# Named Entity Recognition: A Literature Survey

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In this report, we explore various methods that are applied to solve NER. In section 1, we introduce the named entity problem. In section 2, various named entity recognition methods are discussed in three three broad categories of machine learning paradigm and explore few learning techniques in them. In the first part, we discuss various supervised techniques. Subsequently we move to semi-supervised and unsupervised techniques. In the end we discuss about the method from deep learning to solve NER.

## 1 Introduction

Named Entity Recognition(NER) is one of the major task in Natural Language Processing(NLP). NER is an active area of research for past twenty years. A lot of progress has been made in detecting named entities but NER still remains a big problem at large.

The main focus of this work is improving the NER system for Indian Languages using supervised and unsupervised methods. We explore various statistical measure for identifying Named Entities, study the deep learning/Neural Network approaches for Named entity recognition. In this chapter we give an introduction to the Named Entity Recognition task, its application and motivation for pursuing research in this area.

### 1.1 What is Named Entity?

In data mining, a named entity is a word or a phrase that clearly identifies one item from a set of other items that have similar attributes. In the expression *named entity*, the word *named* restricts the scope of entities that have one or many rigid designators that stands for a referent. Usually, Rigid designators include proper names, but it depends on domain of interest that may refer the reference word for object in domain as named entities. *For example*, in molecular biology and bio-informatics, entities of interest are *genes* and *gene products.*

### 1.2 Named Entity Recognition Task

Named Entity Recognition(NER) is the process of locating a word or a phrase that references a particular entity within a text. The NER task first appeared in the Sixth Message Understanding Conference (MUC-6) Sundheim (1995) and involved recognition of entity names (people and organizations), place names, temporal expressions and numerical expressions.

In MUC-6, Named entities(NEs) were categorized into three types of label, each of which uses specific attribute for a particular entity type. Entities and their labels were defined as follows:

- **ENAMEX**: person, organization, location
- **TIMEX**: date, time
- **NUMEX**: money, percentage, quantity

Example of annotation from MUC-7 data in English:

```
The <ENAMEX TYPE="LOCATION">U.K</ENAMEX> satellite television broadcast-
er said its subscribers base grew <NUMEX TYPE="PERCENT">17.5 percent</N-
UMEX> during <TIMEX TYPE="DATE"> the past year</TIMEX> to 5.35 million
```

Different fine grained or domain dependent annotation schemes have been proposed by many researchers. Consider a example from Lee et al. (2006) in figure 1. Lee et al. (2006) divided the classification of named entities into nine broad classes like person, organization, location, product, art, event, building etc. These classes have been further fine grained into sub categories. In practice, it is convinient to work with coarse classification than fine grain classification due to data sparsity.

## 2 Approaches to NER

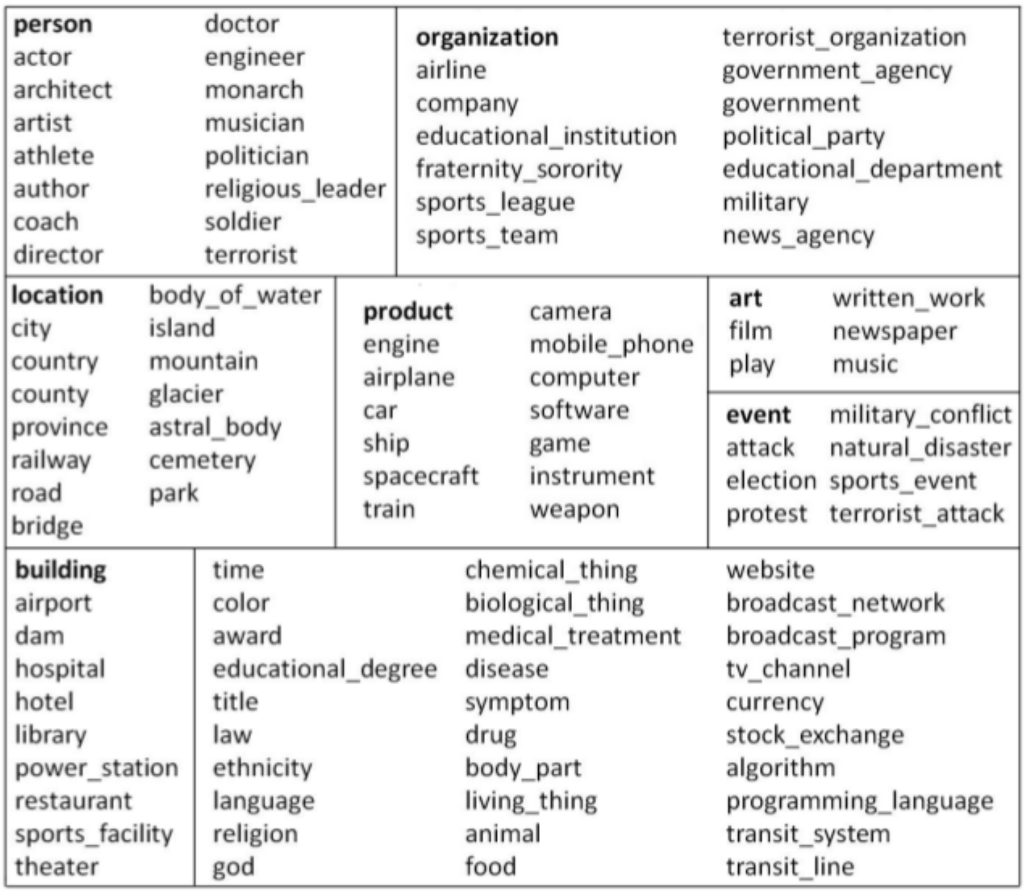
In this section, we will look into some of the methods to NER.

### 2.1 Supervised methods

Supervised methods are class of algorithm that learn a model by looking at annotated training examples. Among the supervised learning algorithms for NER, considerable work has been done using Hidden Markov Model (HMM), Decision Trees, Maximum Entropy Models (ME), Support Vector Machines (SVM) and Conditional Random Fields(CRF). Typically, supervised methods either learn disambiguation rules based on discriminative features or try to learn the parameter of assumed distribution that maximizes the likelihood of training data. We will study each of these methods in detail in next sections.

#### 2.1.1 Hidden Markov Models

HMM is the earliest model applied for solving NER problem by Bikel et al. (1999) for English. Bikel introduced a system, *IdentiFinder*, to detect NER.



| | |
|---|---|
| **person** | doctor |
| actor | engineer |
| architect | monarch |
| artist | musician |
| athlete | politician |
| author | religious_leader |
| coach | soldier |
| director | terrorist |

| | |
|---|---|
| **organization** | terrorist_organization |
| airline | government_agency |
| company | government |
| educational_institution | political_party |
| fraternity_sorority | educational_department |
| sports_league | military |
| sports_team | news_agency |

| | |
|---|---|
| **location** | body_of_water |
| city | island |
| country | mountain |
| county | glacier |
| province | astral_body |
| railway | cemetery |
| road | park |
| bridge | |

| | |
|---|---|
| **product** | camera |
| engine | mobile_phone |
| airplane | computer |
| car | software |
| ship | game |
| spacecraft | instrument |
| train | weapon |

| | |
|---|---|
| **art** | written_work |
| film | newspaper |
| play | music |

| | |
|---|---|
| **event** | military_conflict |
| attack | natural_disaster |
| election | sports_event |
| protest | terrorist_attack |

| |
|---|
| **building** |
| airport |
| dam |
| hospital |
| hotel |
| library |
| power_station |
| restaurant |
| sports_facility |
| theater |

| | | |
|---|---|---|
| time | chemical_thing | website |
| color | biological_thing | broadcast_network |
| award | medical_treatment | broadcast_program |
| educational_degree | disease | tv_channel |
| title | symptom | currency |
| law | drug | stock_exchange |
| ethnicity | body_part | algorithm |
| language | living_thing | programming_language |
| religion | animal | transit_system |
| god | food | transit_line |

