Unit III

3 Language Modelling

Syllabus

Probabilistic language modeling, Markov models, Generative models of language, Log-Liner Models, Graph-based Models

N-gram models : *Simple n-gram models, Estimation parameters and smoothing, Evaluating language models,* ***Word Embeddings / Vector Semantics :*** *Bag-of-words, TFIDF, word2vec, doc2vec, Contextualized representations (BERT)*

Topic Modelling : *Latent Dirichlet Allocation (LDA), Latent Semantic Analysis, Non Negative Matrix Factorization*

Contents

3.1 Introduction

- Natural language processing is different than that of formal languages or programming languages. This is primarily because,
  - Formal languages / programming languages, can be fully specified.
  - All the reserved words in formal language can be defined and identified vice a versa.
- However, it is not possible with natural language. Natural languages are not designed; they evolve continually and therefore there is no formal specification.
- In case of formal languages, there are formal rules for parts of the language and heuristics, but natural language that does not confirm is often used.
- Natural languages involve vast numbers of terms that do not create ambiguities for human brains but create ambiguities in understanding by means of computers.
- An alternative approach is to specify the model of the natural language.
- The key knowledge of the almost 70 years of research in natural language processing can be captured through the use of a small number of formal models or theories.
- Language models are a crucial component in the Natural Language Processing (NLP).
- These language models power all the popular NLP applications we are familiar with - Google Assistant, Siri, Amazon's Alexa, etc.

Language modeling for NLP

- Statistical Language Modeling or Language Modeling and LM for short, is the development of probabilistic models that are able to predict the next word in the sequence given the words that precede it.
- A language model learns the probability of word occurrence based on examples of text. Simpler models may look at a context of a short sequence of words, whereas larger models may work at the level of sentences or paragraphs. Most commonly, language models operate at the level of words.
- A language model can be developed and used standalone, such as to generate new sequences of text that appear to have come from the corpus.
- Language modeling is a root problem for a large range of natural language processing tasks. More practically, language models are used on the front-end or back-end of a more sophisticated model for a task that requires language understanding.
- Language modeling is central to many important natural langua ,e proces sing tasks.
- Recently, neural-network-based language models have demonstrated better performance than classical methods both standalone and as part of more challenging natural language processing tasks.

- There may be formal rules for parts of the language, and heuristics, but natural language that does not confirm is often used. Natural languages involve vast numbers of terms that can be used in ways that introduce all kinds of ambiguities, yet can still be understood by other humans.
- Further, languages change, word usages change: it is a moving target. Nevertheless, linguists try to specify the language with formal grammars and structures. It can be done, but it is very difficult and the results can be fragile.
- An alternative approach to specifying the model of the language is to learn it from examples.
- There are primarily two types of language models :
  1. **Statistical language models** : These models use traditional statistical techniques like N-grams, Hidden Markov Models (HMM) and certain linguistic rules to learn the probability distribution of words.
  2. **Neural language models** : These are new in the NLP town and have surpassed the statistical language models in their effectiveness. They use different kinds of neural networks to model language.
- These models and theories are all drawn from the standard toolkits of Computer Science, Mathematics and Linguistics and should be generally familiar to the experts in the respective fields. One can re-visit these terms (highlighted below) from the course Theory of Computation in the earlier years of Computer Science/ Computer Engineering.

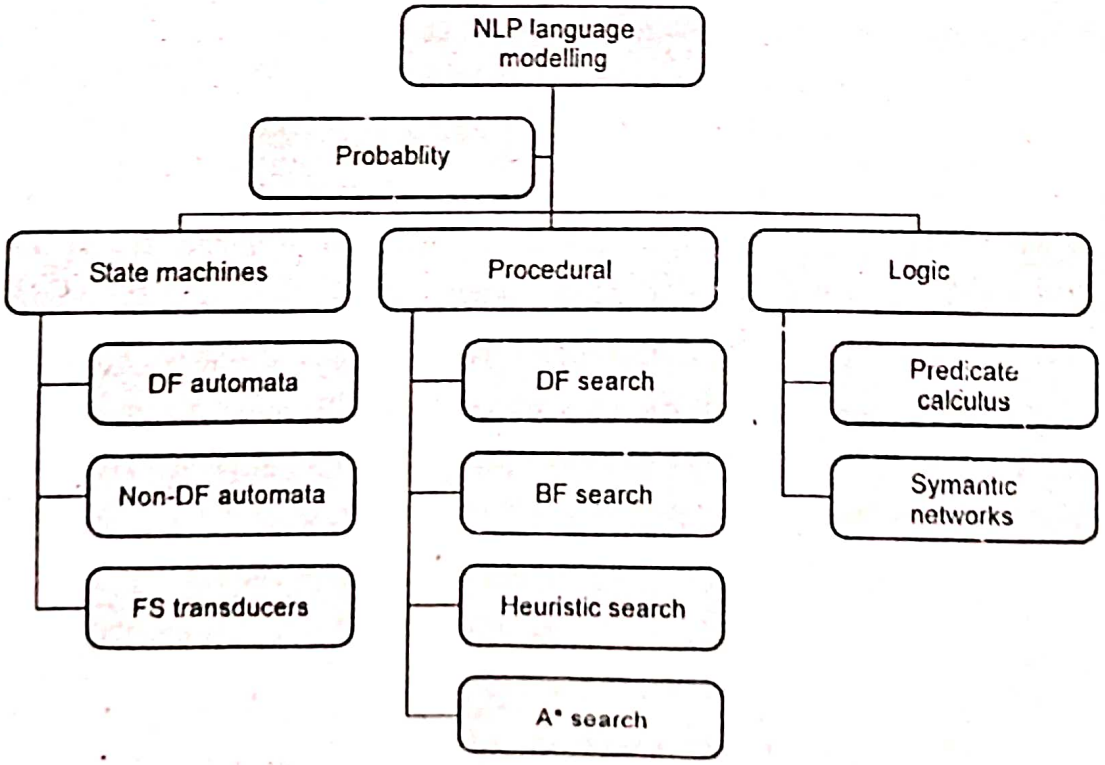

Fig. 3.1.1 Spectrum of NLP language modeling

Statistical language model

- A statistical language model is a probability distribution over sequences of words.
- Given such a sequence, say of length m, it assigns $P(w_1, ... w_m)$ a to the whole sequence.
- The language model provides context to distinguish between words and phrases that sound phonetically similar.
  For example, in English, the phrases "do raid" and "do red" sound similar, but mean different things.
- Data sparsity is a major problem in building language models. This is primarily due to limitations in data modelling. Most possible word sequences are not observed in training.
- One solution is to make the assumption that the probability of a word only depends on the previous n words. This is known as an n-gram model or unigram model when n = 1.
- The unigram model is also known as the bag of words model.
- Estimating the relative likelihood of different phrases is useful in many natural language processing applications, especially those that generate text as an output.
- Discussed as in above example, of "do raid" and "do red", sounds are matched with word sequences.
- Ambiguities are easier to resolve when evidence from the language model is integrated with a pronunciation model and an acoustic model.
- Language models are used in information retrieval in the query likelihood model. There, a separate language model is associated with each document in a collection.
- Documents are ranked based on the probability of the query Q in the document's language model M_d : $P(Q \mid M_d)$. Commonly, the unigram language model is used for document ranking.

Review Questions

1. *What is language modeling ?*
2. *Explain types of language models.*

3.2 Probabilistic Language Modeling

- Probabilistic language models determine word probability by analyzing text data.
- They interpret this data by feeding it through an algorithm that establishes rules for context in natural language.

- Later these models apply these rules in language tasks to accurately predict or produce new sentences.
- The model essentially learns the features and characteristics of basic language and uses those features to understand new phrases.
- A popular idea in computational linguistics is to create a probabilistic model of language.
- Such a model assigns a probability to every sentence in English in such a way that more likely sentences (in some sense) get higher probability.
- In case of the need of disambiguation between two possible sentences, the model picks the sentence with the higher probability.
- Probabilistic language models are distributions over sentence
- There are several different probabilistic approaches to modeling language, which vary depending on the purpose of the language model.
- From a technical perspective, the various types differ by the amount of text data they analyze and the algorithm they use to analyze it.
- Some popular probabilistic language models are :
  1. Unigram : Words generated one at a time, drawn from a fixed distribution.
  2. Bigram : Probability of word depends on previous word.
  3. Tag bigram : Probability of part of speech depends on previous part of speech, probability of word depends on part of speech.
  4. Maximum entropy (Exponential) : The model evaluates text using an equation that combines feature functions and n-grams.
  5. Continuous space : This type of model represents words as a non-linear combination of weights in a neural network.
- Any complex probabilistic language models is recommended for NLP tasks, because natural language itself is extremely complex and always evolving.
- As a result, an exponential model or continuous space model might be better than an n-gram for NLP tasks, because they are designed to account for ambiguity and variation in language.

Review Question

1. *Explain probabilistic language modeling.*

3.3 Markov Models

- Markov model is an un-précised model that is used in the systems that does not have any fixed patterns of occurrence i.e., randomly changing systems.

- Markov model is based upon the fact of having a random probability distribution or pattern that may be analyzed statistically but cannot be predicted precisely.
- In Markov model, it is assumed that the future states only depend upon the current states and not the previously occurred states.
- There are four common Markov models out of which the most commonly used is the hidden Markov model.

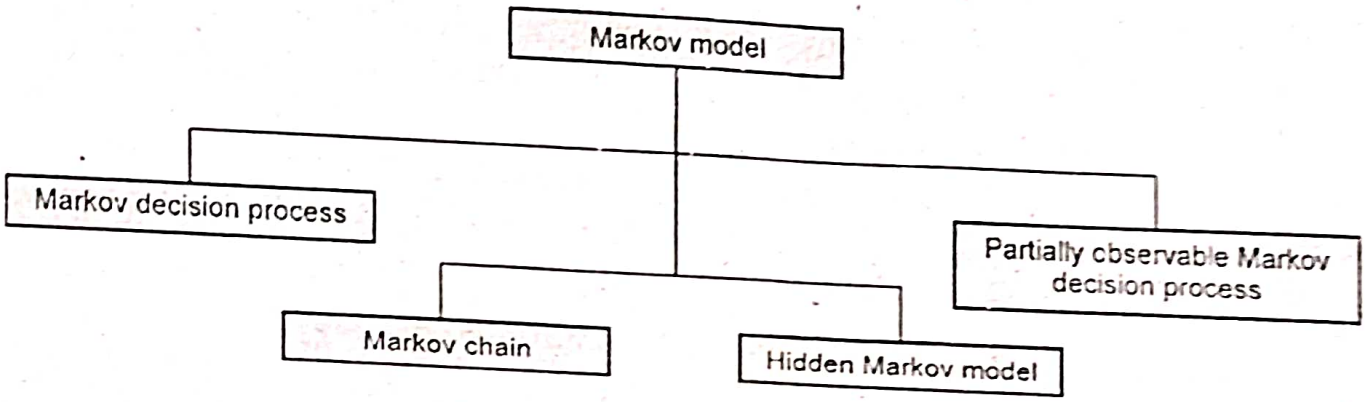

Fig. 3.3.1 Types of Markov models

- For NLP, a Markov chain can be used to generate a sequence of words that form a complete sentence, or a hidden Markov model can be used for named-entity recognition and tagging parts of speech.
- For machine learning, Markov decision processes are used to represent reward in reinforcement learning.
- The Hidden Markov model (popularly known HMM) is a probabilistic model which is used to explain or derive the probabilistic characteristic of any random process.
- It basically says that an observed event will not be corresponding to its step-by-step status but related to a set of probability distributions.

Markov model of natural language

- Claude Shannon approximated the statistical structure of a piece of text using a simple mathematical model known as a Markov model.
- A Markov model of order 0 predicts that each letter in the alphabet occurs with a fixed probability.
- We can fit a Markov model of order 0 to a specific piece of text by counting the number of occurrences of each letter in that text and using these counts as probabilities.

- For example, if the input text is "agggcagegggcg", then the Markov model of order 0 predicts that each letter is 'a' with probability 2/13, 'c' with probability 3/13 and 'g' with probability 8/13.
- The following sequence of letters is a typical example generated from this model.

a g g c g a g g g a g c g g c a g g g g . . .

- An order 0 model assumes that each letter is chosen independently. This does not coincide with the statistical properties of English text since there is a high correlation among successive letters in an English word or sentence. For example, the letters 'h' and 'r' are much more likely to follow 't' than either 'c' or 'x'.
- We obtain a more refined model by allowing the probability of choosing each successive letter to depend on the preceding letter or letters.
- A Markov model of order k predicts that each letter occurs with a fixed probability, but that probability can depend on the previous k consecutive letters (k-gram)

Hidden Markov Model

- In Hidden Markov Model, every individual states has limited number of transitions and emissions.
- Probability is assigned for each transition between states. Hence, the past states are totally independent of future states.
- The fact that HMM is called hidden because of its ability of being a memory less process i.e. its future and past states are not dependent on each other.
- Since HMM is rich in mathematical structure it can be implemented for practical applications. This can be achieved on two algorithms called as :
  - Forward algorithm.
  - Backward algorithm.
- The main goal of HMM is to learn about a Markov chain by observing its hidden states.
- Considering a Markov process X with hidden states Y here the HMM solidifies that for each time stamp the probability distribution of Y must not depend on the history of X according to that time.
- Refer to the Hidden Markov chain in below figure, that indicates the N states with probability indicated by the weight of transition arch.

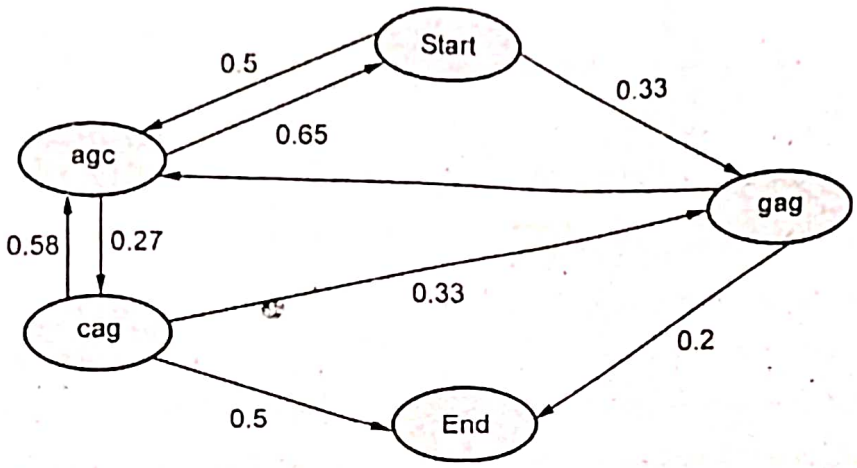

Fig. 3.3.2 Example of Hidden Markov chain for NLP application

- The applications where the HMM can be used have sequential data like time series data, audio and video data and text data or NLP data.
- A prominent NLP application of the HMM is in the Part-of-Speech tagging.

