile domainsWithOneAnnotation\Top300tlinks\toptfineGrained.ser.gz -testFile domainsWithOneAnnotation\Top300tlinks\toptfineGrained.ser.gz -tes
```

Figure 3.41: All 3 Domains Fine Grained Top 500 Links Runned With Sport Fine Grained Top 300 Links

```
CRFClassifier tagged 2978 words in 1 documents at 2749,77 words per second.

Entity P R F1 TP FP FN
Aircraft 1,0000 1,0000 1,0000 1 0 0

PublicTransitSystem 0,8333 0,7143 0,7692 5 1 2
Ship 1,0000 1,0000 1 0 0 0
Totals 0,8750 0,7778 0,8235 7 1 2

C:\Dev\stanford-ner-2017-06-09\symbol{9}java -Xmx11g -cp stanford-ner.jar edu.stanford.nlp.ie.crf.CRFClassifier -loadClassifier mo delsWithOneAnnotation\Top500Links\ner-All3DomainsTop500LinksFineGrained.ser.gz -testFile domainsWithOneAnnotation\Top10Links\TransportationFineGrainedTop10Links.tsv
```

Figure 3.42: All 3 Domains Fine Grained Top 500 Links Runned With Transportation Fine Grained Top 10 Links

```
CRFClassifier tagged 24544 words in 1 documents at 3821,86 words per second.

Entity P R F1 TP FP FN

Aircraft 1,0000 1,0000 1,0000 23 0 0

Automobile 1,0000 1,0000 1,0000 3 0 0

Infrastructure 1,0000 0,9545 0,9767 21 0 1

PublicIransitysystem 0,9796 0,9231 0,9505 48 1 4

Ship 1,0000 1,0000 1,0000 5 0 0

SpaceShuttle 1,0000 1,0000 1,0000 5 0 0

SpaceStation 1,0000 1,0000 1,0000 1 0 0

SportsClub 0,0000 1,0000 1,0000 1 0 0

SportsClub 0,0000 1,0000 0,0000 0 1 0

Train 1,0000 1,0000 1,0000 1 0 0

Train 1,0000 1,0000 1,0000 1 0 0

C:\Dev\stanford-ner-2017-06-09>java -Xmx11g -cp stanford-ner.jar edu.stanford.nlp.ie.crf.CRFClassifier -loadClassifier mc
delsWithOneAnnotation\Top500Links\ner-All3DomainsTop500LinksFineGrained.ser.gz -testFile domainsWithOneAnnotation\Top1000Links\transportationFineGrainedTop100Links.tsv
```

Figure 3.43: All 3 Domains Fine Grained Top 500 Links Runned With Transportation Fine Grained Top 100 Links

```
CRFClassifier tagged 73646 words in 1 documents at 3209,68 words per second.

Entity P R F1 TP FP FN
Aircraft 1,0000 1,0000 1,0000 102 0 0
Automobile 1,0000 1,0000 1,0000 20 0 0
Infrastructure 1,0000 8,9640 0,9817 107 0 4
Politician 0,0000 1,0000 1,0000 0,0000 0 1 0
PublicTransitSystem 0,9917 0,9715 0,9815 239 2 7
Ship 1,0000 1,0000 1,0000 1,0000 14 0 0
SpaceShuttle 1,0000 1,0000 1,0000 1 0 0
SpaceStation 1,0000 1,0000 1,0000 0 0 0 0
SportsClub 0,0000 1,0000 1,0000 0 0 0 0
SportsClub 0,0000 1,0000 0,0000 0 1 0
Train 1,0000 1,0000 1,0000 0,0000 0 1 0
Train 1,000 1,0000 1,0000 0,0000 5 0 0
Totals 0,9860 0,9782 0,9821 494 7 11

C:\Dev\stanford-ner-2017-06-09\java -Xmx11g -cp stanford-ner.jar edu.stanford.nlp.ie.crf.CRFClassifier -loadClassifier modelsWithOneAnnotation\Top300Links\Text{insportation}\Top500Links\Text{insportation}\Top500Links\Text{insportation}\Top500Links\Text{insportation}\Top500Links\Text{insportation}\Top500Links\Text{insportation}\Top500Links\Text{insportation}\Top500Links\Text{insportation}\Top500Links\Text{insportation}\Top500Links\Text{insportation}\Top500Links\Text{insportation}\Top500Links\Text{insportation}\Top500Links\Text{insportation}\Top500Links\Text{insportation}\Top500Links\Text{insportation}\Top500Links\Text{insportation}\Top500Links\Text{insportation}\Top500Links\Text{insportation}\Top500Links\Text{insportation}\Top500Links\Text{insportation}\Top500Links\Text{insportation}\Top500Links\Text{insportation}\Top500Links\Text{insportation}\Top500Links\Text{insportation}\Top500Links\Text{insportation}\Top500Links\Text{insportation}\Top500Links\Text{insportation}\Top500Links\Text{insportation}\Top500Links\Text{insportation}\Top500Links\Text{insportation}\Top500Links\Text{insportation}\Top500Links\Text{insportation}\Top500Links\Text{insportation}\Text{insportation}\Text{insportation}\Text{insportation}\Text{insportation}\Text{insportation}\Text{insportation}\Text{insportation}\Text{insportation}\Text{insportation}\Text{insportation}\Text{insportation}\Text{insportation}\Text{insportation}\
```

Figure 3.44: All 3 Domains Fine Grained Top 500 Links Runned With Transportation Fine Grained Top 300 Links

Figure 3.45: Politics Fine Grained Top 300 Links Runned With All 3 Domains Fine Grained Top 100 Links

Figure 3.46: Politics Fine Grained Top 500 Links Runned With All 3 Domains Fine Grained Top 100 Links

Figure 3.47: Politics Fine Grained Top 500 Links Runned With All 3 Domains Fine Grained Top 300 Links