Figure 1: Fined grained entity tagset

According to Bikel's formulation of the problem in the *Identifinder* system, only a single label can be assigned to a word in context. Therefore, the model assigns to every word, either one of the desired classes or the label NOT-A-NAME to represent "none of the desired classes". State diagram for his model is shown in Figure-2 For tagging a sentence, the task is to find the most likely sequence of name-classes(NC) given a sequence of words(W):

$$\max Pr(NC|W)$$

HMM is a generative model, i.e. it tries to generate the data, sequences of words W, and labels NC from distribution parameters.

$$Pr(NC|W) = \frac{Pr(W, NC)}{Pr(W)}$$

The Viterbi algorithm Forney (1973) is used to maximize $Pr(W, NC)$ through the entire space of all possible name-class assignments. Bikel modeled the generation in three steps:

- Select a name-class *nc*, conditioned on the previous name-class and previous word.
- Generate the first word inside the name-class, conditioning on the current and previous name-

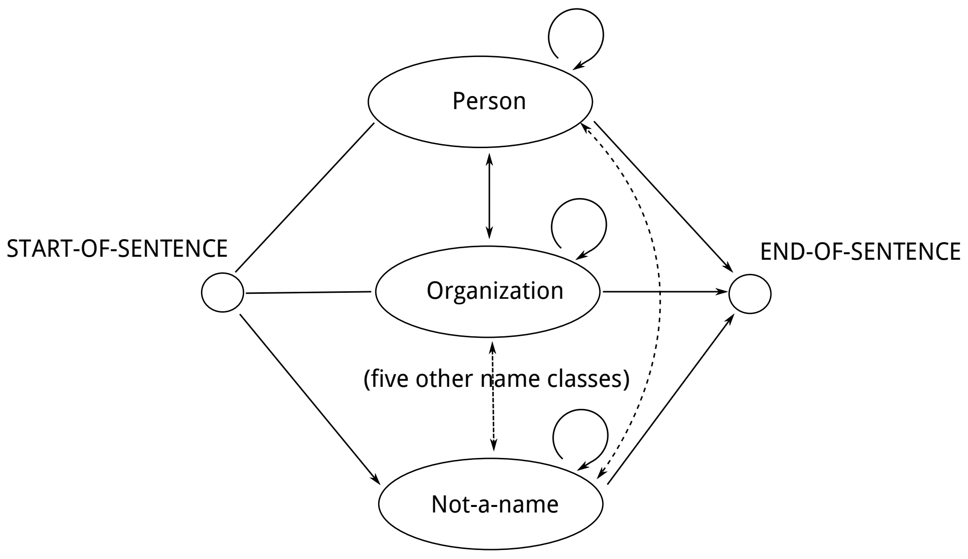


Figure 2: State Diagram for Identifier

classes.

$$Pr(nc|nc_{-1}, w_{-1}).Pr(< w, f >_{first} |nc, nc_{-1})$$

- Generate all subsequent words inside the current name-class, where each subsequent word is conditioned on its immediate predecessor

$$Pr(< w, f > | < w, f >_{-1}, nc)$$

There is also a distinct end marker "+end+", so that the probability may be computed for any current word to be final word of its name-class

$$Pr(< +end+, other > | < w, f >_{final}, nc)$$

Consider an example :

Mr. Jones eats.

Correct annotation for such a sentence is:

Mr. <ENAMEX TYPE="PERSON">Jones</ENAMEX> eats.

Then a max likelihood equation from the search space would be:

```
Pr(NOT-A-NAME | START-OF-SENTENCE, +end+) * Pr(\Mr." | NOT-A-NAME, START
-OF-SENTENCE) * Pr(+end+ | "Mr.", NOT-A-NAME) * Pr(PERSON | NOT-A-NAME ,
"Mr.") * Pr("Jones" | PERSON, NOT-A-NAME) * Pr(+end+ | "Jones" PERSON) *
Pr(NOT-A-NAME | PERSON, "Jones") * Pr("eats" | NOT-A-NAME, PERSON) * Pr(
"." | \eats", NOT-A-NAME) * Pr(+end+ | ".", NOT-A-NAME)* Pr(END-OF-SENTE-
NCE | NOT-A-NAME ".")
```

IdentiFinder reported NE accuracy of 94.9% and 90% for a mixed case English (MUC-6 data and a collection of Wall Street Journal documents) and mixed case Spanish (MET-1 data, comprised of articles from news agencies AFP) respectively.

Zhou and Su (2002) modified the IdentiFinder model by using mutual information. Given a token sequence $G_1^n = g_1\ g_2\ g_3\ \cdots\ g_n$, the goal of the learning algorithm is to find a stochastically optimal tag sequence $T_1^n = t_1\ t_2\ t_3\ \cdots\ t_n$ that maximizes

$$Pr(T_1^n|G_1^n) = \log Pr(T_1^n) + \log \frac{Pr(T_1^n, G_1^n)}{Pr(T_1^n)\ Pr(G_1^n)}$$

Unlike IdentiFinder, Zhou's model directly generates original NE tags from the output words of the noisy channel. Zhou's model assumes mutual information independence while HMM assumes conditional probability independence.

The HMM-based chunk tagger gave an accuracy of 96.6% on MUC-6 data and 94.1% on MUC-7 data.

### 2.1.2 Maximum Entropy based Model

Maximum entropy model, unlike HMM, are discriminative model. Given a set of features and training data, the model directly learns the weight for discriminative features for classification. In Maximum entropy models, objective is to maximize the entropy of the data, so as to generalize as much as possible for the training data. In ME models each feature is associated with parameter $\lambda_i$. Conditional probability is thus obtained as follows:

$$P(f|h) = \frac{\prod_i \lambda_i^{g_i(h,f)}}{Z_\lambda(h)}$$
$$Z_\lambda(h) = \sum_f \prod_i \lambda_i^{g_i(h,f)}$$

Maximizing the entropy ensures that for every feature $g_i$, the expected value of $g_i$, according to M.E. model will be equal to empirical expectation of $g_i$ in the training corpus.

Finally, Viterbi algorithm is used to find the highest probability path through the trellis of conditional probabilities which produces the required valid tag sequences.

**The MENE system**

The MENE system from Borthwick (1999) uses an extraordinarily diverse set of knowledge sources in making its tagging decisions, It makes use of broad array of gazetteers and dictionaries of single or multi-word terms like first name, company name, corporate suffixes. It uses wide variety of feature like binary features, lexical features, section features, external systems output, consistency and reference resolution.

The 29 tags of MUC-7 form the space of futures for the maximum entropy formulation of NE detection. A maximum entropy solution to this allows the computation of $p(f|h)$ for any $f$ from the space of possible futures, $F$, for every $h$ from the space of possible histories, $H$. A history of all the conditional data that helps the maximum entropy model to make decisions about the possible future.

Accuracy reported for the MENE system on MUC-7 data is 88.80%.

**Curran's ME Tagger**

Curran and Clark (2003) applied the maximum entropy model to the named entity problem. They used the softmax approach to formulate the probability $P(y|x)$. The tagger uses the model of the form :

$$P(y|x) = \frac{1}{Z(x)} \exp(\sum_{i=1}^{n} \lambda_i f_i(x, y))$$

where $y$ is the tag, $x$ is the context and $f_i(x, y)$ is the feature with associated weight $\lambda_i$.

Hence the overall probability for the complete sequence of $y_1 \cdots y_n$ and words sequence $w_1 \cdots w_n$ is approximated as:

$$P(y_1 \cdots y_n | w_1 \cdots w_n) \approx \prod_{i=1}^{n} Pr(y_i|x_i)$$

where $x_i$ is a context vector for each word $w_i$. The tagger uses beam search to find the most probable sequence given the sentence.

Curran reported the accuracies of 84.89% for the English test data and 68.48% for the German test data of CoNLL-2003 shared task.

### 2.1.3 SVM Based Models

Support Vector Machine was first introduced by Cortes and Vapnik (1995) based on the idea of learning a linear hyperplane that separate the positive examples from negative example by large margin. Large margin suggests that the distance between the hyperplane and the point from either instances is maximum. The points closest to hyperplane on either side are known as support vectors.

Figure-3 shows the geometric interpretation. The linear classifier is based on two parameters, a weight vector $W$ perpendicular to the hyperplane that separates the instances and a bias b which determines the offset of the hyperplane from the origin. A sample x is classified as positive instance if $f(x) = wx + b > 0$ and negative otherwise. If the data points are not linearly separable, then a slack is used to accept some error in classification. This prevents the classifier to overfit the data. When there are more than two classes, a group of classifiers are used to classify the instance.