Review Questions

1. *What are Markov models.*
2. *Explain Markov model of natural languages.*
3. *Explain Hidden Markov Model.*

3.4 Generative Models for Language

- The generative model is a single platform for diversified areas of NLP that can address specific problems relating to read text, hear speech, interpret it, measure sentiment and determine which parts are important.
- This is achieved by process of elimination once the relevant components are identified. Single platform provides same model generating and reproducing optimized solutions and addressing different issues.
- Generative models are one of the most promising approaches towards this goal. To train a generative model we first collect a large amount of data in some domain (e.g., think millions of images, sentences, or sounds, etc.) and then train a model to generate data like it. The intuition behind this approach follows a famous quote from Richard Feynman.
- Generative models have many short - term applications. But in the long run, they hold the potential to automatically learn the natural features of a dataset, whether categories or dimensions or something else entirely.

- Mathematically, we think about a dataset of examples x1, x2 ,x3, ... xn as samples from a true data distribution p(x).
- In the example image below, the region shows the part of the image space that, with a high probability (over some threshold) contains real images and black dots indicate our data points (each is one image in our dataset).
- Now, the model also describes a distribution $\hat{p}(x)$ that is defined implicitly by taking points from a unit Gaussian distribution and mapping them through a (deterministic) neural network-our generative model.

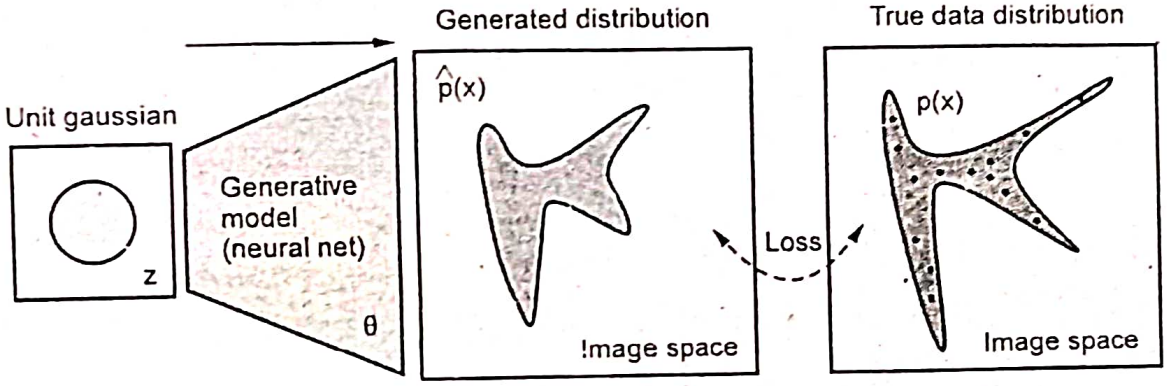

Fig. 3.4.1 Generative model example

Three approaches to generative models

Most generative models have this basic setup, but differ in the details. Here are three popular examples of generative model approaches to give you a sense of the variation :

- **Generative Adversarial Networks (GANs)**
  - This is already discussed above, pose the training process as a game between two separate networks : A generator network (as seen above) and a second discriminative network that tries to classify samples as either coming from the true distribution p(x) or the model distribution $\hat{p}(x)$.
  - Every time the discriminator notices a difference between the two distributions the generator adjusts its parameters slightly to make it go away, until at the end (in theory) the generator exactly reproduces the true data distribution and the discriminator is guessing at random, unable to find a difference.
- **Variational Autoencoders (VAEs)**
  - It allow us to formalize this problem in the framework of probabilistic graphical models where we are maximizing a lower bound on the log likelihood of the data.

- **Autoregressive models**
  - Models such as PixelRNN instead train a network that models the conditional distribution of every individual pixel given previous pixels (to the left and to the top).
  - This is similar to plugging the pixels of the image into a char-rnn, but the RNNs run both horizontally and vertically over the image instead of just a 1D sequence of characters.

Review Question

1. *Explain generative models language.*

3.5 Log Linear Model

- Log-linear models, which are very widely used in natural language processing. A key advantage of log-linear models is their flexibility
- Log-linear models have become a widely-used tool in NLP classification tasks.
- A log-linear model consists of the following components :
  - A set X of possible inputs.
  - A set Y of possible labels. The set Y is assumed to be finite.
  - A positive integer d specifying the number of features and parameters in the model.
  - A function $f : X \times Y \rightarrow R^d$ that maps any (x, y) pair to a feature-vector f(x, y).
  - A parameter vector $v \in R^d$.
- Log-linear models assign joint probabilities to observation/label pairs $(x, y) \in X \times Y$ as follows :

$$P_{\vec{\theta}}(x, y) = \frac{\exp\left(\vec{\theta} \cdot \vec{f}(x, y)\right)}{\Sigma_{x,y} \exp\left(\vec{\theta} \cdot \vec{f}(x, y)\right)}$$

where ~θ is a R-valued vector of feature weights

~ f is a function that maps pairs (x, y) to a nonnegative R-valued feature vector.

- These features can take on any form; in particular, unlike directed, generative models (like HMMs and PCFGs), the features may overlap, predicting parts of the data more than once.
- Each feature has an associated θ_i, which is called its weight. Maximum likelihood parameter estimation (training) for such a model, with a set of labeled examples, amounts to solving the following optimization problem. Let $\{(x_1, y*1), (x_2, y*2), \ldots, (x_m, y*m)\}$.

Review Question

1. *Explain log linear model.*

3.6 N-Gram Model, Simple N Gram Models

- To understand concept of n gram models consider the example sentence.
- Please turn your homework .....
- We want to predict the next word which can be 'in', 'over' but definitely it will not the word 'the'. This is known as word prediction and can be done using probabilistic models called as n-gram models.
- In n-gram model from sequence of n-token words the next word is predicted from previous n - 1 words.
- It is difficult to compute probability of any word sequence w.
- It can be computed by decomposing it based on chain rule of probality as :

$$P(w) = P(w_1 \ldots w_t) = (P)(w_1) \prod_{i=1}^{+} P(w_i/w_{i-1}\, w_{i-2} \ldots w_2 w_1)$$

- But as individual product terms also cannot be computed directly n-gram approximation will be useful.
- By considering the assumption of history equivalence class that n–1 are useful for predicting a given word, n-gram model can be defined as :

$$P(w) \approx \prod_{i=1}^{+} P(w_i | w_{i-1}, \ldots w_{i-n+1})$$

- This is based on markov assumption that current word only depends on n – 1 preceding words and in dependent of all the other given words.
- So n-gram model is also called as $(n-1)^{-th}$ order Markov model.
- Based on length of n the models can be formalized as : for n = 2 → biagram → considering two word sequence of words ex. "please turn" or "turn your" for n=3 → trigram → considering three word sequence of words ex: "please turn your" or "turn your homework" and so on for n = 4,5, etc.

Review Question

1. *Explain N Gram model.*

3.7 Estimation Parameter and Smoothing

- Generally n-gram probabilities are estimated by combining maximum likelihood criterion with parameter smoothing.
- The maximum likelihood estimate can be obtained as

$$P(w_i \mid w_{i-1}, w_{i-2}) = \frac{C(w_i, w_{i-1}, w_{i-2})}{C(w_{i-1}, w_{i-2})}$$

Where $C(w_i, w_{i-1}, w_{i-2})$ is count of trigram w_{i-2}, w_{i-1}, w_i in training data.

- Smoothing is the process of flattening the peakes in n-gram probability distribution by redistributing probability mass. Also zero estimates are replaced by some small nonzero values.
- One of the common smoothing technique is called as back off.
- It splits n-grams whose count in training data fall below predetermined threshold T and also whose count exceed the threshold.
- The backed off probability P_{BO} for w_i given w_{i-1}, w_{i-2} is computed as

$$P_{BO}(w_i \mid w_{i-1}, w_{i-2}) = \begin{cases} d_c P(w_i \mid w_{i-1}, w_{i-2}) \text{ it } C > T \\ d(w_{i-1}, w_{i-2}) P_{BO}(w_i \mid w_{i-1}) \text{ otherwise} \end{cases}$$

Where $C \rightarrow$ count of (w_i, w_{i-1}, w_{i-2})

$d_c \rightarrow$ discounting factor applied to higher order distribution.

- It is a parameter estimation method in which set of parameters of a model are considered as random variable, which is governed by previous statistical distribution posterior distribution,
- $P(\theta|S)$ is given using Bay's rule as

$$P(\theta|S) = \frac{P(S \mid \theta) P(\theta)}{P(s)}$$

Where $S \rightarrow$ training sample with sequence of words $w_1 \ldots\ldots w_t < P(w_1), \ldots,$

$P(w_k) >$ (where k is vocabulary size)

$\theta \rightarrow$ Set of parameters

= for unigram model $P(w_1 \mid h_1 \ldots\ldots, P(w_k|h_k)) >$ for n-gram

$P(\theta) \rightarrow$ Prior distribution over different possible values of θ

- A point estimate of θ is done by Maximum a Posteriori (MAP) criteria as follows.

$$\theta_{MAP} = \underset{\theta \in \Theta}{\text{argmax}}\ P(\theta \mid s) = \underset{\theta \in \Theta}{\text{argmax}}\ P(S \mid \theta)\ P(\theta)$$

Where Θ is space for possible assignments for θ

- The expected value of θ for sample S is given as :

$$\theta_B = E[\theta \mid S] = \int_{\Theta} \theta\ P(\theta \mid S)\ d\theta$$

$$= \frac{\int_{\Theta} \theta\ P(S \mid \theta)\ P(\theta)\ d\theta}{\int_{\Theta} P(S \mid \theta)\ P(\theta)\ d\theta}$$

- With the increase of monolingual data scaling of language is required to handle sets of bilions or trillions of words.
- In this case exact probability computations and in turn parameter estimation is not feasible.
- So to handle the large data, complete data required for training is divided into partitiones.
- Probabilities derived from each partition are stored in separate physical location.
- The language model server handles this data which is distributed over a cluster of independent nodes.
- Clients request statistics from this server during runtime.
- These models facilitate scalabity for handling large amount of data, also new data can be added dynamically.
- The disadvantage is slow speed due to networking overheads.
- Another variation can be use of large scale. Distributed language at second pass rescoring stage.
- In this first pass hypothesis is done using smaller language models.
- One more approach is storing large scale, language models in working memory of a single machine.
- The concept of bloom filter is used for this purpose.
- The corpus statistics is stored in memory efficient and randomized data structure called as Bloom filter in quantized manner.

Review Questions

1. *Explain the concept of estimation parameter and smoothing.*
2. *Explain large scale languages models.*

3.8 Evaluating Language Model

- Evaluating the performance of language model is the best way to include it in an application and check the performance of that application. This process is called as extrinsic evaluation.
- But as it is expensive at times, another way of evolution i.e. intrinsic evolution is used.
- In intrinsic evolution a metric is used to quickly evaluate the improvements in language model.
- Two criterias used for intrinsic evaluation of language model are.

1. Coverage rate

- It measures percentage of n-grams in test set
- Sometimes there are cases where same unknown words appear they are called as Out Of Vocabulary (OOV) words which cannot be handled by this type.

2. Perplexity

- It considers the fact that among two probabilistic models the model which fits the test data is the better one.

Review Question

1. *How to evaluate language model ?*

3.9 Bag of Words

- In NLP the input to various algorithms for different applications is in text form.
- But these machine learning algorithms cannot work on the raw text.
- The text must be converted to numbers for further processing.
- More specifically the vectors of these numbers representing text are generated.
- Bag Of Words (BOW) representation is used to convert text into fixed length vectors.
- BOW moded takes into account the frequency of occurrence of words in input text document.
- It focuses on two things :
  1. Vocabulary of known words.
  2. Measure of presence of these known words.

- The word 'Bag' in bag of words is analogous to the bag of items. When we fill the bag the order of the items is discarded, similarly in bag of words model represents unordered set of words irrespective of their position in the document.
- It only considers the frequency of words in the text.
- Let's consider the following example to understand how bag of words model works stepwise.

Step 1 : Step 1 includes collection of data. Consider each of the following sentences as text documents.

- The dog sat
- The dog sat in the hat
- The dog with the hat

Step 2 :

- Step 2 includes designing the vocabulary.
- All the words present in document set are listed.
- In out example the words formed are : the, dog, sat, in, the, hat, with.

Step 3 :

- Step 3 includes computation of the frequency of the occurrence of words in the document.
- In our example it can be list as :

Document	the	dog	sat	in	hat	with
the dog sat	1	1	1	0	0	0
the dog sat in the hat	2	1	1	1	1	0
the dog with the hat	2	1	0	0	1	1

- With the 6 distinct words and their frequency of occurrence in the document, now we can write fixed length vector for each document as follows :
  - The dog sat → [1, 1, 1, 0, 0, 0]
  - The dog sat in the hat → [2, 1, 1, 1, 1, 0]
  - The dog with the hat → [2, 1, 0, 0, 1, 1]
- The drawback of BOW model is, we loose the context of the document.
- BOW model only tells what words will appear in the document with them frequency but it doesn't tell where they occurred.

