Entity linking with people entities on Wikipedia

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Abstract
This paper introduces a new model that uses named entity recognition, coreference resolution, and entity linking techniques, to approach the task of linking people entities on Wikipedia people pages to their corresponding Wikipedia pages if applicable. Our task is different from general and traditional entity linking because we are working in a limited domain, namely, people entities, and we are including pronouns as entities, whereas in the past, pronouns were never considered as entities in entity linking. We have built 2 models, both outperforms our baseline model significantly. The purpose of our project is to build a model that could be used to generate cleaner data for future entity linking tasks. Our contribution include a clean data set consisting of 50 Wikipedia people pages, and 2 entity linking models, specifically tuned for this domain.

1 Introduction
Entity linking is a developing and interesting field in natural language processing research. It has been used in improving the performance of information retrieval system, information summarization, and many such other applications. One of the issues in current entity linking research is the lack of data sets, and the data sets that are available are noisy, so as to contribute towards this shortcoming, we have built a model which could be used to generate training data set for entity linking tasks. The major difference between the conventional entity linking systems and our model is that, our model not only recognizes the entities in a text but also recognizes the pronouns referring to those entities. We have manually annotated Wikipedia pages to evaluate the performance of our model. We have restricted our experiment only to Wikipedia pages about people, and our model recognizes only the entities addressing a particular person, the entities include pronouns as well as proper nouns. Given a Wikipedia page on people, our model will find person name entities, and pronouns and link them to their corresponding Wikipedia page. We have worked on data of a single domain (people) and we have achieved pretty good results using our model. We have used F1 score to evaluate the performance of our model as well as to evaluate the performance of the components of our model, which are Named Entity Recognition, coreference resolution. We have used Stanford’s Named entity recognition and Stanford’s coreference resolution in our experiment.

We will briefly summarize the related works to each component in our model in section 2. In section 3, we will thoroughly explain our data, since it is an important contribution in our project. We will also explain our experiment settings. We will present our baseline model, and our optimized models in detail. We include diagrams for both to give a better and visual understanding of our models. We provide analysis on our model, based on the performance of our model on different type of samples in our test data set. Section 4 is the conclusion we have reached from this project. Section 5 proposes possible future works that could potentially improve the performance of the models presented in this paper.

2 Related Work
To the best of our knowledge, this is the first time that this task has been attempted. However, there are related works for each component in our model, namely, named entity recognition, coreference resolution, and TagMe entity linking model.
We used Stanford’s named entity recognition in the mention detection phase of our model. Stanford’s named entity recognition is a linear chain Conditional Random Field model. The model is similar to the baseline local+Viterbi model in [Finkel et al., 2005], but with added distributional similarity based features. We use Stanford’s NER to extract all people’s names in a Wikipedia page, but since we are working on a limited domain, we have added ruled based features to the NER model.

We used Stanford’s coreference resolution in the mention detection phase of our model, in order to link pronouns to the names that they are referring to. Stanford’s coreference resolution implements the multi-pass sieve coreference resolution system based on [Lee et al.] and [Raghunathan et al., 2010]. We also added rule based features to the coreference resolution system, in order to pick up pronouns that have been missed by the system.

We used TagMe entity linking model in our baseline model, and one of our models. TagMe is an entity linking model, originally built for short texts, with Wikipedia as knowledge base. It is introduced in [Ferragina and Scaiella, 2010].

We used Wikipedia search API for the entity linking in one of our models. Wikipedia search API uses Elastic Search, which is a search engine server on Lucene. It is a highly scalable, distributed and full-text search engine. It advances in speed, security, scalability, and hardware efficiency, thus making it a very popular choice among enterprise search engines [Gupta and Nair].

3 Experiment

We have conducted experiments for each individual component in our system, and our integrated systems. We think it is important to evaluate the performance of each individual component in our models, so that we could identify bottlenecks, and propose future improvements. And we record recall, precision, F-1 scores for all the experiments in Results.