McNamee and Mayfield (2002) tackle the problem as binary decision problem,i.e. if the word belongs to one of the 8 classes, i.e. B- Beginning, I- Inside tag for person, organization, location and misc tags. Thus there are 8 classifiers trained for this purpose. All feature used were binary. 258 orthography and punctuation features and 1000 language-related features were used. Window size was 7, that made the number of features used to 8806.

To produce a single label for each token, the set S of possible tags were identified. If S was empty tag O was assigned else most frequent tag was assigned. If both beginning and inside tags were present then beginning tag was chosen.

For CoNLL 2002 data, reported accuracies were 60.97 and 59.52 for Spanish and Dutch respectively.

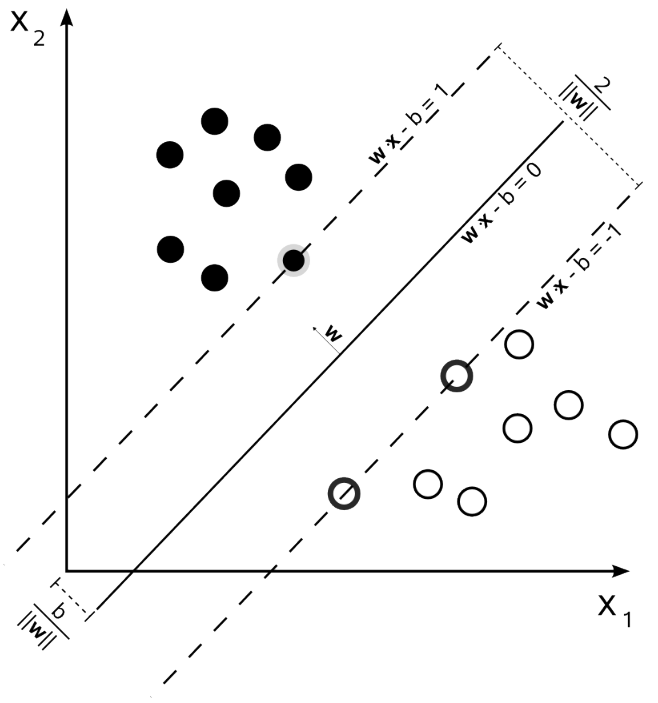


Figure 3: Geometric interpretation for SVM

### 2.1.4 CRF Based Models

Conditional random field were introduced by Lafferty et al. (2001) as a statistical modeling tool for pattern recognition and machine learning using structured prediction. McCallum and Li (2003) proposed a feature induction method for CRF in NE. Let $o =< o_1, o_2, \cdots, o_T >$ be some observed input data sequence, such as a sequence of words in a text inside the document (the values on n input nodes of the graphical model). Let S be a set of FSM states,each of which is associated with a label, l L, (such as ORG). Let $s =< s_1, s_2, \cdots, s_T >$ be some sequence of states, (the values on T output nodes). By the Hammersley Clifford theorem, CRFs define the conditional probability of a state sequence given an input sequence to be

$$P(s|o) = \frac{1}{Z}\exp\left(\sum_{t=1}^{T}\lambda_k f_k(s_{t-1}, s_t, o, t)\right)$$

where $Z$ is the normalization factor obtained by marginalizing over all state sequences, $f_k(s_{t-1}, s_t, o, t)$ is an arbitrary feature function and $\lambda_k$ is the learned weight for each feature function. By using dynamic programming, state transition between two CRF states can be efficiently calculated. The modified forward values, $\alpha_T(s_i)$, to be the "unnormalized probability" of arriving state $s_i$ given the observations $< o_1, o_2, \cdots, o_T >$. $\alpha_0(s)$ is set to probability of starting in each state $s$, and recursively calculated as :

$$\alpha_{t+1}(s) = \sum_{s'}\alpha_t(s')\exp\left(\sum_k \lambda_k f_k(s', s, o, t)\right)$$

The backward procedure and Baum-Welch have been similarly modified. $Z_o$ is given by $\sum_s \alpha_T(s)$. Viterbi algorithm for finding the most likely state sequence given the observation sequence have been modified from its HMM form.

Experiments were performed on CoNLL 2003 shared task data, and achieved an accuracy of 84.04% for English and 68.11% for German.

## 2.2 Semi-Supervised Methods

Semi supervised learning algorithms use both labeled and unlabeled corpus to create their own hypothesis. Algorithms typically start with small amount of seed data set and create more hypothesis' using large amount of unlabeled corpus. In this section, we will have a look at some of the semi-supervised NER system.

### 2.2.1 Bootstrapping based

Motivation for semi-supervised algorithm is to overcome the problem of lack of annotated corpus and data sparsity problem. Semi-supervised usually starts with small amount of annotated corpus, large amount of unannotated corpus and a small set initial hypothesis or classifiers. With each iteration, more annotations are generated and stored until a certain threshold occurs to stop the iterations.

**NER using AdaBoost** Carreras et al. (2002) have modeled the Named entity identification task as sequence labeling problem through BIO labeling scheme.Input is considered as word sequence to label with one of the Beginning of NE (B-) tag, Inside of tag (I-) and outside of NE (O-) tag. Three binary classifiers are used for tagging, one corresponding to each tag.

Orthographic and semantic features were evaluated over a shifting window allowing a relational representation of examples via many simply binary propositional features.

The binary AdaBoost is used to with confidence rated predictions as learning algorithm for the classifiers. The boosting algorithm combines several fixed-depth decision trees. Each tree is learned sequentially by presenting the decision tree a weighting over the examples which depend on the previous learned trees.

The Spanish data corresponds to the CoNLL 2002 Shared Task Spanish data and shows aperformance of 79.28%

## 2.3 Unsupervised Methods

A major problem with supervised setting is requirement of specifying large number of features. For learning a good model, a robust set of features and large annotated corpus is needed. Many languages don't have large annotated corpus available at their disposal. To deal with lack of annotated text across domains and languages, unsupervised techniques for NER have been proposed.

#### 2.3.1 KNOWITALL

KNOWITALL is domain independent system proposed by Etzioni et al. (2005) that extracts information from the web in an unsupervised, open-ended manner. KNOWITALL uses 8 domain independent extraction patterns to generate candidate facts.

For example, the generic pattern ”NP1 such as NPLIST2” indicates that the head of each simple noun phrase(NP) in the list of NPLIST2 is a member of class named NP1. It then automatically tests the plausibility of the candidate facts it extracts using pointwise mutual information (PMI) computed using large web text as corpus. Based on PMI score, KNOWITALL associates a probability with every facts it extracts, enabling it to manage the trade-off between precision and recall. It relies on bootstrapping technique that induces seeds from generic extraction patterns and automatically generated discriminator phrases.

#### 2.3.2 Unsupervised NER across Languages

Munro and Manning (2012) have proposed a system that generates seed candidates through local, cross-language edit likelihood and then bootstraps to make broad predictions across two languages, optimizing combined contextual, word-shape and alignment models. It is completely unsupervised, with no manually labelled items, no external resources, only using parallel text that does not need to be easily alignable. The results are strong, with F ¿ 0.85 for purely unsupervised named entity recognition across languages, compared to just F = 0.35 on the same 37 data for supervised cross-domain named entity recognition within a language. A combination of unsupervised and supervised methods increases the accuracy to F = 0.88. The tests were done on the parallel corpus of English and Haitian Krreyol text messages used in the 2010 Shared Task for the Workshop on Machine Translation.

A sample sentence from the data:

**Kreyol**: Lopital Sacre-Coeur ki nan vil Milot, 14 km nan sid vil Okap, pre pou li resevwa moun malad e lap mande pou moun ki malad yo ale la.

**English**: Sacre-Coeur Hospital which located in this village Milot 14 km south of Oakp is ready to receive those who are injured. Therefore, we are asking those who are sick to report to that hospital.