- The bag-of-words model is a simplifying representation used in natural language processing and information retrieval.
- In this model, a text (such as a sentence or a document) is represented as the bag (multiset) of its words, disregarding grammar and even word order but keeping multiplicity. The bag-of-words model has also been used for computer vision.
- The bag-of-words model is commonly used in methods of document classification where the (frequency of) occurrence of each word is used as a feature for training a classifier.
- The Bag-of-words model is one example of a vector space model. Bag of words is a natural language processing technique of text modeling.
- It is a method of feature extraction with text data. This approach is a simple and flexible way of extracting features from documents.
- Whenever we apply any algorithm in NLP, it works on numbers. We cannot directly feed our text into that algorithm. Hence, Bag of Words model is used to preprocess the text by converting it into a bag of words, which keeps a count of the total occurrences of most frequently used words.
- This model can be visualized using a table, which contains the count of words corresponding to the word itself.
- The approach is very simple and flexible and can be used in a myriad of ways for extracting features from documents.
- A bag-of-words is a representation of text that describes the occurrence of words within a document. It involves two things :
  - A vocabulary of known words.
  - A measure of the presence of known words.
- It is called a "bag" of words, because any information about the order or structure of words in the document is discarded. The model is only concerned with whether known words occur in the document, not where in the document
- A bag of words is a representation of text that describes the occurrence of words within a document.
- The model is only concerned with whether known words occur in the document, not where in the document.
- One of the biggest problems with text is that it is messy and unstructured and machine learning algorithms prefer structured, well defined fixed-length inputs and by using the Bag-of-Words technique we can convert variable-length texts into a fixed-length vector.

Steps of bag of words model :

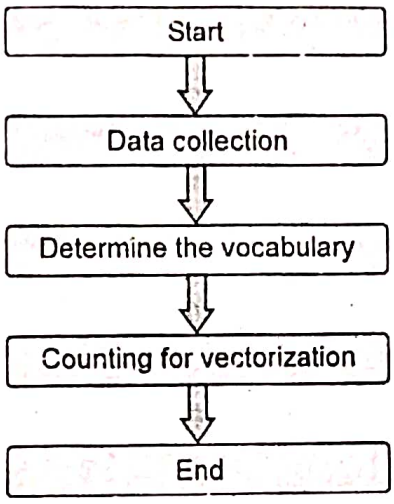

Fig. 3.9.1

Disadvantages of using bag of words model :

- The model ignores the location information of the word. The location information is a piece of very important information in the text.
- Bag of word models doesn't respect the semantics of the word. For example, words 'soccer' and 'football' are often used in the same context.
- The range of vocabulary is a big issue faced by the bag-of-words model.

TF / IDF

- TF-IDF stands for Term Frequency Inverse Document Frequency of records.
- It can be defined as the calculation of how relevant a word in a series or corpus is to a text.
- The meaning increases proportionally to the number of times in the text a word appears but is compensated by the word frequency in the corpus (data-set).

Key concepts in TF / IDF

- Term frequency :
  - In document d, the frequency represents the number of instances of a given word t.
  - Therefore, we can see that it becomes more relevant when a word appears in the text, which is rational.
  - Since the ordering of terms is not significant, we can use a vector to describe the text in the bag of term models.

- For each specific term in the paper, there is an entry with the value being the term frequency.
- The weight of a term that occurs in a document is simply proportional to the term

$$tf(t,d) = \text{count of } t \text{ in } d \text{ / number of words in } d$$

- Document frequency :
  - This tests the meaning of the text, which is very similar to TF, in the whole corpus collection.
  - The only difference is that in document d, TF is the frequency counter for a term t, while df is the number of occurrences in the document set N of the term t.
  - In other words, the number of papers in which the word is present is DF.

$$df(t) = \text{Occurrence of } t \text{ in documents}$$

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- Inverse document frequency :
  - Mainly, it tests how relevant the word is.
  - The key aim of the search is to locate the appropriate records that fit the demand.
  - Since tf considers all terms equally significant, it is therefore not only possible to use the term frequencies to measure the weight of the term in the paper.
  - First, find the document frequency of a term t by counting the number of documents containing the term :

$$df(t) = N(t)$$

where

$df(t)$ = Document frequency of a term t

$N(t)$ = Number of documents containing the term t

- Term frequency is the number of instances of a term in a single document only; although the frequency of the document is the number of separate documents in which the term appears, it depends on the entire corpus.
- Now let's look at the definition of the frequency of the inverse paper. The IDF of the word is the number of documents in the corpus separated by the frequency of the text.

$$idf(t) = N/ df(t) = N/N(t)$$

- The more common word is supposed to be considered less significant, but the element (most definite integers) seems too harsh. We then take the logarithm (with base 2) of the inverse frequency of the paper. So the if of the term t becomes :

$$idf(t) = \log(N/ df(t))$$

- Computation :
  - Tf-idf is one of the best metrics to determine how significant a term is to a text in a series or a corpus.
  - tf-idf is a weighting system that assigns a weight to each word in a document based on its term frequency (tf) and the reciprocal document frequency (tf) (idf).
  - The words with higher scores of weight are deemed to be more significant.
- Usually, the tf-idf weight consists of two terms -
  - Normalized term frequency (tf)
  - Inverse document frequency (idf)
- Hence we get

$$tf\text{-}idf(t, d) = tf(t, d) * idf(t)$$

Applications of TFIDF

- Document classification - Helps in classifying the type and genre of a document.
- Topic modelling - It helps in predicting the topic for a corpus.
- Information retrieval system - To extract the important information out of a corpus.
- Stop word filtering - Helps in removing the unnecessary words out of a text body.

Review Questions

1. *Explain Bag of Words model.*
2. *Explain the concept TF/IDF.*

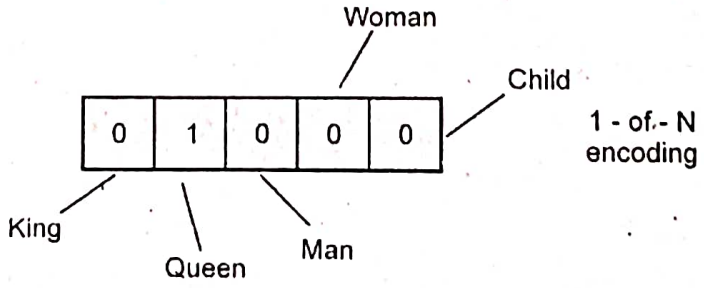
3.10 Word Embedding / Vector Semantics

- As described in the BOW model we have seen how a word in a document can be represented in numerical form as a vector representation.
- In other words this numerical representation of words in called as word embedding.
- We can consider the analogy of RGB representation of colours to understand this concept.
- Section 3.9 illustrates how vector representation can be obtained from sentences in a document.
- Word embedding are classified in two types :
  1. Frequency based embedding
  2. Prediction based embedding

1. Simple frequency based embeddings

One-hot encoding

- Let's start by looking at the simplest way of converting text into a vector.
- We could have a vector of the size of our vocabulary where each element in the vector corresponds to a word from the vocabulary.
- The encoding of a given word would then simply be the vector in which the corresponding element is set to 1 and all other elements are 0.
- Suppose our vocabulary has only five words : King, Queen, Man, Woman and Child. We could encode the word 'Queen' as :



- This simple technique of creating numerical representations is called **One-Hot Encoding.**
- But this is neither scalable and nor smart.
- If we have a vocabulary of ten million words, it would mean that we would need vectors of size 10M, where each word would be represented by a single 1 and all other 9,999,999 elements would be set to 0.

- Besides the sparseness and huge memory requirement issues, this technique is also not able to capture any semantic relationships or context information.
- Tf-Idf is another popular technique for computing frequency based embeddings.

2. Prediction based embeddings

- Prediction based embedding is one of the most sought word embedding technique in NLP.
- These methods were prediction-based as they give the probabilities to the words.
- They proved to be state of the art for tasks like word analogies and word similarities.
- They were also able to achieve algebraic operations tasks.
- Following are the two algorithms in prediction based embedding,

  1. Word2Vec
  2. Doc2Vec
- Refer section 3.11 for word2vec model.

3.11 Word2Vec

- Word2vec is a technique for Natural Language Processing (NLP) published in 2013.
- The word2vec algorithm uses a neural network model to learn word associations from a large corpus of text.
- Once trained, such a model can detect synonymous words or suggest additional words for a partial sentence.
- As the name implies, word2vec represents each distinct word with a particular list of numbers called a vector.
- The vectors are chosen carefully such that they capture the semantic and syntactic qualities of words; as such, a simple mathematical function (cosine similarity) can indicate the level of semantic similarity between the words represented by those vectors.
- Word2vec can utilize either of two model architectures to produce these distributed representations of words : Continuous bag-of-words (CBOW) or continuous skip-gram.
- In both architectures, word2vec considers both individual words and a sliding window of context words surrounding individual words as it iterates over the entire corpus.

3.15 Latent Dirichlet Allocation

Bayesian topic based language models or Latent Dirichlet Allocation (LDA) model.

- Bayesian topic based models are emerged recently in statistical language modeling.
- Blei, Ng and Jordan proposed the first LDA model under Bayesian topic based models.
- LDA model is designed on following assumptions :
  - Each document is considered to be formed of k topics and denoted as Z_1, ... Z_k.
  - Topic specific distribution over a particular word is used to generate a word. k = 1, ...k. probablity vector ϕ_k is generated.
  - The prior probabilities of each topic (θ_k). θ_1, θ_2, ...θ_k are distributed according to Dirichlet distribution with hyper parameters α_1, ...α_k is given as

$$P(\theta_1, ...\theta_k) = \frac{\Gamma(\Sigma_k \alpha_k)}{\pi_k \Gamma(\alpha_k)} \prod_{k=1}^{k} \theta_k^{\alpha_k - 1}$$

- Probablity of complete document with sequence W of t words is given as :

$$P(W \mid \alpha, \phi) = \int P(\theta \mid \alpha) \left(\pi_{i=1}^{t} \sum_{z_i} P(z_i \mid \theta) P(w_i \mid z_i, \phi) \right) d\theta$$

Review Question

1. *Explain latent dirichlet allocation.*

3.16 Latent Semantic Analysis

- Latent Semantic Analysis (LSA) is a technique in natural language processing, in particular distributional semantics, of analyzing relationships between a set of documents and the terms they contain by producing a set of concepts related to the documents and terms.
- LSA assumes that words that are close in meaning will occur in similar pieces of text (the distributional hypothesis).
- A matrix containing word counts per document (rows represent unique words and columns represent each document) is constructed from a large piece of text and a mathematical technique called Singular Value Decomposition (SVD) is used to reduce the number of rows while preserving the similarity structure among columns.

- Documents are then compared by cosine similarity between any two columns.
- Values close to 1 represent very similar documents while values close to 0 represent very dissimilar documents.

Occurrence matrix

- LSA can use a document-term matrix which describes the occurrences of terms in documents; it is a sparse matrix whose rows correspond to terms and whose columns correspond to documents. A typical example of the weighting of the elements of the matrix is tf-idf (term frequency - inverse document frequency) : The weight of an element of the matrix is proportional to the number of times the terms appear in each document, where rare terms are upweighted to reflect their relative importance.

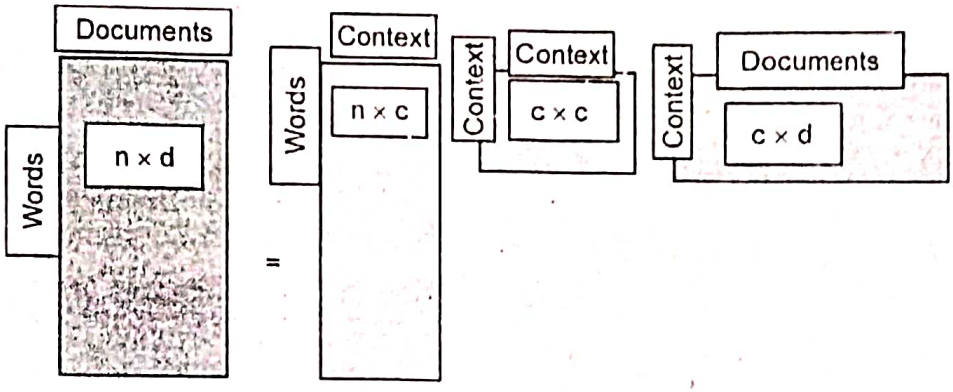


Fig. 3.16.1 LCA occurrence matrix

- This matrix is also common to standard semantic models, though it is not necessarily explicitly expressed as a matrix, since the mathematical properties of matrices are not always used.

Rank lowering

- After the construction of the occurrence matrix, LSA finds a low-rank approximation to the term-document matrix. There could be various reasons for these approximations :
- The original term-document matrix is presumed too large for the computing resources; in this case, the approximated low rank matrix is interpreted as an approximation (a "least and necessary evil").
- The original term-document matrix is presumed noisy : For example, anecdotal instances of terms are to be eliminated. From this point of view, the approximated matrix is interpreted as a de-noisified matrix (a better matrix than the original).

- The original term-document matrix is presumed overly sparse relative to the "true" term-document matrix. That is, the original matrix lists only the words actually in each document, whereas we might be interested in all words related to each document-generally a much larger set due to synonymy.
- This mitigates the problem of identifying synonymy, as the rank lowering is expected to merge the dimensions associated with terms that have similar meanings.
- It also partially mitigates the problem with polysemy, since components of polysemous words that point in the "right" direction are added to the components of words that share a similar meaning.
- Conversely, components that point in other directions tend to either simply cancel out, or, at worst, to be smaller than components in the directions corresponding to the intended sense.

Application of LSA

- Compare the documents in the low-dimensional space (data clustering, document classification).
- Find similar documents across languages, after analyzing a base set of translated documents (cross-language information retrieval).
- Find relations between terms (synonymy and polysemy).
- Given a query of terms, translate it into the low-dimensional space and find matching documents (information retrieval).
- Find the best similarity between small groups of terms, in a semantic way (i.e. in a context of a knowledge corpus), as for example in multiple choice questions MCQ answering model.
- Expand the feature space of machine learning / text mining systems.
- Analyze word association in text corpus.

Review Question

1. *Explain latent semantic analysis.*

3.17 Non Negative Matrix Factorization (NMF)

- Non-Negative Matrix Factorization is a statistical method that helps us to reduce the dimension of the input corpora or corpora.

- Internally, it uses the factor analysis method to give comparatively less weightage to the words that are having less coherence.
- Non-Negative Matrix Factorization (NMF or NNMF), also non-negative matrix approximation is a group of algorithms in multivariate analysis and linear algebra where a matrix V is factorized into (usually) two matrices W and H, with the property that all three matrices have no negative elements.
- This non-negativity makes the resulting matrices easier to inspect. Also, in applications such as processing of audio spectrograms or muscular activity, non-negativity is inherent to the data being considered.