3.1 Data

Since it is the first time that anyone has attempted this specific task, we were not able to find any existing data that we could use to evaluate our system. Hence we manually annotated 50 Wikipedia people pages, including people in sports, chefs, scientist, nobles and etc. The structure of our evaluation data set consists of four columns. In the first column for each of the Wikipedia page in our test data set, we tokenized the texts, so that each line of fist column contains one word/symbol, each row of the spreadsheet represents a word or a symbol and in the following columns we have identified the nature of the token, i.e if its an entity or not. In the second column we identify if the word is a name of a person with a label ‘Y’ (proper noun), in the third column we identify with a label ‘Y’ if the word in the first column is a name of a person and also identify if it is a pronoun referring a person. The last column has the Wikipedia tag, if there exists a wikipedia page for the identified entities (proper nouns and pronouns both). The purpose behind having four columns was to evaluate each component of our model separately, with the annotations in the second column we evaluated the Named Entity Recognition system used in our model, with the annotations in the third column we could evaluate working of combined coreference resolution system and Named entity recognition system in our model and finally with the annotations in the fourth column we could evaluate the entity linking of our system. Some observations noted while annotating data were that, sometimes names of people can be used in various television shows for example “The Oprah Winfrey Show” has the name of a person who has a Wikipedia page but in our annotations we have not recognized it as an entity because it is a name of a show and as a whole it does not count as a name of person similarly some buildings or institutions which are named after people were ignored in the annotation. There were also some pages where awards were named after people, in this case as well we did not identify it as an entity. We annotated 50 Wikipedia pages separately for evaluation purpose. The F1 score of our annotated test data is 97.2.

We also have an XML file for each of the Wikipedia page in our test data set. The XML
files has the information provided in the information box for each person by Wikipedia. They contain information like a person’s first name, last name, gender, profession and etc.. this information we have used in the rule based features, which we would elaborate in the next section. We have chosen to use XML to record these personal information because XML is good at keeping structural data, and easy to parse in Java.

3.2 Approach

In this section, we will introduce the baseline model we used and models that we created, the baseline model uses TagMe and the other model uses Wikipedia search or TagMe. We compare the performance of our model with the baseline model, and report the score in Results section.

3.2.1 Baseline

The baseline model that we used is a combination of named entity recognition, coreference resolution and TagMe. NER is used to only keep the people entities returned by TagMe, TagMe is a general entity linking model with Wikipedia as knowledge base. So it would mark all entities it has detected and link them to Wikipedia pages. We use NER only to keep the people entities, otherwise if we would have used NER to keep all the entities in our model then the recall would have been unnecessarily and incorrectly low. We use coreference resolution, only to keep pronouns and discard the non pronouns detected by the coreference system. Standford’s coreference resolution is also a general model, it marks all expressions, phrases and pronouns referring to a person. For example, on the Andre Trollope Wikipedia page, the first, ‘Sir Andrew Trollope (died 1461) was an English soldier during the later stages of the Hundred Years’ War and at the time of the Wars of the Roses.’, Standford’s coreference resolution would link the phrase “English soldier during the later stages of the Hundred Years Way” to Sir Andrew Trollope. But since the phrase is not a pronoun, we won’t keep it as a potential mention. TagMe is used for entity linking in the baseline model. TagMe is initially built for short texts, but some Wikipedia pages are long. So we set a limit. If the Wikipedia page exceeds the length limit, we will process the Wikipedia page sentence by sentence through TagMe, otherwise, we will put the whole Wikipedia page through TagMe. Even though TagMe is built for short texts, we found that using longer texts improves the accuracy of entity linking in TagMe. We think this is due to the fact that, with longer texts input, more contexts are provided for TagMe to disambiguate potential entities. The flow of the model is shown in figure 1.

We have built 2 models in this project. The mention detection part for both models is the
same, we use named entity recognition, coreference resolution for the mention detection part in both baseline and our model, but we have used rule based features for optimization in our models. The difference between our two models is that one uses Wikipedia search API for entity linking, and the other uses TagMe for entity linking. The general flow of our models is shown in the next page.