## 3 Informative measures

### 3.1 Features

Feature engineering is a foremost essential task of NER for all classifiers. In this section, we describe various features that have been used in existing NER systems. Features are descriptors or characteristic attributes of words designed for algorithmic consumption. Features can be specified in numerous ways using boolean values, numeric or nominal values. For example, a hypothetical NER system may be represented using 3 attribute:

- A Boolean attribute with the value true if the first character of the word is capitalized and false otherwise
- A numeric attribute corresponding to the length, in characters, of the word
- A nominal attribute corresponding to the lowercased version of the word

With above of set of features, the sentence "The president of Apple eats an apple." . This sentence can be represented using following feature vectors:

```
<true,3,"the">,<false,9,"president">,<false,2,"of">,<true,5,"apple">,
<false,4,"eats">,<false,2,"an">,<false,5,"apple">
```

Usually, the NER problem is resolved by applying a rule system over the features. For instance, a system might have two rules, a recognition rule: "capitalized words are candidate entities" and a classification rule:" the type of candidate entities of length greater than 3 words is organization". Specifying these helps to identifying the entities to certain extent. However, real systems tend to be much more complex and their rules are often create or expanded by automatic learning algorithm. Next, we describe the features that are most often used for the identification of named entities. We organize the them in 2 categories: Word-level features and List lookup features.

### 3.1.1 Word level features

Word level features are related to the character level feature of words. They specifically describe word case, punctuation, numerical value and special characters. Table **??** lists subcategories of word-level features.

### 3.1.2 Digit pattern

Digits can express wide range of useful information such as dates, percentages, intervals, identifiers etc. Certain patterns of digits gives strong signal about the type of named entities. For example, two digits and four digit numbers can stand for years and when followed by an "s", they can stand for a decade. Digits followed by units stands for quantity such as 10Kg.

### 3.1.3 Common word ending

Morphological features are essentially related to the words affixes and root word. Named entities also has common suffixes features. For example, various city names have common suffix *"pur"* like in Nagpur, Raipur, Jaipur, Udaipur and so on. A system should learn that a human profession often ends in *"ist"* like in cyclist, journalist etc.

| **Features Examples** | **Examples** |
|---|---|
| Case | Starts with a capital letter<br>Words is all uppercased<br>The word is mixed case (e.g., eBay, McDonald) |
| Punctuation | Ends with period, has eternal period (e.g., Prof., B.B.C.)<br>Internal apotrophe, hyphen or ampersand (e.g. O'Reilly) |
| Digit | Digit pattern<br>Cardinal and ordinal<br>Roman number<br>Word with digits |
| Character | Possessive mark, first person pronoun<br>Greek letters |
| Morphology | Prefix, suffix, singular version, stem<br>Common ending |
| Part-of-speech | Proper name, verb, noun, foreign words |
| Function | Alpha, non-alpha, n-gram<br>Lowercase, uppercase version<br>Pattern, summarized pattern<br>Token length, phrase length |

Table 1: Word level features for NER

### 3.1.4 Functions over words

Features can be extracted by applying functions over words. An example a feature can be created by applying a non alpha function over the word to create word level features like $nonAlpha(I.B.M.) = ....$ Another method is to use character n-grams as features.

### 3.1.5 Patterns and summarized patterns

Pattern feature is to map words onto a small set patterns over character types. For instance, a pattern feature might map all uppercase letters to "A", all lower case letters to "a", all digits to "0" and punctuation to "-":

x="I.B.M": getPattern(x)="A-A-A-"

x="Model-123": getPattern(x)="Aaaaa-000"

The summarized pattern features is a condensed form of the above pattern feature in which consecutive similar pattern types that are repeated are removed. For instance, for the preceding example:

x="I.B.M": getPattern(x)="A-A-A-"

x="Model-123": getPattern(x)="Aa-0"

### 3.1.6 List lookup features

Lists are the privileged feature in NER. The terms *"gazetteers"*, *"lexicon"* and *"dictionary"* are used interchangeably with the term *"list"*. List feature signifies a *is a* relationship for the entities included in the list. (e.g., Delhi is a city). If a word is included in the list, the probability of this word appearing in a sentence to be named entity is high.

- General dictionary Common nouns listed in a dictionary are useful, for instance, in the disambiguation of capitalized words in ambiguous position (e.g. sentence beginning). Mikheev et al. (1999) reports that from 2677 words in ambiguous position in a given corpus, a general dictionary lookup allows identifying 1841 common nouns out of 1851 (99.4%) while only discarding 171 named entities out of 826 (20.7%). In other words, 20.7% of named entities are ambiguous with common noun in that particular corpus.

- Words part of organization names Many researchers propose to recognize organization names using the words that commonly occur in their names. For instance, knowing that "pvt. ltd." is frequently used in the organization names could lead to recognition of "Bharti airtel pvt. ltd." and "". Similar rule applies to frequently occurring words in names of organization like Indian, General, State etc. Some researchers also exploit the fact that organization often include name of person as "Tata institute of Fundamental Research". Similarly geographical names can be good indicators of organizational names as in "Bharat Heavy Electrical Limited". Organizational designators like "inc" and "corp" also plays great role in detecting organization names.

- List Lookup Techniques For list lookup to work, candidate word should exactly match at least one element of a pre-existing list. However, we may want to allow some flexibility in matching conditions. Three lookup strategies could be used to effective use list lookup for NER.
  - Inflected form of words should be considered as valid matches. For examples, technology should match technologies.
  - Candidate words can be "fuzzy-matched" against the reference words in the list using some threshold function on edit-distance. This helps to minimize small spell variation between two words.
  - Reference list can be accessed using the Soundex algorithm which normalizes candidate words to their respective Soundex codes. This code is a combination of the first letter of a word plus a three digit code that represents its phonetic sound. Hence, similar sounding names like Lewinskey (soundex=1520) and Lewinsky(soundex=1520) are equivalent in respect.

Introduction to Deep Learning In this chapter, we explain what it means by *Deep Learning.* We explore the algorithms in deep learning. We also describe a vector space model for representing words in a lower dimensional latent vector space known as *distributed word vector representation.* Deep learning is one of the techniques which allow us to learn features independently than rigorously hand-crafting features for algorithm. In the next section, we give a basic introduction to Deep learning.

# 4 What is Deep Learning ?

Deep learning is set of machine learning algorithms that attempt to learn layered model of inputs, commonly know as *neural nets.* Each layer tries to learn a concept from previous input layer. With each subsequent layer deep learning algorithm attempts to learn multiple levels of concept of increasing complexity/abstraction. Most of the current machine learning algorithm works well because of human designed representations and features. Algorithm then just becomes a optimization problem to adjust weights to best make a final prediction. Deep learning is about representation learning with good features automatically.

## 4.1 Neural Network

Most successful deep learning methods involve neural networks. Deep learning is just a fancy name given to deep neural networks. Neural networks are inspired by central nervous system of animals. In neural network, primary computation node is know as neuron. Neurons are connected to one another using synapses. The strength of connection defines the importance of an input from the receiving neuron. Neural connection adjust the connection strength to learn new pattern in input.

Artificial neural networks are mathematical modelling of biological neural network. In artificial neural network, each neuron is a perceptron with weighted inputs. Weights are analogous to connection strength

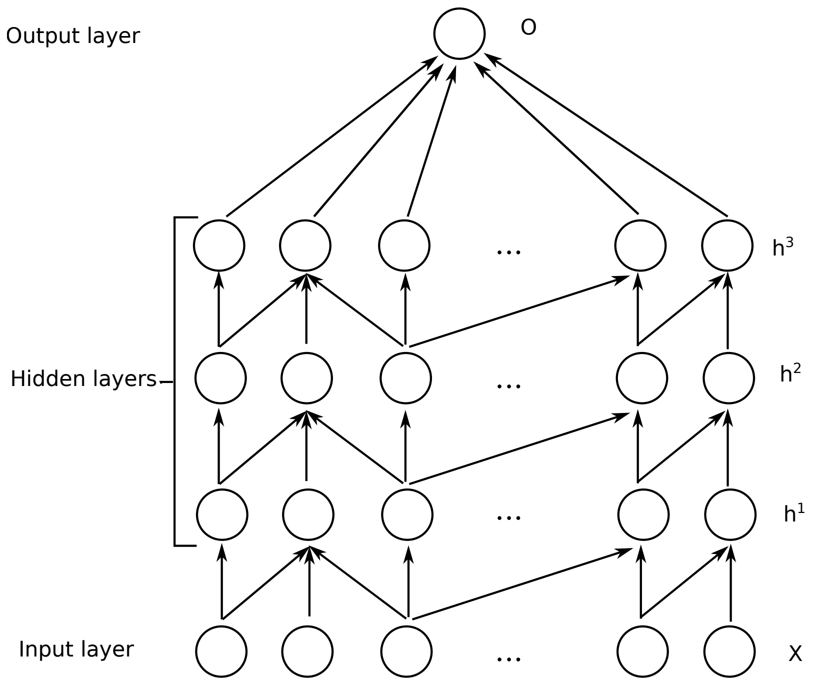


Figure 4: Neural Network

in biological neural networks. For computational efficiency, layered architecture is used for connections. There are connections only among consecutive layers. As in Figure -4, raw input is fed at the bottom most layer. With each layer, network tries to learn input pattern that help to correctly classify new examples.