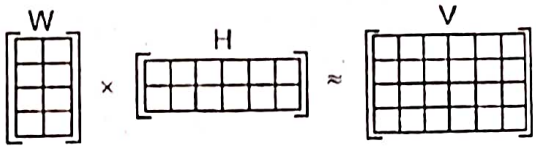


Illustration of approximate non-negative matrix factorization : The matrix **V** is represented by the two smaller matrices **W** and **H**, which, when multiplied, approximately reconstruct **V**.

Fig. 3.17.1 Non-Negative matrix factorization illustrated

- Since the problem is not exactly solvable in general, it is commonly approximated numerically.
- NMF finds applications in such fields as astronomy, computer vision, document clustering, missing data imputation, chemometrics, audio signal processing, recommender systems and bioinformatics.

Review Question

1. *Explain Non-negative matrix factorization.*

❑❑❑

Unit IV

4 Information Retrieval using NLP

Syllabus

Information Retrieval : *Introduction, Vector Space Model*

Named Entity Recognition : *NER System Building Process, Evaluating NER System Entity Extraction, Relation Extraction, Reference Resolution, Coreference resolution, Cross Lingual Information Retrieval.*

Contents

4.1 Information Retrieval : Introduction

- Information retrieval field mainly contain two broad tasks, first is storage and second is retrieval of all manner of media.
- IR task focuses on storage of text documents and their retrieval according to user's request.
- With IR context, a word in document refer to unit of text in the system, which is indexed and available for retrieval.
- Documents can be of different types for example, newspaper, articles, encyclopedia entries or simply small paragraphs and sentences.
- Some terminologies used in IR systems are,

  collection → Set of documents to satisfy user queries.

  term → Lexical item in collection.

  query → User's information need in set of terms.
- The architecture of Ad hoc IR system is shown in Fig. 4.1.1.

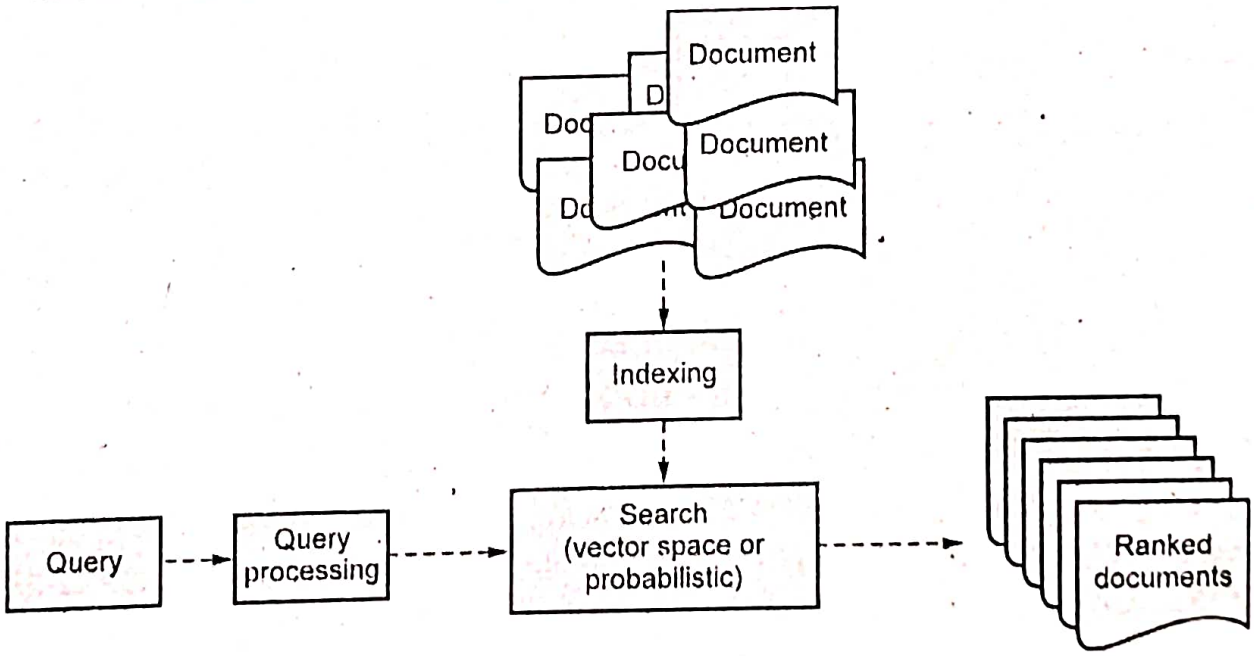


Fig. 4.1.1 The architecture of an Ad hoc IR system

4.2 Vector Space Model

- In this the documents and queries are represented as vectors.
- Vector consists of features which represent the words present in the collection.

- Consider the example of Potato fries out recipe on internet oil in this recipe if the terms Potato, fires and salt occur term frequencies 8, 2, 7 and 4 respectively then the vector can be written as

$$\vec{d}_j = (8, 2, 7, 4)$$

- So in general for document d_j, a vector is written as,

$$\vec{d}_j = (w_{1,j}, w_{2,j}, w_{3,j}, \ldots, w_{n,j})$$

where $\vec{d}_j \rightarrow$ A document

$w_{n,j} \rightarrow$ Weight that term n in document j.

- Query can be written in same way

  so query q for Potato fries can be written as,

$$\vec{q} = (1, 1, 0, 0)$$

- In general it is written as,

$$\vec{q} = (w_{1,q}, w_{2,q}, w_{3,q}, \ldots, w_{n,q})$$

  N → Dimensions in vector = Total number of terms in complete collection.

- Now consider another document recipe for Potato curry. Let's consider the vector as,

$$\vec{d}_k = (6, 0, 0, 0)$$

- If the query is written for Potato fries then it should match document d_j then to d_k.
- If we use features and queries representing a document as dimensions in multidimensional space then feature weights are used to locate documents in that particular space.
- A point in this space represents user's query translated into vector.
- This is shown graphically in Fig. 4.2.1.
- The similarity between vectors is measured by angle between the vectors.
- As shown in the Fig. 4.2.1 the query is considered more similar to d_j than to d_k as the angle between query and d_j is smaller.
- Typically a cosine metric is used in this type of retrieval.
- The distance between two documents is measured by cosine of the angle between them.

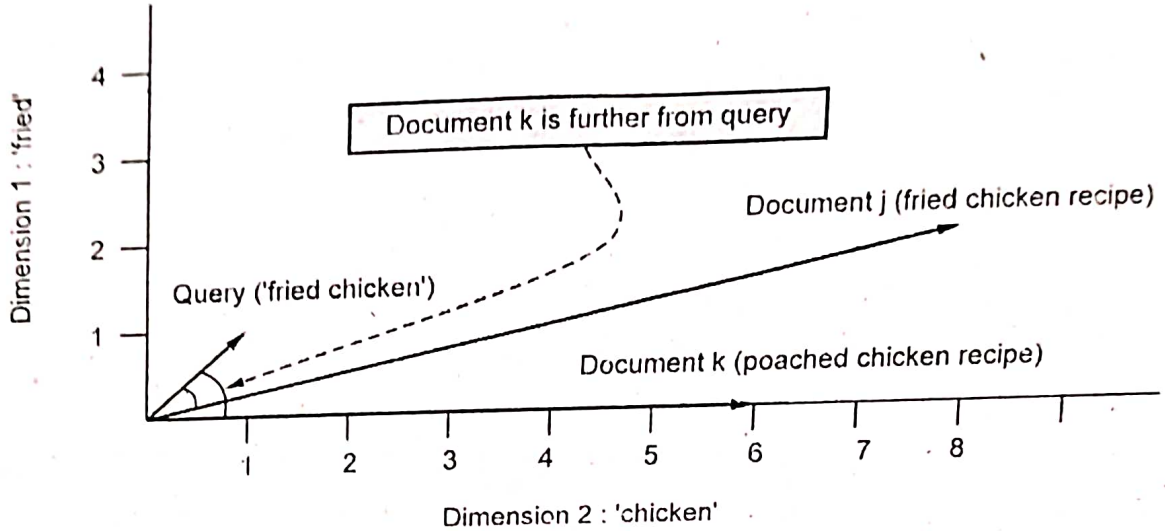


Fig. 4.2.1 A graphical illustration of the vector model for information retrieval, showing the first two dimensions (fried and chicken) and assuming that we use raw frequency in the document as the feature weights

- For identical document cosine value is 1.
- If the documents don't share common terms, the value of cosine is 0.
- The equation for cosine is written as,

$$S_{lm}(\vec{q}, \vec{d_j}) = \frac{\left(\sum_{i=1}^{N} w_{i,q} \times w_{i,j}\right)}{\sqrt{\sum_{i-1}^{N} w_{i,q}^2} \times \sqrt{\sum_{i=1}^{N} w_{i,j}^2}}$$

- Cosine can also be considered as normalized dot product i.e. it is a dot product between two vectors divided by lengths of two vectors.
- The numerator of cosine is dot product given by formula,

$$\text{Dot - product}(\vec{x}, \vec{y}) = \vec{x} \cdot \vec{y} = \sum_{i=1}^{N} x : \times y :$$

- The denominator of cosine is represented by lengths of vector, where vector length is given as,

$$|\vec{x}| = \sqrt{\sum_{i=1}^{N} x_i^2}$$

- So a document retrieval system simply accepts user's query, creates vector representation, compare it with vector representing all the documents and finally the result is sorted, which is list of ranked documents according to their similarity with query.

Evaluation of IR systems :

- The basic tools for measuring performance IR system are,

  1. Precision 2. Recall.

- It is assumed that returned item is divided in two categories : The relevant results and irrelevant results.
- So precision can be stated as fraction of returned relevant documents.
- Recall is fraction of all possible relevant documents contained in return set.
- Let's consider,

  T → Total ranked documents as a result of given query

  R → Relevant documents from T

  N → Remaining irrelevant documents

  U → Relevant documents in the collection as a whole for given query.

Now the precision and recall measures can be given as,

$$\text{Friction} = \frac{|R|}{|T|}$$

$$\text{Recall} = \frac{|R|}{|U|}$$

- The drawback is, these measures are not sufficient to measure the performance of the ranked retrieval of the system as these are not dependent on rank.

Review Question

1. *Explain vector space model.*

4.3 Named Entity Recognition

- Named-Entity Recognition (NER) (also known as (named) entity identification, entity chunking, and entity extraction) is a subtask of information extraction that seeks to locate and classify named entities mentioned in unstructured text into pre-defined categories
- Named entity recognition (NER) – also called entity identification or entity extraction – is a natural language processing (NLP) technique that automatically identifies named entities in a text and classifies them into predefined categories.
- Entities can be names of people, organizations, locations, medical codes, time expressions, times, quantities, monetary values, percentages and more.

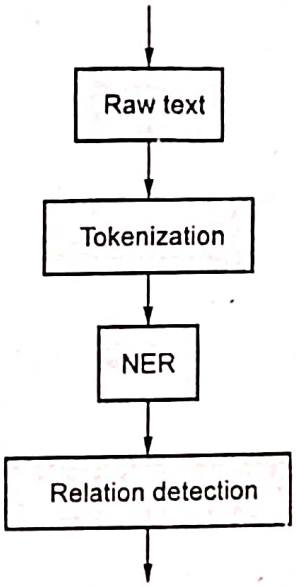


Fig. 4.3.1 Named Entity Recognition (NER) in NLP

NER example : In the sentence "Dheerubhai Ambani Founded Reliance Industries in India " we can identify three types of entities :

<Person> → Dheerubhai Ambani

<Company> → Reliance Industries

<Location> → India

- Recognition of these entities is done through machine learning and Natural Language Processing (NLP).
- With named entity recognition, one can extract key information to understand what a text is about or merely use it to collect important information to store in a database. NER systems have been created that use linguistic grammar-based techniques as well as statistical models such as machine learning. Hand-crafted grammar-based systems typically obtain better precision, but at the cost of lower recall and months of work by experienced computational linguists.
- Statistical NER systems typically require a large amount of manually annotated training data.
- Popular NER platforms include :
  1. GATE supports NER across many languages and domains out of the box, usable via a graphical interface and a Java API.
  2. OpenNLP includes rule-based and statistical named-entity recognition.
  3. SpaCy features fast statistical NER as well as an open-source named-entity visualizer.
- APIs for NER - There are TWO types of NER APIs

- Open-source named entity recognition APIs
  1. **Open-source APIs are for developers :** They are free, flexible and entail a gentle learning curve. Here are a few options :
     - **Stanford Named Entity Recognizer (SNER) :** This JAVA tool developed by Stanford University is considered the standard library for entity extraction. It's based on Conditional Random Fields (CRF) and provides pre-trained models for extracting person, organization, location and other entities.
     - **SpaCy :** A Python framework known for being fast and very easy to use. It has an excellent statistical system that you can use to build customized NER extractors.
     - **Natural Language Toolkit (NLTK) :** This suite of libraries for Python is widely used for NLP tasks. NLKT has its own classifier to recognize named entities called ne_chunk, but also provides a wrapper to use the Stanford NER tagger in python.
- SaaS named entity recognition APIs
  1. SaaS tools are ready-to-use, low-code, and cost-effective solutions. Plus, they are easy to integrate with other popular platforms.
  2. Monkey Learn, for example, is a text analysis SaaS platform that you can use for different NLP tasks, one of which is named entity recognition. You can use MonkeyLearn's ready-built API to integrate pre-trained entity extraction models or you can easily build your own custom named entity extractor in just a few simple steps.
- NER used in
  1. **Classifying content for news providers :** News and publishing houses generate large amounts of online content on a daily basis and managing them correctly is very important to get the most use of each article.

     Named entity recognition can automatically scan entire articles and reveal which are the major people, organizations and places discussed in them.

     Knowing the relevant tags for each article help in automatically categorizing the articles in defined hierarchies and enable smooth content discovery.
  2. **Efficient search algorithms :** If for every search query the algorithm ends up searching all the words in millions of articles, the process will take a lot of time. Instead, if Named Entity Recognition can be run once on all the articles and the relevant entities (tags) associated with each of those articles are stored separately, this could speed up the search process considerably.