We use named entity recognition to extract names of people from a Wikipedia page. Then since we are limiting our domain only to people, we can get last name, first name, middle name if applicable, gender and if available profession from the information box provided in the Wikipedia page. Using this information in form of XML files we added some rule based features to the model after running the Wikipedia page through NER. We run through the Wikipedia page again, to see if the model finds any token that matches with the person’s first name or last name or middle name, and it marks that token as a potential mention of this person. Also, we created a list of titles e.g Sir, Lord, Miss, Dr. etc. in English. If the model finds that the first letter of the token is capitalized, and the token is in the list of titles, and it is followed by a person’s name, then it identifies the title to be a part of the person’s name. Additionally, we noticed that sometimes people are referred as name + location, especially nobles in ancient Europe. For example, Margarate of Anjou is a French queen. Her name was Margarate, and she was from Anjou, which is a city in France. The Stanford’s NER is only able to pick up Margarate as a potential mention, but if we only use Margarate to link this mention, there could be thousands of people with first name Margarate in Wikipedia, so it is necessary to include the location as well. NER will mark location entities. So if we found a person entity followed by of, and then a location entity, the model will mark these as potential mention.

For the TagMe model, we will run each sentence that has at least one potential mention through TagMe API, and record the labels it returns. With NER, we only keep the labels for the entities that are recognized as person or link to a person.

For the Wikipedia search model, we run each of the potential mention through Wikipedia search API, and if it returns more than 1 hits, we will record the top one’s label as the label for that mention. If a mention consists of more than one token, we will put the tokens together, separated by space, and then put them into Wikipedia search API. In this part, since we are only using the top 1 hit returned by Wikipedia, we rely on Wikipedia’s search algorithm, which is Elastic Search. Elastic search can be used for full-text search. It provides scalable searching. And it has near real time performance, and can support multitenancy.

We use Stanford’s coreference resolution in our model, to link pronouns to the people that they are referring to. After coreference resolution, we have added rule based features to the model. As mentioned previously, we also only keep pronouns marked by Stanford’s coreference resolution in this project. Since we could possibly get gender from Wikipedia, and then we would run through the document again, and if the model finds a unmarked pronoun that matches this person’s gender, it will link the token to this person. For example, if the person is male, and the model found unlinked pronouns in [he,him,his,himself], then the model would link this mention with the person. The same logic applied to females, but the pronouns list is [she,her,herself]. We also include [I,my,myself] in the pronouns, as some Wikipedia pages contain quotations, which has pronouns such as I referring to the person. We didn’t include plural pronouns, like our, them, in our project, because they cause further complication in coreference resolution. And it is impractical to link one entity to multiple Wikipedia pages.

3.3 Results

Our model is an optimized version of the baseline model for the mention detection part. We use the exactly same components, with rule based features in our models. We have chosen a limited domain, so we could make some assumptions on the data, which we used to build the rule based features. For the entity linking, we experimented with 2 different entity linking mechanism. We have done experiments on each individual component of our model vs. the baseline model, and also our integrated model vs. the baseline model. For all experiments, we record recall, precision, and F-1 scores. Results are shown in the table below:
In the above table R stands for Recall, P stands for Precision and F stands for F1 score. As we can see from the experiment results, our model has increased performance significantly over the baseline model. System with Wikipedia search as the entity linked has the best performance, reaching 82.7 in F-1 score. The results we got for both our models have achieved significantly better results than the baseline model, in precision, recall and F-1 score. NER in our model has good scores in both recall and precision, which means the model is able to pick up most of the people names mentioned in the Wikipedia page. Mention detection is basically People names and Pronouns. The recall and precision scores for mention detection is very good. So our model is able to find the majority of potential mentions. For entity linking with Wikipedia search, our best performing model, recall is good while precision is not as good. We will discuss possible ways to improve the entity linking in Future Work section.