Primary computation node in neural network is a perceptron. Perceptron does a supervised classification of an input into one of the several possible non-binary outputs. It is a linear classifier that makes prediction using weighted sum of input feature vector. Mathematically, perceptron can be written as

$$y = f(z)$$
$$\text{where } z = \sum w_i * x_i = W^T X$$

If $f$ is unity function then a perceptron is equivalent to a linear regression model. If $f$ is sigmoid function then the preceptron acts as logistic regression.

### 4.2 Backpropogation algorithm

Backpropogation algorithm, proposed by Rumelhart et al. (1988), is one of the most successful training algorithm to train a multilayer feed forward network. A backpropogation algorithm learns by example. Algorithm takes examples as input and it changes the weights in the network links. When the network is fully trained, it will give the required output for a particular input.

Basic idea of backpropogation algorithm is to minimize the error with respect to input by propogating error adjustments on the weight of the network. Backpropogation algorithm uses gradient decent method that calculates the squared error function with respect to the weights of the network. The squared error function is

$$E = \frac{1}{2} \sum_{n \in training} (t^n - y^n)^2$$

$$\begin{aligned} \text{where } t &= \text{target output} \\ y &= \text{actual output of the output node} \end{aligned}$$

Now differentiating the above error function gives

$$\frac{\delta E}{\delta W_i} = \frac{dE}{dy^n} \frac{dy^n}{dz^n} \frac{\delta z^n}{\delta W_i}$$

Major problems with backpropogation algorithm can be summarized as

- As we backpropogate deep into the network, gradient progressively gets diminished after each layer. Below certain depth of output neuron, correction signal is very minimal.
- Since the weights are initialized randomly, backpropogation is susceptible to getting stuck local minima.
- In usual setting, we can only use labeled data. It defeats the motivation for neural network as brain can learn from unlabeled data.

## 5 Recent Advances

In this section, we will introduce recent advances in the field of deep learning. New revival of the field is due to new algorithms that can be learn better features but are trained greedily for a layer. These layers are then stacked one above the other to learn higher level features. Each layer learns a feature and the layer above it learns higher level of level of features from the features of the layer below.

In the next section, we will discuss two major methods, autoencoder, denoising autoencoder and Deep Belief Network(DBN). DBN has probabilistic connotation while autoencoder and denoising autoencoder are non-probabilistic. These algorithms are usually applied in unsupervised settings but can be modified for supervised settings.

## 5.1 Autoencoder

An autoencoder neural network is an unsupervised learning algorithm that applies backpropogation setting target values to be equal to input values. In essence, we try to identity function, so that the input $x^s$ is similar to x. Learning identity function may seem trivial but by applying certain constraints, we can identify interesting structure about the data.

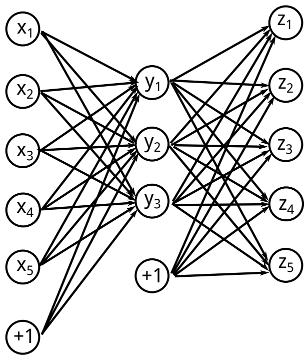


Figure 5: Autoencoder

An autoencoder takes input $x \in [0,1]^d$ and maps it into latent representation $y \in [0,1]^{d'}$ through a deterministic mapping

$$y = f(Wx + b)$$

where $f$ is an non-linearity function like sigmoid or tanh. Now this latent representation $y$ is mapped to output $z$ which is a reconstruction of original input $x$ using a similar transformation

$$z = f(W'y + b')$$

We need to learn the parameters $W$, $b$, $W'$, $b'$ for the model. Formulation is optimized such that average reconstruction error is minimized. Reconstruction error can be optimized in many ways like traditional square error or by using cross entropy depending on the input distribution. Reconstruction error for cross entropy is defined as

$$L(x,z) = H(B_x||B_y) = -\sum_{k=1}^{d}[x_k log z_k + (1 - x_k) log(1 - z_k)]$$

By minimizing the above equation, we minimize the number of bits needed to represent information in $y$ instead of representing it from $x$. As a result, we capture the main the factors of variation in the data similar to projection on principal component. Since the factors learned are smaller than the input factors, there is a loss in information about the input. Hope is that the compression learned would be good for input from training examples but not for a random input. In essence, autoencoder gives a reconstruction mechanism in which it gives low reconstruction error rate to test examples drawn from a similar distribution as training but a high reconstruction error for a uniformly chosen input vector.

## 5.2 Denoising Autoencoder

Autoencoder suffer from a problem that it may learn identity function rather than learning pattern in the input. To learn more a robust features and prevent the network to learn identity function, we try to reconstruct the input from a corrupted version of it. Denoising autoencoder [Vincent et al. (2008)] is a stochastic version of autoencoder.

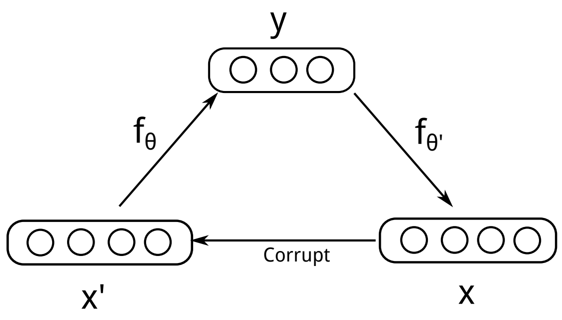


Figure 6: Denoising autoencoder

A denoising autoencoder first corrupt the input $x$ by randomly setting some bits of input to zero(or some other randomization process) to get corrupted input $x'$. Then it mapped to hidden layer

$$y = f(Wx' + b)$$

d

Then we try to reconstruct a $z$ using

$$z = f(W'y + b')$$

We want the $z$ to be as close as possible to original to input $x$. As before in autoencoder, the parameters here too are trained to minimize the average reconstruction error $L(x, y) = H(B_x||By)$. Complete process is shown in Figure-6

# 6 Distributed Representation

In this chapter, we explore distributed word representation models. In cognitive science, central problem is to understand how agents represent information that enables them to behave in sophisticated ways. One big contention is whether the representation is localized or distributed. Contention remains whether knowledge is stored in specific, discrete region of brain or entire cortex. But with advent of connectionist models in mathematics, distributed representation has found great attention.

Major benefit of using distributed representation is sharing of features to represent instance a knowledge. In most basic sense, a distributed representation is one that is spread out over a set of features for representation as opposed to localized approach where each feature is independent of each other. In next section, we see distributed representation for words in detail.

## 6.1 Distributed representation for words

A word representation is a mathematical object associated the each word, often a vector. Each dimension of the vector represents a feature and might even have a mathematical interpretation. Value of each dimension represents the amount of activity for that particular feature.

In machine learning, one of the most obvious model of representing a word is *one-hot vector representation*. In this representation only one of the computing element is active for each entity element. For example, if the size of vocabulary is $|V|$ then word $w$ can be represented as vector of size $|V|$ in which the index of word $w$ is only active and rest are set to zero.

```
Home : [0,0,0,0,....,1,....,0,0]
House: [0,0,0,0,..,1,..,0,0,0,0]
```

This representation is known as local representation. It is easy to understand and implement on hardware. But this representation has many flaws of itself. As in example shown above, if we want the correlation between *Home* and *House*, the representation fails to show any correlation between the terms.