3. **Powering content recommendations :** One of the major uses cases of named entity recognition involves automating the recommendation process.
4. **Customer support :** There are a number of ways to make the process of customer feedback handling smooth and named entity recognition could be one of them.
5. **Research papers :** An online journal or publication site holds millions of research papers and scholarly articles. There can be hundreds of papers on a single topic with slight modifications. Segregating the papers on the basis of the relevant entities it holds can save the trouble of going through the plethora of information on the subject matter.

4.3.1 NER System Building Process

- Anything which is referred by a proper name is called as **named entity.**
- Table 4.3.1 shows entity types and their categories.

Type	Tag	Sample categories
People	PER	Individuals, fictional characters, small groups.
Organization	ORG	Companies, agencies, political parties, religious groups, sports teams.
Location	LOC	Physical extents, mountains, lakes, seas.
Geo-political entity	GPE	Countries, states, provinces, counties.
Facility	FAC	Bridges, buildings, airports.
Vehicles	VEH	Planes, trains, and automobiles.

Table 4.3.1 A list of generic named entity types with the kinds of entities they refer to

- Named Entity Recognition (NER) is a process of finding the part of text containing proper names and to identify and classify the entitie's types.
- NER systems take into account various entity types like people, places, organizations, commercial products, weapons, biological entities and many more.
- Sometimes the proper names are signaled based on their surrounding contexts.

  For example :

  If in a text word Dr. appears then we can say that the next word is a name of a person.
- Concept of named entity is further extended to the entities of practical importance known as temporal, for example, dates, expressions, times, named events, etc. Some represent numerical expressions like measurements, counts, prices etc.

Ambiguity in named entity recognition :

- Two types of ambiguities exist in NER.

  1] The ambiguities which arise due to reference resolution problem :

  - In some cases it may happen that same name can be used for different entities.
  - **For example :** JFK can be used to address former president or his son.

  2] The ambiguities which arise due to cross type confusion :

  - It may happen that same name can refer to a person as well as some school name or airport name.
  - For example : In extension with previous example along with name of person JFK can also refer to a school name or airport name.

NER as sequence labeling :

- To address the problem of NER word by word sequence labeling task is used.
- In this approach the assigned tags can capture both the boundary and type of detected entities.
- The classifiers are trained for labelling the tokens in a text with tags. These tags indicate the presence of specific kinds of named entities.

Review Questions

1. *What is named entity recognition ?*
2. *What are open source named entity recognition API's ?*
3. *Explain NER system building process.*

4.4 Evaluating NER System Entity Extraction

Evaluation of named entity recognition :

- Recall, precision and F, measures matrices are used for evaluation of NER.

  where

  Recall ratio of the number of correctly labelled responses to total responses eligible for labelling

  Precision = Ratio of the number of correctly labelled responses to total labelled

  F measure = Way to combine above two measures into single matrix.

$$\text{So, } F_\beta = \frac{(\beta 2 + 1)\, PR}{\beta 2\, P + R}$$

Where $\beta \rightarrow$ Weights the importance of recall of precision.

$\beta >$ 1 Favor recall

$\beta <$ 1 Favor precision

β = 1 Recall and precision are balanced

In this case f can be written as $f_1 = \frac{2PR}{P+R}$.

Review Question

1. *How to evaluate NER system ?*

4.5 Reference Resolution

- To understand the concept of reference resolution, lets consider following example.
- "Lakshmi is studying in 10^{th} standard. She is a very good singer and participated in many music programs. The performance of this 16 years old is also excellent in academics."
- In the above passage there is mention of one person named Lakshmi.
- The linguistic expressions like her, she are used to denote an individual is known as reference.
- Reference resolution is a task to determine what entities are referred to by which linguistic expressions.
- Referring expression (for ex. she) is a haliral language expression used to perform reference.
- The referred entity is called as reference (for ex. Lakshmi).
- Reference to an entity which is previously introduced in discourse is called anaphora and the referring expression is called as amaphoric. For ex. Pronoun, she and 16 years old are anaphoric.
- Two referring expressions used to refere same entity are said to corefer.
- So typically the task of reference resolution involve two tasks :
  1. Coreference resolution
  2. Pronominal anaphora resolution
- Coreference resolution is the task to find out referring expressions referring to same entity.
- Pronominal anaphora resolution is the task to find out antecedent for single pronoun.
- For ex. : antecedent of she is Lakshmi. We need to find out the given a pronoun she, its antecedent is Lakshmi.

- Pronominal anaphora resolution can be considered as subtask of coreference resolution.
- There are various algorithms which can be used for this purpose. Some of them are :
  1. Hobbs algorithm
  2. Centering algorithm
  3. Log linear algorithm

Review Question

1. *What is reference resolution ?*

4.6 Coreference Resolution

- Coreference resolution is the task of finding all expressions that refer to the same entity in a text. It is an important step for a lot of higher level NLP tasks that involve natural language understanding such as document summarization, question answering and information extraction.
- Coreference Resolution in particular, is the process of resolving pronouns to identify which entities are they referring to. It is also a kind of Reference Resolution. The entities resolved may be a person, place, organization, or event.

Review Question

1. *Explain coreference resolution.*

4.7 Cross Lingual Information Retrieval (CLIR)

- Humans have the unique ability to express themselves through different mediums of communication like : Oral, written, through images and pictures, through gestures and sign language, etc.
- Out of these, oral and written communication in natural language facilitates the fastest way of conveying the ideas, so they are very popular.
- Written communication is advantageous as it preserves the information manually as well as electronically.
- Around 7000 languages exist in the world, out of which very few are used across the globe.

- English language has the greatest internet presence, even though it is not the most spoken language in the world.
- With the advancements in technology, a humongous amount of e-text is getting generated across the world.
- The e-text may contain :
  1. Documents in different languages
  2. Multilingual documents
  3. Images with captions in different languages.
- People with linguistic diversity have started using their mother tongue for searching the documents present in various domains and languages.
- While using search engines, query based information retrieval is a common way.
- With this context in simple words Cross-Lingual Information Retrieval (CLIR) is retrieving information in one language based on the query written in another language.
- The users can search document databases in multiple languages and retrieve information in a form that is useful to them, even though they don't have linguistic competence in the target languages.
- CLIR is important for countries like India where a very large fraction of people are not conversant with English and thus don't have access to the vast store of information on the web.
- Searching distributed, unstructured, heterogeneous, multilingual data is the goal of CLIR system.

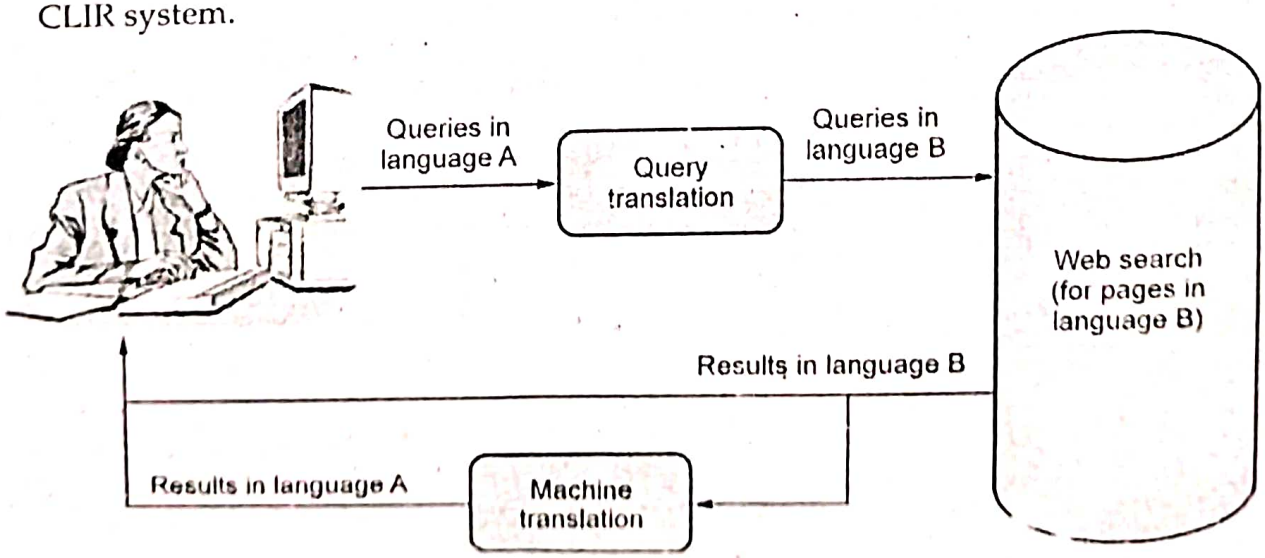


Fig. 4.7.1 CLIR system

- As shown in the Fig. 4.7.1, a user can enter a query in any language. For example, Hindi. If the relevant information is present in language B (For example English), the query is first translated to language B. After the web search the retrieved information in language B is again translated to language A, and results are displayed to the user.

Different approaches of CLIR are :

1. **Query translation approach :**
   - As shown in the Fig. 4.7.2, the query is translated to the target document language.
   - This is the most appropriate approach, as the query is shorter and fast to translate than a complete document.
   - One disadvantage can be, query translation can suffer from translation ambiguity due to the limited context.

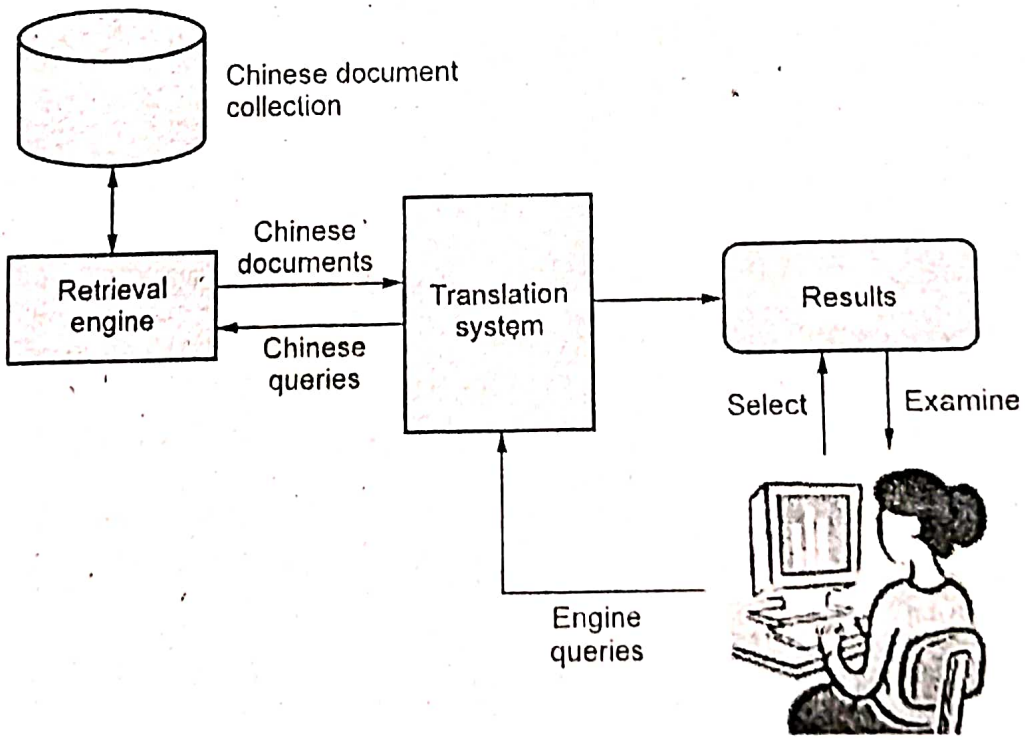


Fig. 4.7.2

2. Document translation approach :

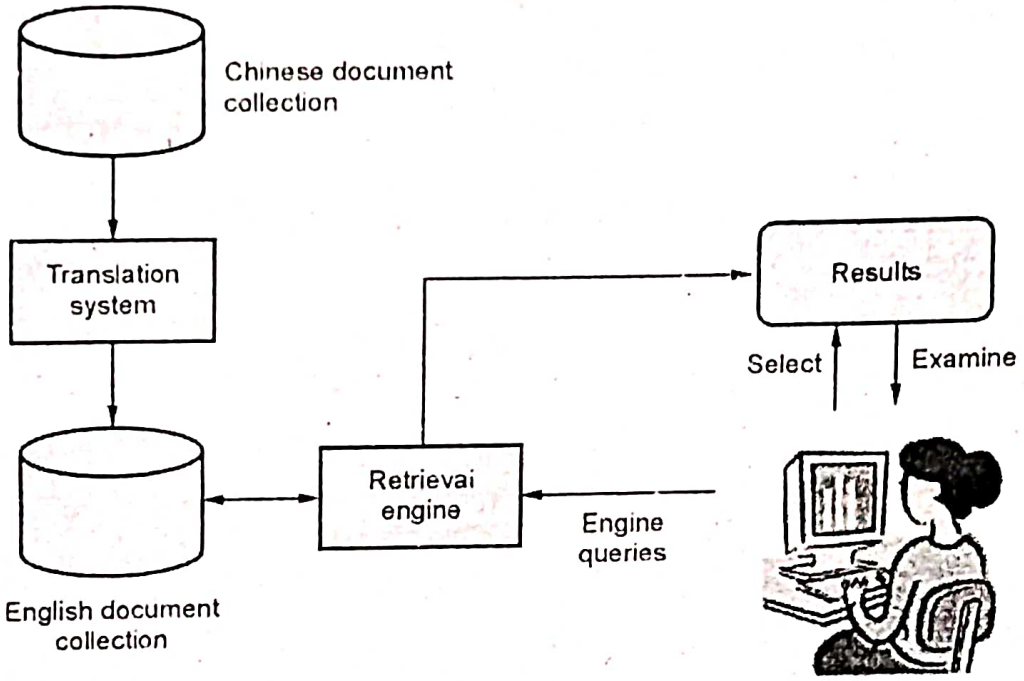


Fig. 4.7.3

- As shown in the Fig. 4.7.3, the documents in target language are translated to source language.
- Document translation can provide more accurate translation due to richer contexts.
- Advantage of document translation is, it's easy for the user to understand the document easily once it is retrieved.

3. Interlingua based approach :

- In this the documents and the query are both translated into some common third Interlingua (like UNL).
- This approach generally requires huge resources as the translation needs to be done online.