### 3.4 Analysis

We have analyzed the performance of our model on each sample of the test data set, and found the following:

- The model has, in general, better performance in modern people than ancient people. We think the reason is: In the past, there are very few first names available, so there are a lot of duplicate names. The only way to distinguish between these names are using the titles, for example, Richard Woodville, first Earl of Rivers. It’s only possible to find the correct Wikipedia page for this person if his title is included. Including the title complicates the mention detection. There are multiple cases to consider for including titles.

- Name+of+Place: For example, Margaret of Anjou, where Anjou is a city in France. If we want to find the correct
Wikipedia page using Wikipedia search, we have to input Margarate of Anjou, Margarate alone won’t work, as there are so many people on Wikipedia with first name Margarate. Hence to find the correct Margarate in Wikipedia adding the place is essential, likewise for many other historical figures, it is necessary to have the place in input along with the name.

– Name+,+Title: In case of nobles, sometimes, they were referred by their full name followed by their title, like Richard Woodville, first Earl of Rivers. In noble families, father and son used to have the same name, the only difference was in the titles. For example, if the father is nth Earl of Warwick, and the son is (n+1)th Earl of Warwick, the identity of the father and son is only distinguished by the number (n)th. Without titles the identity of father and son would be the same and there will be no way to distinguish one from another, hence it is necessary to get the title of a historical figure, if it exists.

– Title+Name: Noble people could also be referred to as their title followed by their first name, like King Edward VI. In this case, it’s usually important to include the suffix, because there might be many people with the same title and first name, so that the suffix is the only way to distinguish them, like King Edward VI and his son King Edward V.

– If we consider people from further past, like ancient Roman people, the entity disambiguation for the people in the ancient Rome, becomes even harder, because back in ancient Roman empire, there were only few first names available. Without enough historical background, even humans may find it difficult to identify these entities. For example, Gaius Julius Caesar is the full name for Caesar. Gaius can be a name, and it can also be used as a title, like Gaius Caeser, which is a different person from Gaius Julius Caesar.

* There are also some complications in modern names of people. There are some common English first and last names. If multiple people have the same first and last name, there are a few ways that Wikipedia uses to distinguish them.

– If the people have different middle name, Wikipedia will include their middle name in the label to distinguish them. So it’s necessary for our model to also include middle name in searches.

– If middle name is not available, Wikipedia would use profession to distinguish these people. For example, Katie Cook and Katie Cook(writer). Sometimes, the personal info box provided by Wikipedia contains profession information, which we could use in our model. When profession is not available in the info box, entity linking becomes more complicated.

– Some people, usually actors/actresses, have stage name, which is different from their real name, like the real name of Vin Diesel is Mark Sinclair. In this case, it is important to use both the stage name and the real name for mention detection and entity linking.

* Sometimes, Wikipedia will use nicknames or abbreviations to refer to people. For example, Alex for Alexander, Liz for Elizabeth and etc. In the Wikipedia page for Alex Guar-naschelli, his true first name is Alexandra, but through the Wikipedia page, he is referred to as Alex for most occurrences.

Based on our observation, on Wikipedia people pages, most pronouns refer to the person about whom the wikipedia page is, whereas for other people mentioned in the page, Wikipedia rarely refers them by pronouns, since other people in that page need not be mentioned frequently, as the page is not about them. Given this observation, including gender in our model helps improving the performance in coreference resolution part in our model.

4 Conclusion

As per our knowledge, this is the first time that this topic was attempted. Although there exist Entity linking systems, which identify entities in a
given text, but there aren’t any entity linking systems that detect pronouns as entities and link them to a Wikipedia page. Use of such a Entity linking system in Information retrieval and summarization should improve the overall working of these applications. Our contribution includes a clean dataset consisting of 50 samples of Wikipedia pages from Wikipedia about people, and our models. We manually annotated 50 samples, and cross-annotated them for evaluation purpose. Our data covers a wide range of people, from modern to ancient, and covers multiple professions. Our model performs better than previous successful models in NER, Coreference Resolution and Entity Linking combined. Our model is an optimized version of the baseline model, and it is optimized and tuned for this specific area, Wikipedia people pages. This model would definitely help in creating good data sets for training purposes in entity linking tasks and we look forward to improving this system further. Our model could be used to generate cleaner training set for future entity linking tasks.