Lets take an example of POS tagging. We have

Training: "Dog slept on the mat"

Testing: "Cat slept on the mat"

By using localized vector representation, these two sentence would have completely different representation. Hence, a algorithm which has seen only *"Dog"* during training would fail to tag *"Cat"* during testing.

Distributed representation would represent these words in some lower dimensional dense vector of real values with each dimension representing a latent feature for word model. Distributed representation could be like :

```
Home : [0.112,0.432,.......,0.341]
House: [0.109,0.459,.......,0.303]
```

Distributed representation helps to solve the problem of sparsity. For words that are rare in the labeled training corpus, parameters estimated through one-hot representation will be poor. More over, the model cannot handle the word that do not appear in the corpus. Distributed representation are trained using large unlabeled corpus using an unsupervised algorithm. Hope is that the distributed representation would capture semantic and syntactic properties of word and would have a similar representation for syntactically and semantically related words.

For example, in the above example of POS tagging, even when we haven't seen *Cat* during training, distributed representation of *Cat* would be similar to *Dog*. Algorithm will be able to classify *Cat* with similar tag as it would have learned for *Dog*.

## 6.2 Training distributed word representation

Plethora of methods exists for dimensionality reduction and word representation. Usually, researcher use clustering for dimensionality reduction. There are mainly two types of clustering algorithms:

- **Hard clustering** : Class based model learn word classes based on distributional information. Words are then represented according to the representative of the class. Examples of hard clustering can be Brown clustering, Exchange clustering etc.
- **Soft clustering** : Soft clustering models learn for each cluster/topic a distribution over the words of how likely that word is in each cluster. Examples of soft clustering model are Latent Semantic Analysis (LSA/LSI), Latent Dirichlet Analysis (LDA), HMM clustering etc.

A continuous space word vector space representation differ significantly from traditional clustering methods. Words are represented using high dimensional dense vectors in continuous space with no boundaries. In this study, we mainly focus on vector-space word representation that are learned by input layer of a neural networks. We will see three different methods based on neural network to learn vector representation from a large unannotated corpus.

### 6.2.1 Neural Probabilistic Language Model

Neural Probabilistic Language Model were introduced by Bengio et al. (2003). Method proposed by Bengio et al. is one of the first methods that introduces word vector representation to capture semantic similarity between the words. Primary aim of the paper is to develop a language model that overcomes the curse of dimensionality. For language model to be robust, it needs to generalize over the training instance. In higher dimensions, it is important how the algorithm distributes it probabilities mass around the training points. A algorithm performs better if probability mass is distributed where it matter rather than distributing it in all dimensions uniformly. Neural probabilistic model helps to achieve such important properties.

In short, the proposed approach can be summarized as follow :

1. associate each word with a distributed word feature vector
2. model the joint probability of word sequences in terms of the feature vectors of the words in sequence
3. learn word vectors and parameters of joint probability function simultaneously

The objective is to learn a good model $f(w_t, \cdots, w_{t-n+1}) = \hat{P}(w_t|w_1^{t-1})$ that give high out-of-sample likelihood. The function $f(w_t, \cdots, w_{t-n+1}) = \hat{P}(w_t|w_1^{t-1})$ is decomposed into two parts

1. A mapping $C$ from any element from vocabulary $V$ to a real vector $C(i) \in \mathbb{R}^m$. This is the distributed feature vector associated with every word in vocabulary.

2. The probability function over words, expressed with $C$: a function $g$ maps an input sequence of feature vectors for words in context,$(C(w_{t-n+1}), \cdots, C(w_t))$, to a conditional probability distribution over words in V for the next word $w_t$

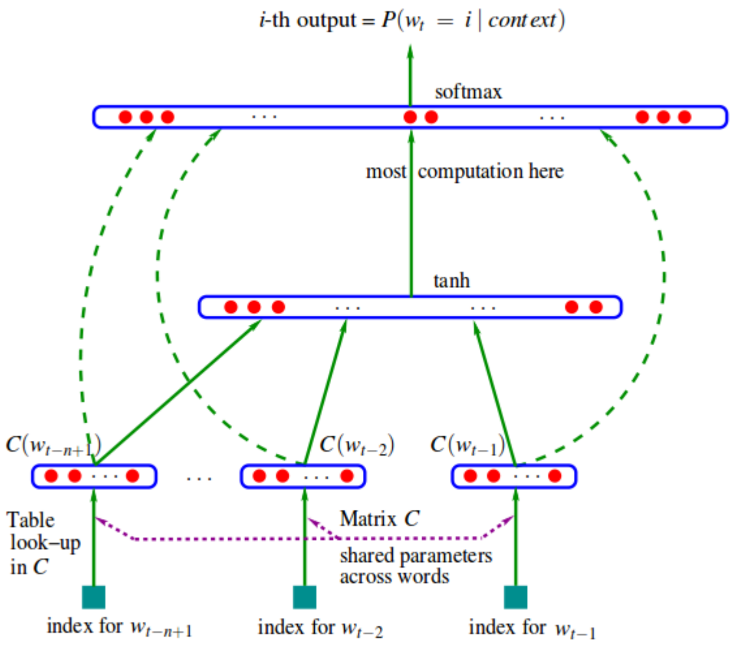


Figure 7: Neural architecture for language modeling

The output of function $g$ is a vector whose $i$-th element estimates the probability $\hat{P}(w_t = i|w_1^{t-1})$ as shown in Figure-7. The function $g$ is implemented either by feed-forward neural network or recurrent neural network or another parametrized function, with parameters $\omega$. So overall parameter set is $\theta = (C, \omega)$. Training is achieved by looking for $\theta$ that maximizes the training corpus regularized log-likelihood:

$$L = \frac{1}{T} \sum \log f(w_t, w_{t-1}, \cdots, w_{t-n+1}; \theta) + R(\theta)$$

where $R(\theta)$ is regularization term. The network is trained in forward and backward pass. In forward pass the network computers the total log-likelihood. In backward pass the gradients are back propagated from the output layer layer to the input layer. The errors are also propagated to the vector mapping $C$ as follow:

```
**loop** $k$ between 1 to n-1
    $C(w_{t-k}) \leftarrow C(w_{t-k})) + \epsilon \frac{\delta L}{\delta x(k)}$
**end loop**
```

where $\frac{\delta L}{\delta x(k)}$ is the the $k$-th block of the vector $\frac{\delta L}{\delta x}$

In this work, word vectors have been in terms of improvement in the measure of test set perplexity (geometric average of $\frac{1}{\hat{P}(w_t|w_1^{t-1})}$. Experiment shows 24% improvement in perplexity on Brown corpus in comparison to n-gram technique.

### 6.2.2 Contrastive criterion learning

Collobert and Weston (2008) in their paper. *A Unified Architecture for Natural Language Processing: Deep Neural Network for Multitask Learning*, proposed a language model that can utilize large unlabeled corpus for learning a distributed representation. Motivation of the paper is to develop a unified architecture that can perform various NLP task like POS tagging, Chunking, Named Entity Recognition and Semantic role labeling.

All of these tasks can be seen as tasks of labeling words or chunks. Against the traditional NLP, wherein features are handcrafted and fed to a classical shallow classification algorithm like Support vector machine (SVM), algorithm should learn the necessary features automatically. Choice of feature is quite empirical and mainly based on trial and error. A better approach would be in which machine learns a good set of features on itself. A deep neural network is used in this study. Features for the network are automatically trained using backpropagation algorithm. Figure-8 summarizes the architecture of the system.