Challenges in CLIR :

1. Translation ambiguity :

- Due to ambiguities in various phases of NLP, more than one translation is possible of the source sentence.
- **For example :** Word "Pooja" can have two meanings, it can be the name of a girl or the second meaning can be worshipping.

2. Phrase identification :

- In some languages like Japanese the words are not separated by white spaces. This may lead to the incorrect translation.

3. **Dictionary coverage :**
   - The linguistic resources in the dictionary can prove as a constraint in performance of the system.
   - Out-of-Vocabulary (OOV) problems.
   - Daily new words are added to the language, which may not be recognized by the system.
   - Apart from traditional CLIR systems, recently cross-lingual word embeddings and neural network based information retrieval systems are becoming increasingly popular
   - Cross-lingual word embeddings can represent words in different languages in the same vector space by learning a mapping from monolingual embeddings.
   - Neural network based information retrieval can produce better representations for documents and queries. In this case the ranking is done directly from relevant labels.

Review Question

1. *Explain cross lingual information retrieval.*

❑❑❑

5 NLP Tools and Techniques

Syllabus

Prominent NLP Libraries : *Natural Language Tool Kit (NLTK), spaCy, TextBlob, Gensim etc.*
Linguistic Resources : *Lexical Knowledge Networks, WordNets, Indian Language WordNet (IndoWordnet), VerbNets, PropBank, Treebanks, Universal Dependency Treebanks.*
Word Sense Disambiguation : Lesk Algorithm Walker's algorithm, WordNets for Word Sense Disambiguation.

Contents

5.1 Prominent NLP Libraries : NLTK

Here is a list of NLP libraries that can be readily used while coding an NLP application. There are numerous NLP libraries designed for specific NLP applications. However Python is the lead programming language that supports most of the NLP libraries. Here is a list of few popular NLP libraries.

Core NLP :

- Stanford CoreNLP comprises of an assortment of human language technology tools. It aims to make the application of linguistic analysis tools to a piece of text easy and efficient. With CoreNLP, you can extract all kinds of text properties (like named-entity recognition, part - of - speech tagging, etc.) in only a few lines of code.
- The tool incorporates numerous Stanford's NLP tools like the parser, sentiment analysis, bootstrapped pattern learning, Part - Of - Speech (POS) tagger, Named Entity Recognizer (NER) and coreference resolution system, to name a few. Furthermore, CoreNLP supports four languages apart from English - Arabic, Chinese, German, French and Spanish.

Scikit - learn :

It provides a wide range of algorithms for building machine learning models in Python.

Natural Language Tool Kit (NLTK) :

NLTK is a complete toolkit for all NLP techniques. NLTK comes with a host of text processing libraries for sentence detection, tokenization, lemmatization, stemming, parsing, chunking, and POS tagging.

Pattern :

Pattern is a text processing, web mining, natural language processing, machine learning, and network analysis tool for Python. It comes with a host of tools for data mining (Google, Twitter, Wikipedia API, a web crawler and an HTML DOM parser), NLP (part-of-speech taggers, n-gram search, sentiment analysis, WordNet), ML (vector space model, clustering, SVM) and network analysis by graph centrality and visualization.

Review Question

1. *Explain NLTK.*

5.2 SpaCy

- SpaCy is an open - source NLP library which is used for data extraction, data analysis, sentiment analysis, and text summarization. SpaCy is an open-source NLP library in Python. It is designed explicitly for production usage - it lets you develop applications that process and understand huge volumes of text.
- SpaCy can preprocess text for Deep Learning. It can be used to build natural language understanding systems or information extraction systems. SpaCy is equipped with pre-trained statistical models and word vectors. It can support tokenization for over 49 languages. SpaCy boasts of state - of - the - art speed, parsing, named entity recognition, convolutional neural network models for tagging and deep learning integration.

Review Question

1. *What is SpaCy.*

5.3 TextBlob

- It provides an easy interface to learn basic NLP tasks like sentiment analysis, noun phrase extraction, or pos - tagging. TextBlob is a Python (2 and 3) library designed for processing textual data. It focuses on providing access to common text - processing operations through familiar interfaces. TextBlob objects can be treated as Python strings that are trained in Natural Language Processing.
- TextBlob offers a neat API for performing common NLP tasks like part - of - speech tagging, noun phrase extraction, sentiment analysis, classification, language translation, word inflection, parsing, n - grams, and WordNet integration.

PyNLPl :

- Pronounced as 'pineapple,' PyNLPl is a Python library for Natural Language Processing. It contains a collection of custom-made Python modules for Natural Language Processing tasks. One of the most notable features of PyNLPl is that it features an extensive library for working with FoLiA XML (Format for Linguistic Annotation).
- PyNLPl is segregated into different modules and packages, each useful for both standard and advanced NLP tasks. While you can use PyNLPl for basic NLP tasks like extraction of n-grams and frequency lists and to build a simple language model, it also has more complex data types and algorithms for advanced NLP tasks.

Quepy :

Quepy is used to transform natural language questions into queries in a database query language.

Review Questions

1. *Explain TextBlob.*
2. *Explain PyNLPI.*

5.4 Gensim

- Gensim works with large datasets and processes data streams. Gensim is a Python library designed specifically for "topic modeling, document indexing and similarity retrieval with large corpora." All algorithms in Gensim are memory-independent, w.r.t., the corpus size and hence, it can process input larger than RAM.
- With intuitive interfaces, Gensim allows for efficient multicore implementations of popular algorithms, including online Latent Semantic Analysis (LSA / LSI / SVD), Latent Dirichlet Allocation (LDA), Random Projections (RP), Hierarchical Dirichlet Process (HDP) or word2vec deep learning.

Review Question

1. *What is Gensim ?*

5.5 Linguistic Resources : Lexical Knowledge Networks

- Lexical knowledge is essential for semantic analysis .
- Traditionally, semantic information in computational lexicons is limited to notions such as selectional restrictions or domain-specific constraints, encoded in a "static" representation.
- Lexical Knowledge Networks (LKN) are resources which are critical for most NLP applications.
- This is evidenced by the success of the efforts on wordnets which are now regarded as indispensable for work on semantic search, knowledge based machine translation, summarization, question answering and such other high end NLP applications.
- Lexical Knowledge Bases (LKBs), also known as **lexico-semantic resources**, provide information about words and potentially entities and are at the core of knowledge-based approaches.
- They are widely used in a variety of NLP tasks (e.g., word sense disambiguation, information retrieval and question answering), all the more so since their traditional

limitations (i.e., lack of language and domain-specific coverage) have recently started to fall.

- Beside the long-established process of expert-based resource creation (e.g., WordNet), web technologies have enabled the collaborative, crowd-based construction of resources (e.g., Wikipedia and Wiktionary).
- This contributed to significantly widen the scope of the available machine-readable knowledge and in the context of an already diverse landscape of LKBs, it encouraged and motivated even more the need to integrate different resources so as to make the best of them all.
- Parameters vital for building Lexical Knowledge Networks are,
  - Domains addressed by the structure
  - Principles of construction
  - Methods of construction
  - Representation
  - Quality of database
  - Applications
  - Usability mechanisms for software applications and users : APIs, record structure, User interfaces
  - Size and coverage.

IndoNet as an example of Lexical knowledge networks

- IndoNet is a multilingual lexical knowledge base for Indian languages.

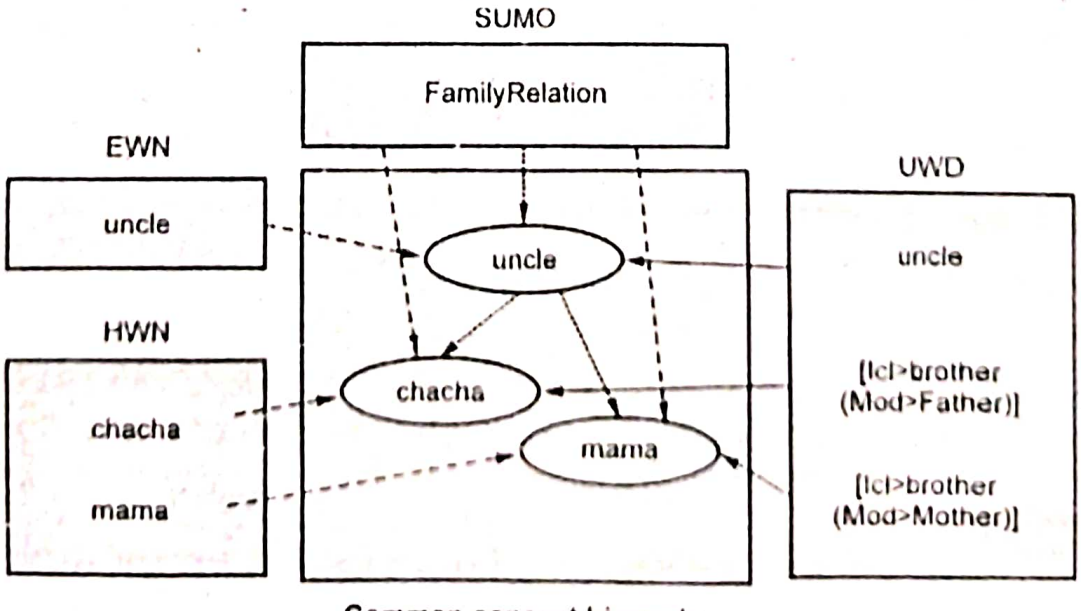


Fig. 5.5.1 Example of IndoNet structure

- It is a linked structure of wordnets of 18 different Indian languages, Universal Word dictionary and the Suggested Upper Merged Ontology (SUMO).
- ndoNet is encoded in Lexical Markup Framework (LMF), an ISO standard (ISO-24613) for encoding lexical resources.

Review Questions

1. *Explain Lexical knowledge networks.*

5.6 WordNets

- In this world people communicate with each other in more than 7000 languages.
- Written communication is the most popular form of communication.
- Any text comprises sentences which are formed by basic text units i.e words.
- Automatic understanding, analysis and preprocessing of text and in turn words is a challenging task for the NLP system.
- Typically this is done with the help of lexicons.
- A lexicon is a vocabulary of a person, language or branch of knowledge.
- Text in the textual data is mapped to the lexicon which helps us to understand the relationships between the words.
- WordNet is the lexical resource which helps us find word relations, synonyms, grammers, etc.
- WordNet is useful in solving many NLP applications like machine translation, sentiment analysis, etc.
- WordNet is a network of words linked by lexical and semantic relations and is freely and publicly available.
- The words in WordNet are related by synonymy, for example the words shut and close or car and automobile possess the same concept and can be interchanged as per the context. All such words are grouped into unordered sets or synsets.
- Under synsets nouns, verbs, adjectives and adverbs are grouped into sets of cognitive synonyms.
- Synsets are interlinked by means of conceptual-semantic and lexical relations.
- WordNet can be confused with thesaurus as, just like thesaurus it is collection words based on their meaning but following are the unique points of WordNet :
    - Along with word forms WordNet also interlinks specific senses of words. Due to this, words that are found in close proximity to one another in the network are semantically disambiguated.

- WordNet labels the semantic relations among words, whereas the groupings of words in a thesaurus does not follow any explicit pattern other than meaning similarity.

- The major relations which are covered in WordNet are shown in below Table 5.6.1 :

Semantic Relation	Syntactic Category	Examples
Synonymy (similar)	N, V, Aj, Av	Pipe, tube rise, ascend sad, unhappy rapidly, speedily.
Antonymy (opposite)	Aj, Av, (N, V)	Wet, dry powerful, powerless friendly, unfriendly rapidly, slowly.
Hyponumy (subordinate)	N	Sugar maple, maple maple, tree tree, plant.
Meronymy (part)	N	brim, hat gin, martini ship, fleet.
Troponomy (manner)	V	March, walk whisper, speak
Entailment	V	Drive, ride divorce, marry
Note : N = Nouns Aj = Adjectives V = Verbs Av = Adverbs		

Fig. 5.6.1

- Reference : Semantic relations in WordNet. Source : Miller 1995, Table 5.6.1.
- Following are meanings of the relations mentioned in the table :
  - Synonymy : Words with the same meaning.
  - Polysemy : Words with more than one sense.
  - Hyponymy/Hypernymy : Words which are having is-a relation.
  - For example : Peacock is a type of bird. Likewise, bird is a hypernym of Peacock.
  - Meronymy/Holonymy : Words with part-whole relation. For example : Beak is meronym of bird since beak is part of a bird's anatomy. Likewise, bird is holonym of beak.
  - Antonymy : Words which are lexically opposite. For example : Hot, cold.
  - Troponymy : Applies to verbs. For example, whisper is a troponym of talk since whisper elaborates on the manner of talking.

- Many WordNets are built across the world for various languages. Few of them are listed in the below table :

Language	Resource name	Developer(s)
Multilingual (South African languages/isiZulu, isiXhosa, Setswana, Sesotho sa Leboa, Tshiven.a, Sesotho, isiNdebele, Siswati & Xitsonga	African Wordnet (AfWN)	University of South Africa & South African Centre for Digital Language Resources, Pretoria, South Africa
Multilingual (Hindi/ Indonesian/ Japanese/ Lao/ Mongolian/ Burmese/ Nepali/ Sinhala/ Thai/ Vietnamese)	Asian WordNet	National Electronics and Computer Technology Center (NECTEC) – Thai Computational Linguistics Laboratory (TCL) – NICT, Kyoto, Japan
Multilingual (English/ Spanish/ Catalan/ Basque/ Italian)	Multilingual Central Repository	University of the Basque Country – Department of Software, Technical University of Catalonia (UPC)
English	WordNet 3.01	Princeton University
Hindi, Marathi, Sanskrit	Hindi WordNet	Indian Institute of Technology Bombay Powai, Mumbai
	Marathi WordNet	
	Sanskrit Wordnet	

5.7 Indian Language WordNet

- IndoWordNet (Bhattacharyya, P. (2010). Indowordnet. In Proc. of LREC-10. Citeseer.) is a WordNet consisting of wordnets for major Indian languages.
- The languages covered are : Assamese, Bengali, Bodo, Gujarati, Hindi, Kannada, Kashmiri, Konkani, Malayalam, Manipuri, Marathi, Nepali, Oriya, Punjabi, Sanskrit, Tamil, Telugu, and Urdu.
- These wordnets have been created by expanding the expansion approach of Hindi WordNet as a pivot, which is partially linked to English WordNet.