Since we are using rule based features to optimize the model, and these rules work only for the pages about people in Wikipedia search, these rules will no longer hold in another domain, so the model is not portable. But by adding new rules, the model could possibly be extended to other domains.

5 Future Work

Based on our results and analysis, there are some things that can be done in the future to improve the performance of the model:

- Collect more data. There are only 50 samples in our testing data set. This is mainly due to the time constraint of our project. Annotating Wikipedia pages is very time consuming. With more data in the testing data set, the performance of the models can be evaluated more thoroughly and fairly. It would help especially to include people from more areas. Currently, our samples include people from sports(mainly cricketers), chefs, scientist, and nobles. It doesn’t make sense to extend the areas of people in our current data set, because if we include more areas, the number of people in each area would decrease, and the result may lose its statistical significance. So more data samples are necessary if the areas of people need to be extended.

- Use more information provided in the info box. For most Wikipedia people pages, there are information box available, which provides the birth date, first, middle and last name, professions, and etc. It would be beneficial to use more of these information in the model for identifying mentions. For example, in the Barack Obama information box, his full name, occupations, his spouse’s name, his children’s name, his predecessors’ and successors’ name and etc. are provided. These could all be incorporated into the model to help identify mentions, and possibly link mentions.

- Improve the rule-based features. It’s possible to improve the rule-based features with linguistics. For example, adding a more comprehensive list of titles, or possible patterns of how people’s names can be represented.

- Re-ranking Wikipedia search results. Currently in our model, we only take the topmost result returned from Wikipedia search API, thus we rely solely on Wikipedia’s search algorithm for entity linking. In the future, this part could be improved and instead of taking the topmost result, we can configure the model to take the top N results from Wikipedia search API, and re-rank them locally. Word embeddings are a meaningful way of representing entities, hence Word embedding could be used to rank the similarities between the entity and search results. we tried to use Word2Vec from Google, but it hard to find the names of people in its vocabulary list hence, the out of vocabulary ratio is too high for names of people. This is the reason why it was not useful. A more suitable vocabulary is necessary if word embedding is to be used.

- Adding neural network. Based on the analysis, it is necessary and important to include context for entity linking. Convolutional neural network is known to be good at extracting contextual features. So, to further enhance the model we can train a neural network so that we can extract contextual features and use those features along with the vector representation of an entity. The combination of the entity vector representation and con-
textual feature vector can be done in many ways, one way to do it is concatenation, to form a fixed size vector which represents an entity along with the contextual information. And we can use this vector representation for comparison with all wikipedia titles/articles. Doing this might improve the accuracy of the model. But a limitation, to this enhancement is the requirement of large training data set to train the neural network and training a neural network is computationally exhaustive and expensive. If a neural network is added to the model, significantly more training data is needed.

References
Paolo Ferragina and Ugo Scaiella. Tagme: On-the-fly annotation of short text fragments (by wikipedia entities). 2010.

Jenny Rose Finkel, Trond Grenager, and Christopher Manning. Incorporating non-local information into information extraction systems by gibbs sampling. *Proceedings of the 43nd Annual Meeting of the Association for Computational Linguistics (ACL 2005),* pp. 363-370, 2005.

Pragya Gupta and Sreeja Nair. Survey paper on elastic search. *International Journal of Science and Research (IJSR).*

Heeyoung Lee, Yves Peirsman, Angel Chang, Nathanael Chambers, Mihai Surdeanu, and Dan Jurafsky. Stanford’s multi-pass sieve coreference resolution system at the conll-2011 shared task. 2011.

Karthik Raghunathan, Heeyoung Lee, Sudarshan Rangarajan, Nathanael Chambers, Mihai Surdeanu, Dan Jurafsky, and Christopher Manning. A multi-pass sieve for coreference resolution. 2010.