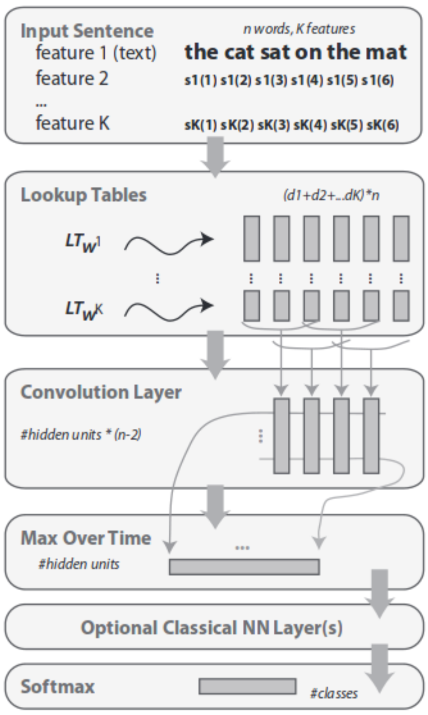


Figure 8: Multitask learning architecture

Foundation of the multitask learning lies in learning very good word representation from which higher level feature could be extracted for the specific needs of a task. In Collobert et al. (2011), detailed explanation of unsupervised trainer is presented first introduced in Collobert and Weston (2008). Collobert et al. proposes a pairwise ranking approach based on Cohen et al. (1999). Motivation of ranking pair of phrases is to score a legal phrase higher than an incorrect phrase. Figure-9 shows the network

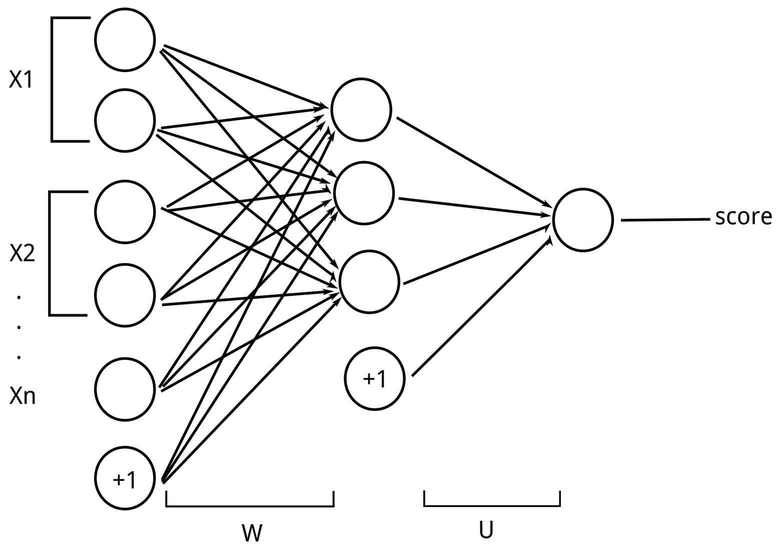


Figure 9: Network architecture for discriminative learning

design. Architecture considers a window approach network with parameters $\theta$ which outputs a score $f_\theta(x)$ given a window of text $x = [w]_1^{d_win}$. As in Figure-9, network consists of one non-linear hidden layer and a scoring node as the output.

$$\begin{aligned} a &= s(W^T x + b) \\ f_\theta(x) &= U^T a \\ a_c &= s(W^T x_c + b) \\ f_\theta(x_c) &= U^T a_c \\ \theta \rightarrow \sum_{x \in \Phi} \sum_{w \in D} & \max(0, 1 - f_\theta(x) + f_\theta(x_c)) \end{aligned}$$

Network is first shown a positive sample and then a corrupted sample. Scores $f_\theta(x)$ and $f_\theta(x_c)$ are obtained. If the sample don't separate substantially, then the error is propagated back in the network to adjust the parameters of the network. In next approach, we will see the model that improve the runtime of the architecture.

### 6.2.3 Combined Bag of Words Approach (CBOW)

In the previous model, we see that the architecture proposed generally has four layer. At the input layer, N previous words are encoded using 1 of V coding, where V is the size of vocabulary. The input layer is then projected to projection layer P of dimensionality $NxD$, using shared projection matrix. This step was implicit in the method of concatenating feature vectors from a lookup table. Model becomes complex for computation between projection and hidden layer as values are real and dense. For a window size $N = 5$, projection layer could be of size 250 to 1000, while the hidden layer size could be typically 250 to

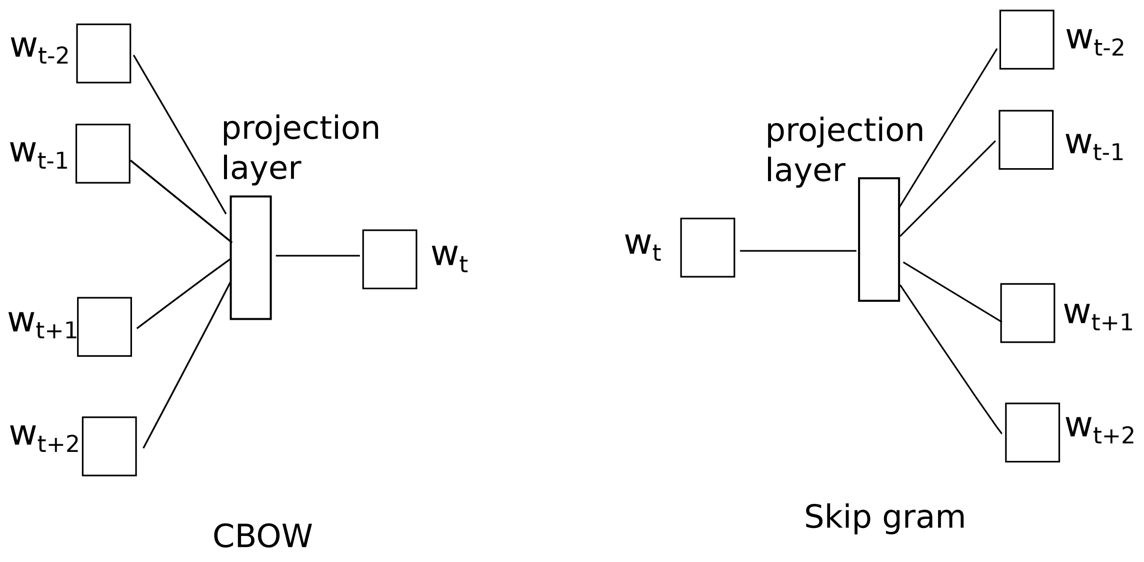


Figure 10: CBOW and Skip gram approach

750 units. Moreover, hidden layer compute probability distribution over all the words in the vocabulary expect in contrastive estimation method. Thus the complexity per each training example is

$$Q = N \times D + N \times D \times H + H \times V$$

In above equation $H \times V$ is the dominating term because of non-linear nature of the layer. To avoid the complexity of hidden layer , a new log linear model is proposed to avoid non-linear hidden layer but able to represent data as precisely as neural networks. Continuous bag of word architecture removes the hidden layer abd the projection layer is shared for all words (not just the projection matrix). All words from a window gets projected into the same position (their vectors are averaged). Since the order of words is not important, model is called bag-of-word model. A log linear classifier is used to classify the current word given the window $w$ along the past and future of the word under consideration. Weight matrix between the input and projection layer is shared for all inputs. A further optimization is obtained using hierarchical softmax. Complexity can be expressed as:

$$Q = N \times D + D \times \log_2(V)$$

### 6.2.4 Continuous Skip-gram approach

In the same paper, Mikolov et al. (2013) proposes second efficient model to generate word representation. Architecture is similar to CBOW but instead of predicting the current word based on context, method tries to maximize classification of a word based on other words in a sentence. Method uses current word as an input to the projection layer and try to predict the words within certain range before and after the current word.

Figure 10 shows the architecture of the model. The complexity of the model can be expressed as :

$$Q = C \times (D + D \times \log_2(V))$$

here $C$ is maximum distance from which we want to predict the word. We random choose $R$ between 1 and $C$ and then we use R words from past and R words from the future. Since the words are randomly chosen we skip some of the words in context and hence the name skip-gram is used for model.

## 6.3 Semantic and syntactic information in representation

Continuous word representation capture lot of syntactic and syntactic similarities of words in their dense compact representation. Many linear dependencies among the words are captured using the model discussed in previous section. As we will show in result section of the report, semantic and syntactic similarities between the words are well captured by the model. Representation for all the states were similar in the vector space. All person names , city names were distinctly represented in the space. Syntactic properties like many inflectional form of word ,*viz.* dukan and dukhano ,were nearest neighbor of each other.