- The expansion approach adopted for IndoWordNet creation is as follows (https://aclanthology.org/L18-1728.pdf) :
  1. Creation of a Hindi synset with synonymous words.
  2. Mapping of the synset with relations such as hypernymy and hyponymy etc.
  3. Tagging of the synset with an ontological category.
  4. Allotment of a unique synset ID to the concept de4604 scribed in the synset.
  5. Creation of the same synset in the other Indian languages leading to an implicit linkage of relations, ontological categories.

Review Question

1. *Explain Indian Language WordNet.*

5.8 VerbNet

- VebNet (VN), developed by kipper and Schuler is the largest on-line verb lexicon currently available for English. (Reference : Schuler, Karin Kipper, "VerbNet : A broad-coverage, comprehensive verb lexicon" (2005))
- VN is a domain independent broad coverage verb lexicon which has mapping to other lexical resources like WordNet, FrameNet, etc.
- It is a verb lexicon compatible with WordNet but with explicitly stated syntactic and semantic information.
- It uses Levin verb classes to systematically construct lexical entries.
- VN is organized into verb classes to achieve syntactic and semantic coherence among members of a class.
- Each verb class in VN is completely described by thematic roles, selectional restrictions on the arguments and frames consisting of a syntactic description and semantic predicates with a temporal function.
- Classes are hierarchically organized to ensure that all their members have common semantic and syntactic properties.

Review Question

1. *Explain VerbNet.*

5.9 PropBank

- PropBank is a corpus that is annotated with verbal propositions and their arguments - a "proposition bank".
- Although "ProbBank" refers to a specific corpus produced by Martha Palmer et al., the term PropBank is also coming to be used as a common noun referring to any corpus that has been annotated with propositions and their arguments.
- PropBank is a corpus of text annotated with information about basic semantic propositions created by Martha Palmer.
- It is created by adding predicate-argument relations to the syntactic trees of Penn Treebank.
- In PropBank the arguments of each predicate are annotated with their semantic roles in relation to the predicate.
- PropBank annotation also requires the choice of a sense id (also known as a 'frameset' or 'roleset' id)for each predicate.
- For each verb in every tree which presents the phrase structure of the sentence, a PropBank instance is created which consists of the sense id of the predicate and its arguments labeled with semantic roles.
- It provides consistent argument labels across different syntactic realizations of the same verb.

  For e.g. : [ARG0 Devika]broke [ARG1 the window]

  [ARG1 The window] broke
- In the above example the arguments of the verbs are labeled as numbered arguments : Arg0, Arg1, Arg2 and so on.
- As shown in Table 5.9.1 the arguments are tagged as core arguments (label type ARGN, where N = 0 to 5) or adjunctive arguments (label type ARGM-X, where X = TMP for temporal, LOC for locative, etc.)

Table 5.9.1 : List of adjunctive arguments in PropBank - ARGMS

Tag	Description	Example
ARGM-LOC	Locative	*the museum, in Westborough, Mass*
ARGM-TMP	Temporal	*now, by next summer*
ARGM-MNR	Manner	*heavily, clearly, at a rapid rate*
ARGM-DIR	Direction	*to market, to Bangkok*
ARGM-CAU	Cause	*In response to the ruling*
ARGM-DIS	Discourse	*for example, in part, Similarly*
ARGM-EXT	Extent	*at $38.375, 50 points*
ARGM-PRP	Purpose	*to pay for the plant*
ARGM-NEG	Negation	*not, n't*
ARGM-MOD	Modal	*can, might, should, will*
ARGM-REC	Reciprocals	*each other*
ARGM-PRD	Secondary predication	*to become a teacher*
ARGM	Bare ARGM	*with a police escort*
ARGM-ADV	Adverbials	*(none of the above)*

- For e.g. Core arguments for predicates operate and author are shown in Table 5.9.2.

Table 5.9.2 : Argument labels associated with the predicate operate.01 (sense : work) and for author.01 (sense : to write or construct) in the PropBank corpus

Predicate	Argument	Description
operate.01		
	ARG0	Agent, operator
	ARG1	Thing operated
	ARG2	Explicit patient (thing operated on)
	ARG3	Explicit argument
	ARG4	Explicit instrument
author.01		
	ARG0	Author, agent
	ARG1	Text authored

Review Question

1. *What is PropBank ?*

5.10 Treebanks

- Due to ambiguous nature of a language two knowledge acquisition problems arise in syntaclic analysis.
  1. Due to difficulty in exploration of all the possibilities based on part of speech tags mentioned for a particular word.
  2. Due to difficulty in understanding the feasible meaning of sentence due to ambiguity in syntactic analysis.
- To address these problems a data driven approach called as **treebank** can be adapted.
- Treebank is collection of sentences.
- Each sentence in treebank contains complete syntax analysis.
- Human expert provides feasible analysis of the sentence. Annotation guidelines are provided before annotation process.
- Treebank contains annotations of syntactic structure for large set of sentences.
- Superviced machine learning techniques are used to train the parser from the training data extracted from tree banks.
- The first knowledge acquition problem is addressed by providing syntactic analysis directly instead of grammer.
- The second knowledge acquisition problem is solved as for each sentence in a treebank the most feasible syntactic analysis is provided.
- Using supervised machine learning techniques are used to learn scoring function for all possible syntax analysis.

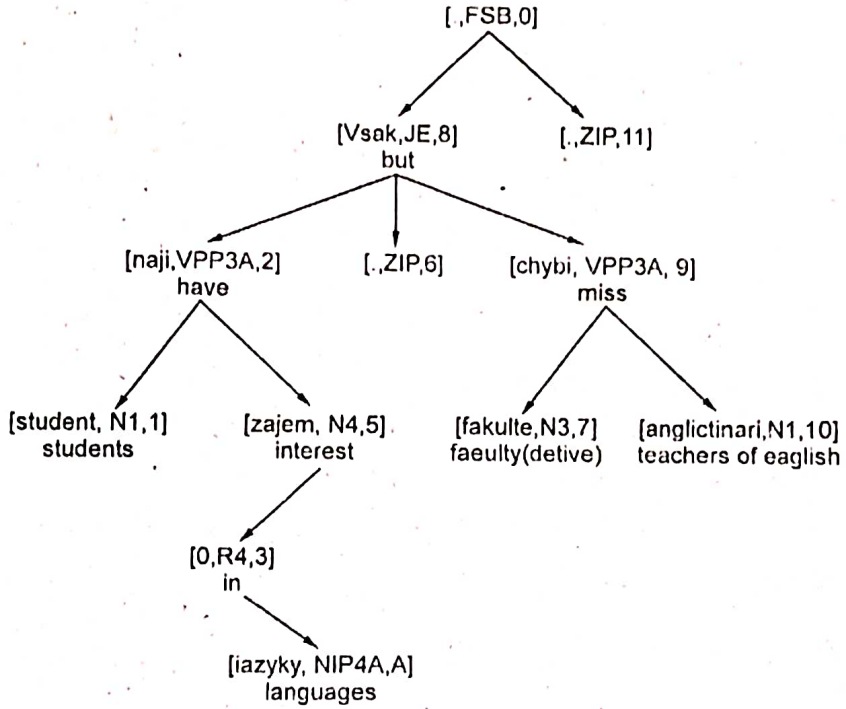
Review Question

1. *Explain Treebanks.*

5.11 Universal Dependency Treebanks

- Dependency graphs connects head of a phrase to its dependents.
- According to definition of Co NLL, in dependency graph nodes are words of input sentence and arcs are binary relations from head to dependent.

- It labelled dependency parsing a label is assigned to each dependency relation between head and dependent word.
- The example dependency graph for Czech sentence from Prague Dependency Treebank is shown in Fig. 5.11.1.
- It is observed that dependency analysis make minimal assumption about syntactic structure for avoiding annotation of hidden structure like empty elements to represent missing arguments of predicates.



The students are interested in languages, but the faculty is missing teachers of English

Fig. 5.11.1 : An example of a dependency graph syntax analysis for a Czech sentence taken from Prague Dependency Treebank. Each node in the graph is a word, its part of speech, and the not of the word in the sentence, for example [fakulte, N3, 7] is the seventh wood in the sentence with F tag N3, which also tells us that the word has dative case. The node [#, ZSB,0] is the root node of dependency tree. The English equivalent is provided for each node

- Projectivity is the constraint on syntactic analysis due to effect of linear order of words on dependencies between words.
- The example shown in Fig. 5.11.2 shows the english sentence with the requirements of crossing dependencies.

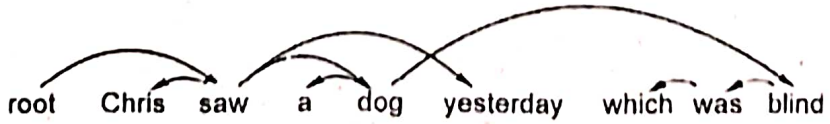


Fig. 5.11.2 : An unlabeled nonprojective dependency tree with a crossing dependency

5.12 WSD : Lesk Algorithm

- In early days word sense disambiguation used to done using dictionary sense definitions.
- These are the man made resources and now this has become historical data which is available in archived publication.
- Despite of the fact that this information is not available today, some algorithms and techniques are still useful.
- The first and very simple algorithm was proposed by lesk and these first generation algorithms are based on computerized dictionaries.
- Lesk algorithm is further simplified as shown in Fig. 5.12.1 Algorithm 5.12.1.

Algorithm 5.12.1 : Pseudocode of the simplified Lesk algorithm

The function COMPUTEOVERLAP returns the number of words common to the two sets

Procedure : SIMPLIFIED_LESK (word, sentence) **returns** best sense of *word*

```
1. best-sense ← most frequent sense of word
2. max-overlap ← 0
3. context ← set of words in sentence
4. for all sense ∈ senses of word do
5.     signature ← set of words in gloss and examples of sense
6.     overlap ← COMPUTEOVERLAP (signature, context)
7.     if overlap gt max-overlap then
8.         max-overlap ← overlap
9.         best-sense ← sense
10.    end if
11.    end for
12.    return best-sense
```

Fig. 5.12.1 : Algorithm 5.12.1

Review Question

1. *Explain Lesk Algorithm.*

5.13 Walker's Algorithm

- To understand the concept of word sense disambiguation let's consider following example.
  1. I went to bank to withdraw money.
  2. I went to bank to fetch water.

- In the above example the same word 'bank' has appeared in two different senses and contexts.
- In computational lexical semantics it is required to examine the contextual word tokens and to figure out which sense of word is used.
- This task is known as Word Sense Disambiguation (WSD).
- WSD is the task of selecting the correct sense for a word.
- WSD is essential part of many important NLP applications like question answering, information retrieval and text classification where the use of wrong senses of words can create disasters.
- Typically any WSD algorithms, input is a word in context and fixed inventory of possible word senses. The output is a correct word sense.
- The task for which WSD is done decides nature of input and inventory of senses used.
- For example : If the task is of machine translation from English to Spanish, sense tag inventory for an English word can be set of Spanish translations. But if the task is automatic indexing of medical articles inventory can be MeSH (Medical Subject Headings) thesaurus entries.

Review Question

1. *Explain Walker's algorithm.*

5.14 WordNets for WSD

- The main requirement of supervised WSD is we need labeled data.
- If we have hand labeled data with proper word senses, then using supervised WSD can be used to extract features from the text.
- These features can be used to predict the senses and a classifier can be learned for assigning correct senses from the features.
- These are two broad steps in supervised WSD :
  1. Creative extraction for supervised learning.
  2. Training a classifier.

1. Feature extraction for supervised learning :

- In this step features, predicting word sense are extracted.
- First preprocessing is performed which includes POS tagging, stemming and lemmatization.

- A feature vector is generated, which contains numeric values for this linguistic information.
- This feature vector can be used as an input to machine learning algorithms.
- Features are classified in two classes :
  a) Collocational features
  b) Bag of words features.

a) Collocational features :

- Collocation refers to a group of words that often go together or occur together.
- Some examples of collocation are,
  - To feel free → please feel free to take a seat
  - To deposit a check → I would like to deposit this check
  - Deeply regret the loss of someone → I deeply target the loss of your loved one.
- Collocational features takes into account the information about specific positions present to the left or right of the target word.
- Consider the example :

  An electric guitar and bass player stand off to one side not really part of the scene, just as a sort of nod to gringo expectational perhaps. Consider 'bass' as a target word the collocation feature vector can be written considering two words to the left and to the right with their respective parts of speech.
- The collocation feature vector can be written for the above examples POS.

  $[w_{i-2}, POS_{i-2}, w_{i-1}, POS_{i-1}, w_{i+1}, POS_{i+2}]$

  [guitar, NN and CC, player, NN, Stand, VB]

b) Bag-Of-Words :

- Concept of bag of words is explained in detail in section 3.10.
- In WSD task using BOW concept a target word is kept as center and the context region surrounding the target word is small, symmetric, fixed size window.
- Stop words are not used as features and the vector is limited to BOW considering small number of frequently occurring words.
- Again consider the same bass example in BOW vector with 12 most frequent words feature set in written as [fishing, big, sound, player, fly, rod, pound, double, runs, playing, guitar, band] with window size 10 the above feature set is written as binary vector

  [0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0]

2. Training a classifier :

- Once the features are extracted, along with the training data is used to train sense classifier.
- Among the classifiers, Naive Bayes and decision list approaches are used mostly for the task of WSD.
- Naive Bayes classifier for WSD : Naive Bayes classifier is used to find the best sense $\hat{s}$ out of all possible senses S for feature vector $\vec{f}$, i.e.

$$\hat{s} = \underset{s \leftarrow S}{\text{argmax}} \; P(s | \vec{f})$$

- To understand formulation of Naive Bayes classifier, let's consider BOW vector for 20 words having 2^{20} possible feature vectors.
- To solve this problem, first the problem in reformulated in Bayesian manner as

$$\hat{s} = \underset{s \in S}{\text{argmax}} \frac{P(\vec{f} | s) \, P(s)}{P(\vec{f})}$$

- In this equation vector $\vec{f}$ for available data with each sense S is very sparse. But in tagged training set the information about individual feature value pair is having greater presence.
- So an independent assumption is made naively that features are independent of each other.
- Considering this the approximation for $P(\vec{f} | s)$ is written as

$$P(\vec{f} | s) \approx \prod_{j=1}^{n} P(f_i | s)$$

- $P(\vec{f})$ is same for all the senses, it is condensed that it will not affect final ranking.
- With this assumption Naive Bayes classifier for WSD in given as

$$\hat{s} = \underset{S \in s}{\text{argmax}} \; P(s) \prod_{j=1}^{n} P(f_j | s)$$

- To train naive bayes classifier each of the above probability is estimated.
- The prior probability of each sense P(s), the maximum likelihood estimate of the probability from sense-tagged training corpus in calculated by number of times sense s_i occurrance and dividing it by total count of target word w_j.