```
CRFClassifier tagged 97089 words in 1 documents at 5454,44 words per second.

Entity P R F T TP FP FN

Aircraft 0,0000 0,0000 0,0000 0 0 23

Athlete 0,2817 0,5556 0,3738 20 51 16

Automobile 0,0000 0,6000 0,0000 0 0 3

Coach 1,0000 0,6067 0,8000 2 0 1

Infrastructure 0,0000 0,0000 0,0000 0 0 0 22

Politician 0,0000 0,0000 0,0000 0 0 0 20

Politician 0,0000 0,0000 0,0000 0 0 55

PublicTransitSystem 0,0000 0,0000 0,0000 0 0 55

PublicTransitSystem 0,0000 0,0000 0 0 0 52

Ship 0,0000 0,0000 0,0000 0 0 5

SpaceShuttle 0,0000 0,0000 0,0000 0 0 5

SpaceStation 0,0000 0,0000 0,0000 0 0 5

Spacestation 0,0000 0,0000 0,0000 0 0 1

SportsEvent 0,9706 0,7674 0,8571 33 1 10

SportsEague 0,8852 0,8182 0,8584 54 7 12

SportsEague 0,8852 0,8182 0,8584 54 7 12

SportsTeague 0,8852 0,8182 0,8584 54 7 12

SportsTeam 0,9500 1,0000 0,0000 0 0 0 1

Totals 0,7352 0,3292 0,4547 211 76 430

C:\Dev\stanford-ner-2017-06-09\java -Xmx11g -cp stanford-ner.jar edu.stanford.nlp.ie.crf.CRFClassifier -loadClassifier modelsWithOneAnnotation\Top100Links\All 130mainsTop100LinksFextWithSameProcessedLinks\OndotablerractFineGrained.ser.gz -testFile domainsWithOneAnnotation\Top100Links\All 130mainsTop100LinksFextWithSameProcessedLinks\OndotablerractFineGrained.ser.gz -testFile domainsWithOneAnnotation\Top100Links\All 130mainsTop100LinksFextWithSameProcessedLinks\OndotablerractFineGrained.ser.gz -testFile domainsWithOneAnnotation\Top100Links\All 130mainsTop100LinksFextWitthSameProcessedLinks\OndotablerractFineGrained.ser.gz -testFile domainsWithOneAnnotation\Top100Links\All 130mainsTop100LinksFextWitthSameProcessedLinks\OndotablerractFineGrained.ser.gz -testFile domainsWithOneAnnotation\Top100Links\All 130mainsTop100LinksFextWitthSameProcessedLinks\OndotablerractFineGrained.ser.gz -testFile domainsWithOneAnnotation\Top100Links\All 130mainsTop100LinksFextWitthSameProcessedLinksSonAbstractFineGrained.ser.gz -testFile domainsWithOneAnnotation\Top100Links\All 130mainsTop100LinksFextWitthSameProcessedLinksSonAbstractFineGrained.ser.gz -testFile domainsWith
```

Figure 3.48: Sport Fine Grained Top 300 Links Runned With All 3 Domains Fine Grained Top 100 Links

```
CRFClassifier tagged 97089 words in 1 documents at 5434,29 words per second.