Surprisingly, the vectors model has very nice vector properties. We can answer some analogy question use simple algebraic operations with the vector representation of the words. For example to find a word, that is similar to *small* in the same sense as *biggest* is similar to *big*, we can simply compute $X = vector(\text{"}biggest\text{"}) - vector(\text{"}big\text{"}) + vector(\text{"}small\text{"})$. If we find words with similar representation as $X$ using cosine similarity and use it to answer the query then it is possible that one of the option would be "smallest" among the possibilities.

If large training corpus and big vectors are available and model is trained on them, it is expected that more semantic and syntactic information could be captured using word representation model. We may be able to respond to semantic query like analogy among the capitals of countries. For example , Washington is to USA as Delhi is to India. Word vectors with such semantic properties has lot of potential application in machine translation, information retrieval, question answering systems and many other applications.

# References

Yoshua Bengio, Réjean Ducharme, Pascal Vincent, and Christian Janvin. A neural probabilistic language model. *J. Mach. Learn. Res.*, 3:1137–1155, March 2003. ISSN 1532-4435. URL `http://dl.acm.org/citation.cfm?id=944919.944966`.

Daniel M. Bikel, Richard Schwartz, and Ralph M. Weischedel. An algorithm that learns whats in a name. *Mach. Learn.*, 34(1-3):211–231, feb 1999. ISSN 0885-6125. doi: 10.1023/A:1007558221122. URL `http://dx.doi.org/10.1023/A:1007558221122`.

Andrew Eliot Borthwick. *A maximum entropy approach to named entity recognition.* PhD thesis, New York, NY, USA, 1999. AAI9945252.

Xavier Carreras, Lluís Màrquez, and Lluís Padró. Named entity extraction using adaboost. In *proceedings of the 6th conference on Natural language learning - Volume 20*, COLING-02, pages 1–4, Stroudsburg, PA, USA, 2002. Association for Computational Linguistics. doi: 10.3115/1118853.1118857. URL `http://dx.doi.org/10.3115/1118853.1118857`.

William W. Cohen, Robert E. Schapire, and Yoram Singer. Learning to order things. *J. Artif. Int. Res.*, 10(1):243–270, May 1999. ISSN 1076-9757. URL `http://dl.acm.org/citation.cfm?id=1622859.1622867`.

Ronan Collobert and Jason Weston. A unified architecture for natural language processing: deep neural networks with multitask learning. In *Proceedings of the 25th international conference on Machine learning*, ICML '08, pages 160–167, New York, NY, USA, 2008. ACM. ISBN 978-1-60558-205-4. doi: 10.1145/1390156.1390177. URL `http://doi.acm.org/10.1145/1390156.1390177`.

Ronan Collobert, Jason Weston, Léon Bottou, Michael Karlen, Koray Kavukcuoglu, and Pavel Kuksa. Natural language processing (almost) from scratch. *J. Mach. Learn. Res.*, 12:2493–2537, November 2011. ISSN 1532-4435. URL `http://dl.acm.org/citation.cfm?id=1953048.2078186`.

Corinna Cortes and Vladimir Vapnik. Support-vector networks. In *Machine Learning*, pages 273–297, 1995.

James R. Curran and Stephen Clark. Language independent ner using a maximum entropy tagger. In *Proceedings of the seventh conference on Natural language learning at HLT-NAACL 2003 - Volume 4*, CONLL '03, pages 164–167, Stroudsburg, PA, USA, 2003. Association for Computational Linguistics. doi: 10.3115/1119176.1119200. URL `http://dx.doi.org/10.3115/1119176.1119200`.

Oren Etzioni, Michael Cafarella, Doug Downey, Ana-Maria Popescu, Tal Shaked, Stephen Soderland, Daniel S. Weld, and Alexander Yates. Unsupervised named-entity extraction from the web: an experimental study. *Artif. Intell.*, 165(1):91–134, June 2005. ISSN 0004-3702. doi: 10.1016/j.artint.2005.03.001. URL `http://dx.doi.org/10.1016/j.artint.2005.03.001`.

Jr. Forney, G.D. The viterbi algorithm. *Proceedings of the IEEE*, 61(3):268–278, 1973. ISSN 0018-9219. doi: 10.1109/PROC.1973.9030.

John D. Lafferty, Andrew McCallum, and Fernando C. N. Pereira. Conditional random fields: Probabilistic models for segmenting and labeling sequence data. In *Proceedings of the Eighteenth International Conference on Machine Learning*, ICML '01, pages 282–289, San Francisco, CA, USA, 2001. Morgan Kaufmann Publishers Inc. ISBN 1-55860-778-1. URL `http://dl.acm.org/citation.cfm?id=645530.655813`.

Changki Lee, Yi-Gyu Hwang, Hyo-Jung Oh, Soojong Lim, Jeong Heo, Chung-Hee Lee, Hyeon-Jin Kim, Ji-Hyun Wang, and Myung-Gil Jang. Fine-grained named entity recognition using conditional random fields for question answering. In HweeTou Ng, Mun-Kew Leong, Min-Yen Kan, and Donghong Ji, editors, *Information Retrieval Technology*, volume 4182 of *Lecture Notes in Computer Science*, pages 581–587. Springer Berlin Heidelberg, 2006. ISBN 978-3-540-45780-0. doi: 10.1007/11880592_49. URL `http://dx.doi.org/10.1007/11880592_49`.

Andrew McCallum and Wei Li. Early results for named entity recognition with conditional random fields, feature induction and web-enhanced lexicons. In *Proceedings of the seventh conference on Natural language learning at HLT-NAACL 2003 - Volume 4*, CONLL '03, pages 188–191, Stroudsburg, PA, USA, 2003. Association for Computational Linguistics. doi: 10.3115/1119176.1119206. URL `http://dx.doi.org/10.3115/1119176.1119206`.

Paul McNamee and James Mayfield. Entity extraction without language-specific resources. In *proceedings of the 6th conference on Natural language learning - Volume 20*, COLING-02, pages 1–4, Stroudsburg, PA, USA, 2002. Association for Computational Linguistics. doi: 10.3115/1118853.1118873. URL `http://dx.doi.org/10.3115/1118853.1118873`.

Andrei Mikheev, Marc Moens, and Claire Grover. Named entity recognition without gazetteers. In *Proceedings of the Ninth Conference on European Chapter of the Association for Computational Linguistics*, EACL '99, pages 1–8, Stroudsburg, PA, USA, 1999. Association for Computational Linguistics. doi: 10.3115/977035.977037. URL `http://dx.doi.org/10.3115/977035.977037`.

Tomas Mikolov, Kai Chen, Greg Corrado, and Jeffery Dean. Efficient estimation of word representations in vector space. page to appear, 2013.

Robert Munro and Christopher D. Manning. Accurate unsupervised joint named-entity extraction from unaligned parallel text. In *Proceedings of the 4th Named Entity Workshop*, NEWS '12, pages 21–29, Stroudsburg, PA, USA, 2012. Association for Computational Linguistics. URL `http://dl.acm.org/citation.cfm?id=2392777.2392781`.

David E. Rumelhart, Geoffrey E. Hinton, and Ronald J. Williams. Neurocomputing: foundations of research. chapter Learning representations by back-propagating errors, pages 696–699. MIT Press, Cambridge, MA, USA, 1988. ISBN 0-262-01097-6. URL `http://dl.acm.org/citation.cfm?id=65669.104451`.

Beth M. Sundheim. Overview of results of the muc-6 evaluation. In *Proceedings of the 6th conference on Message understanding*, MUC6 '95, pages 13–31, Stroudsburg, PA, USA, 1995. Association for Computational Linguistics. ISBN 1-55860-402-2. doi: 10.3115/1072399.1072402. URL `http://dx.doi.org/10.3115/1072399.1072402`.

Pascal Vincent, Hugo Larochelle, Yoshua Bengio, and Pierre-Antoine Manzagol. Extracting and composing robust features with denoising autoencoders. pages 1096–1103, 2008.

GuoDong Zhou and Jian Su. Named entity recognition using an hmm-based chunk tagger. In *Proceedings of the 40th Annual Meeting on Association for Computational Linguistics*, ACL '02, pages 473–480, Stroudsburg, PA, USA, 2002. Association for Computational Linguistics. doi: 10.3115/1073083.1073163. URL `http://dx.doi.org/10.3115/1073083.1073163`.