Entity P R F1 TP FP FN

Aircraft 0,0000 0,0000 0,0000 0 0 23

Athlete 0,4359 0,9444 0,5565 34 44 2

Automobile 0,0000 0,0000 0,0000 0 0 3

Coach 1,0000 1,0000 1,0000 3 0 0

Infrastructure 0,0000 0,0000 0,0000 0 0 22

Political 0,0000 0,0000 0,0000 0 0 55

Publiciransitsystem 0,0000 0,0000 0,0000 0 0 55

Publiciransitsystem 0,0000 0,0000 0,0000 0 0 55

SpaceShuttle 0,0000 0,0000 0,0000 0 0 5

SpaceShuttle 0,0000 0,0000 0,0000 0 0 5

SpaceShuttle 0,0000 0,0000 0,0000 0 0 5

SportsClub 0,8889 0,9639 0,9249 80 10 3

SportsEvent 1,0000 0,8837 0,9383 38 0 5

SportsSeague 0,8889 0,9637 0,9275 64 8 2

SportsManager 0,4286 1,0000 0,0000 0,0000 0 0 1

Train 0,0000 0,0000 0,0000 0 0 1

Train 0,0000 0,0000 0,0000 0 0 1

Totals 0,7835 0,4009 0,5304 257 71 384

C:\Dev\stanford-ner-2017-06-09\sjava -Xmx11g -cp stanford-ner.jar edu.stanford.nlp.ie.crf.CRFClassifier -loadClassifier modelsWithOneAnnotation\Top500Links\netartineGrained.ser.gz -testFile domainsWithOneAnnotation\Top100Links\netartineGrained.ser.gz -testFile domainsWithOneAnnotation\Top100Links\netartineGrained.ser.gz -testFile domainsWithOneAnnotation\Top100Links\netartineGrainedSpecified.tsv
```

Figure 3.49: Sport Fine Grained Top 500 Links Runned With All 3 Domains Fine Grained Top 100 Links

Figure 3.50: Sport Fine Grained Top 500 Links Runned With All 3 Domains Fine Grained Top 300 Links

```
CRFClassifier tagged 97089 words in 1 documents at 4669,54 words per second.

Entity P R F1 TP FP FN

Aircraft 1,0000 0,6957 0,8205 16 0 7

Athlete 0,0000 0,0000 0,0000 0 0 36

Automobile 1,0000 1,0000 1,0000 0 0 0 36

Coach 0,0000 0,0000 0,0000 0 0 0 3

Infrastructure 0,8750 0,9545 0,9130 21 3 1

PoliticalParty 0,0000 0,0000 0,0000 0 0 0 203

Politician 0,0000 0,0000 0,0000 0 0 0 55

PublicTransitSystem 0,8696 0,7692 0,8163 40 6 12

Ship 1,0000 0,4000 0,8333 0,9091 5 0 1

SpaceShuttle 1,0000 0,0030 0,0000 0 0 1

SpaceStation 0,0000 0,0000 0,0000 0 0 1

SportsClub 0,0000 0,0000 0,0000 0 0 1

SportsClub 0,0000 0,0000 0,0000 0 0 0 1

SportsEvent 0,0000 0,0000 0,0000 0 0 0 3

SportsEvent 0,0000 0,0000 0,0000 0 0 0 66

SportsBamager 0,0000 0,0000 0,0000 0 0 65

SportsBam 0,0000 0,0000 0,0000 0 0 0 33

Train 1,0000 1,0000 1,0000 1 0 0 0

Totals 0,9072 0,1373 0,2385 88 9 553

C:\Dev\stanford-ner-2017-06-09>java -Xmx11g -cp stanford-ner.jar edu.stanford.nlp.ie.crf.CRFClassifier -loadClassifier mo delsWithOneAnnotation\Top300Links\nervariantorop300Links\nervariantorop300Links\nervariantorop300Links\nervariantorop300Links\nervariantorop300Links\nervariantorop300Links\nervariantorop300Links\nervariantorop300Links\nervariantorop300Links\nervariantorop300Links\nervariantorop300Links\nervariantorop300Links\nervariantorop300Links\nervariantorop300Links\nervariantorop300Links\nervariantorop300Links\nervariantorop300Links\nervariantorop300Links\nervariantorop300Links\nervariantorop300Links\nervariantorop300Links\nervariantorop300Links\nervariantorop300Links\nervariantorop300Links\nervariantorop300Links\nervariantorop300Links\nervariantorop300Links\nervariantorop300Links\nervariantorop300Links\nervariantorop300Links\nervariantorop300Links\nervariantorop300Links\nervariantorop300Links\nervariantorop300Links\nervariantorop300Links\nervariantorop300Links\nervariantorop300Links\nervariantorop300Links\nervariantorop300Links\nervariantorop300Links\nervariantorop300Links\nervariantorop300Links\nervariantorop300Links\nervariantorop300L
```

Figure 3.51: Transportation Fine Grained Top 300 Links Runned With All 3 Domains Fine Grained Top 100 Links

Figure 3.52: Transportation Fine Grained Top 500 Links Runned With All 3 Domains Fine Grained Top 100 Links

Figure 3.53: Transportation Fine Grained Top 500 Links Runned With All 3 Domains Fine Grained Top 300 Links

## 3.3 Summary of results

## 3.3.1 Graphs

## **Conclusion**

# APPENDIX **A**

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