So, $$P(s_i) = \frac{\text{count}(s_i, w_j)}{\text{count}(w_j)}$$

- So in our example of 'bass' if collocational feature guitar occurs 3 times for sense 'bass' and if sense "bass" occurs 60 times in training the maximum likelihood estimate is $P(f_j|s) = 0.05$.

2) Decision list classifier :

- In this, a sequence of tests is applied to each target word feature vector.
- A specific sense is shown by each test.
- A sense is returned with a successful test and in case of failure the next test is applied till end of list.
- Consider the disambiguation of the sense 'bass' from Fig. 5.14.1.
- As shown in Fig. 5.14.1 the first test indicates that if word fish occurs in input context then bass in correct.

Rule		Sense
fish within window	⇒	$bass^1$
stripped bass	⇒	$bass^1$
guitar within window	⇒	$bass^2$
bass player	⇒	$bass^2$
piano within window	⇒	$bass^2$
tenor within window	⇒	$bass^2$
sea bass	⇒	$bass^1$
play/V bass	⇒	$bass^2$
river within window	⇒	$bass^1$
violin within window	⇒	$bass^2$
salmon within window	⇒	$bass^1$
on bass	⇒	$bass^2$
bass are	⇒	$bass^1$

Fig. 5.14.1 An abbreviated decision list for disambiguating the fish sense of bass from the music sense (Yarowsky, 1997)

- In case fish doesn't occur next text is carried out till we obtain the result as true.
- The default test returning trade is mentioned at the last in the list.

- In decision tree classifier then sense in indicated by a particular feature by finding out ratio of the probabilities of senses as follows :

$$\left| \log \left(\frac{P(sense_1|f_i)}{P(sense_2|f_i)} \right) \right|$$

Review Question

1. *Explain WordNets for WSD.*

❑❑❑

Unit VI

6 Applications of NLP

Syllabus

Machine Translation *: Rule based techniques, Statistical Machine Translation (SMT), Cross Lingual Translation, Sentiment Analysis, Question Answering, Text Entailment, Discourse Processing, Dialog and Conversational Agents, Natural Language Generation*

Contents

6.1 Machine Translation

Need of MT

- According to research firm Common Sense Advisory, 72.1 percent of the consumers spend most or all of their time on sites in their own language, 72.4 percent say they would be more likely to buy a product with information in their own language and 56.2 percent say that the ability to obtain information in their own language is more important than price.
- These are just a few of the many reasons that translation has become essential in the modern and ever more globalized world that we live in.
- Machine translation is a tool that can help businesses and individuals in many ways. While machine translation is unlikely to totally replace human beings in any application where quality is really important, there are a growing number of cases that show how effective and useful machine translation can be.
- Machine translation is useful in many areas, including :
  - Highly repetitive content where productivity gains from machine translation can dramatically exceed what is possible with just using translation memories alone (e.g. automotive manuals.)
  - Content that is similar to translation memories but not exactly the same (e.g. government policy documents.)
  - Content that would not get translated otherwise due to cost, scale and volume limitations of human translations (e.g. millions of Chinese, Japanese, Korean and other language patents made available in English.)
  - High-value content that is changing every hour and every day there is time sensitivity (e.g. stock market news.)
  - Content that does not need to be perfect but just approximately understandable (e.g. any website for a quick review.)
  - Knowledge content that facilitates and enhances the global spread of critical knowledge (e.g. customer support.)
  - Content that is created to enhance and accelerate communication with global customers who prefer a self-service model (e.g. knowledgebase.)
  - Content that would normally be too expensive or too slow to translate with a human only translation approach (e.g. many projects that have an insufficient budget for a human only approach.)
  - Increasing the amount of content that can be translated within a budget (e.g. Dell has doubled the amount of content they translate without increasing their translation budget.)

- Real-time communications where it would not be practical for a human to translate (e.g. chat and email.)

Problems of MT

- There are two approaches for machine translation,
  1. Classical machine translation
  2. Statistical machine translation
- In this section we will understand various pre-statistical classical machine translation approaches.
- Three classical MT approaches include,

1. **Direct translation :**
   - Each word is translated as it appears in the source language text.
   - It requires large bilingual dictionary.
2. **Transfer approach :**
   - First input text is parsed and then rules are applied to transform source to target language.
   - Then target language sentence is generated from the parse tree.
3. **Interlingua approach :**
   - Source language text is converted to abstract meaning representation known as interlingua.
   - Afterwards target language is generated from this interlingual representation.

- These three approaches can be represented using vauquois triangle as shown in Fig. 6.1.1.

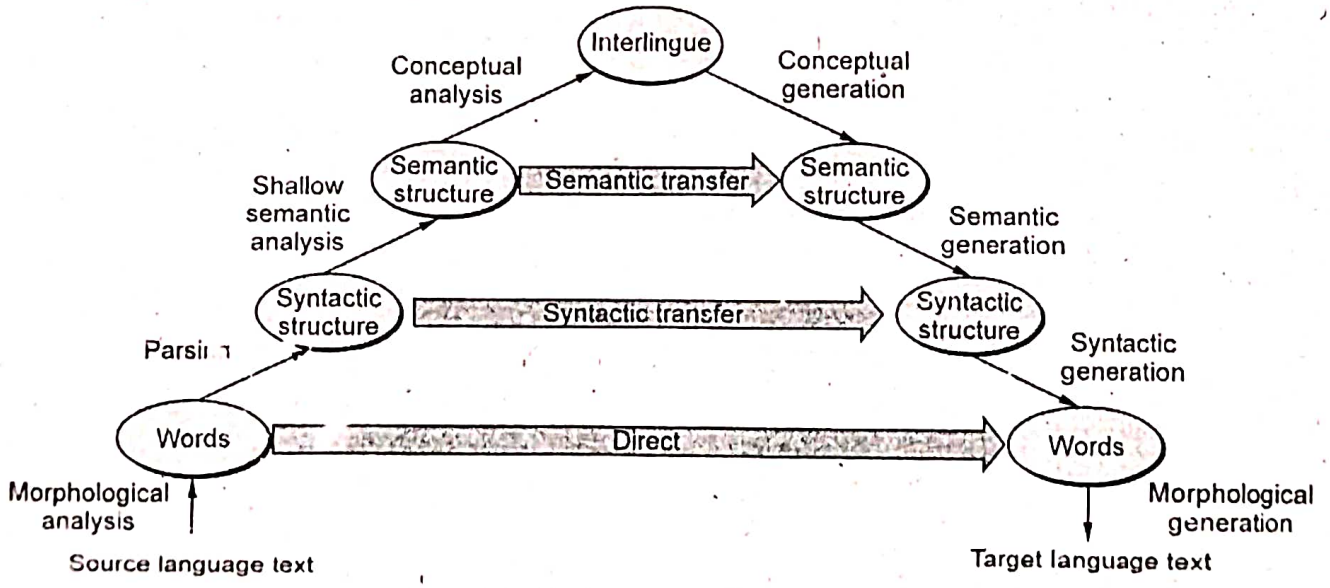


Fig. 6.1.1 The Vauquois (1968) triangle

- Let's try to understand these approaches one by one.

Review Questions

1. *Explain need of machine translation.*
2. *Explain approaches of MT.*

6.2 Rule Based Techniques for MT

- Each language has a specific structure which is unique in its own way.
- To overcome these differences while doing MT contrastive knowledge can be applied, which is knowledge of the differences between two languages.
- This is the basis of transfer model.
- In transfer model there are three phrases,

  1) Analysis

  2) Transfer

  3) Generation.
- The first step is parsing of a source language.
- The parse for MT can be different than parsing for other applications as there is no need of finding out the attachment of prepositional phrases for the sentence 'John saw the girl with binoculars' in transforming it to French.
- After parsing rules and syntactic transfer and lexical transfer need to be applied.
- In syntactic transfer rules source parse tree is modified so that it wil resemble target parse tree as shown in Fig. 6.2.1.

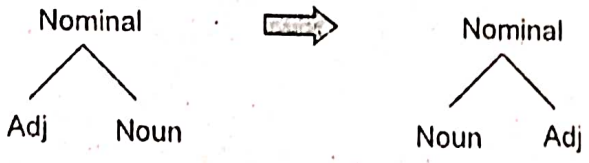


Fig. 6.2.1 A simple transformation that reorders adjectives and nouns

- As shown is Fig. 6.2.1 syntactic transformations operations map one tree structure to another.
- With this mapping we also assume that morphological processing is done where it is understood that didn't is formed by do-PAST plus not, where PAST is a VP. So that in the lexical transfer do is removed not is changed to no and slap is turned to dar una bofetada a as shown in Fig. 6.2.2.
- The second part of transfer based systems is lexical transfer.
- It is uses bilingual dictionary similar to direct transfer.

- May times a word has many different possible translations in the target language where bilingual dictionary can do this job naturally, for example : English word Home as different possible translations in German like House (going home), Hein (Home game), Zu House (being at Home) where through bilingual dictionary it can be figured out that Zu House is most probable translation.

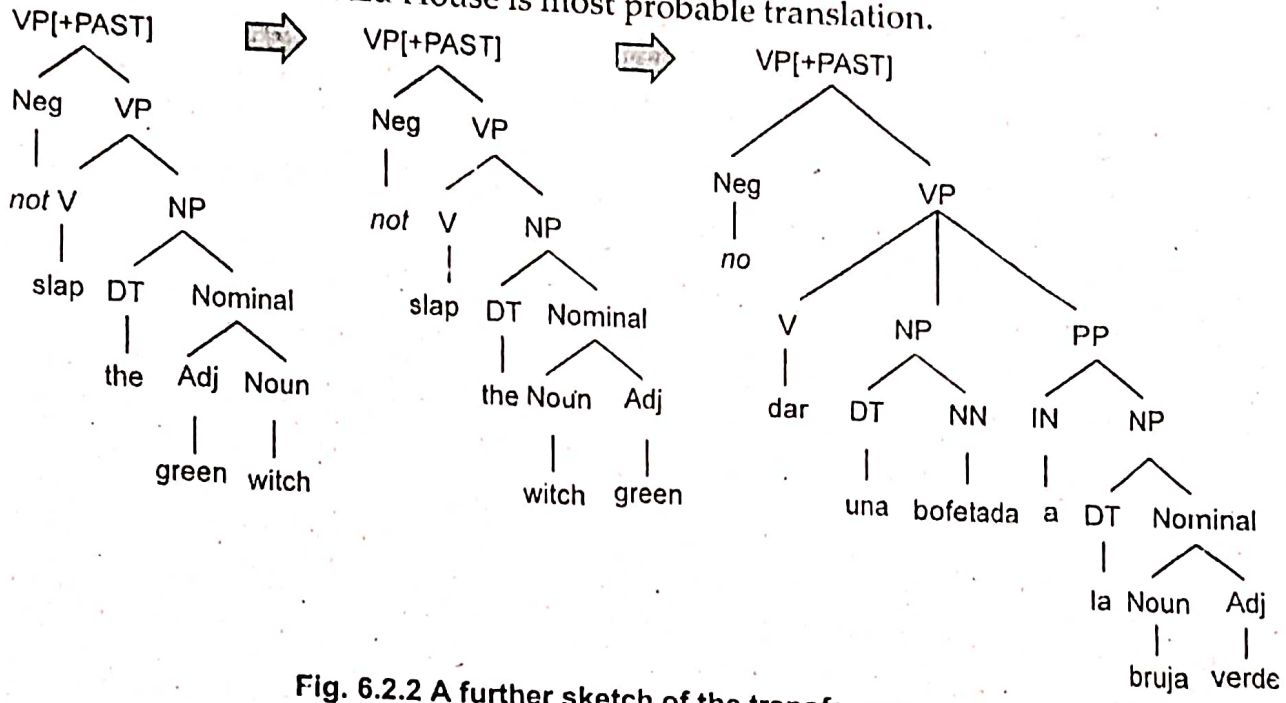


Fig. 6.2.2 A further sketch of the transfer approach

Interleague (Meaning) based MT

- In rule based transfer model i.e. MT we need distinct set of transfer rules for each pair of languages which is sometimes a difficult task for some languages.
- Interlingua approach focuses on the method of extracting meaning of input and expressing it to target language.
- So this can be considered as knowledge based MT, where like contrastive knowledge used in rule based system only standard interpreter and generator can be used for the language.
- Interlingua is a language independent canonical form.
- The basic idea of interlingua is all the sentences in any language carry the same intended meaning.
- Translation is done by doing deep semantic analysis on input from language X and generating interlingual representation which is then transformed to language Y.
- The example interlingual representation is shown in Fig. 6.2.3.

$$\begin{bmatrix} \text{EVENT} & \text{SLAPPING} \\ \text{AGENT} & \text{MARY} \\ \text{TENSE} & \text{PAST} \\ \text{POLARITY} & \text{NEGATIVE} \\ \text{THEME} & \begin{bmatrix} \text{WITCH} \\ \text{DIFFINITENESS} & \text{DEF} \\ \text{ATTRIBUTES} & [\text{HAS-COLOR} \quad \text{GEEN}] \end{bmatrix} \end{bmatrix}$$

Fig. 6.2.3 Interlingual representation of Mary did not slap the green witch

- The example represents even based representation where small fixed set of semantic roles are used to link events with their arguments.
- Interlingual representation can be created from source language text by using semantic analyzer techniques.
- For example in the event Mary and slap semantic role labeler can figure out the AGENT relation.
- Unlike transfer model which need only syntactic parsing more analysis work is needed in interlingua.
- In interlingua most of the translation process can be done using general language processing techniques and modules.
- Some of the drawbacks of this approach are :
  - It requires exhaustive analysis of the semantics involved in a domain and formalize it to ontology which is an additional work.

    For example : In translating of sentence from Japanese to Chinese, universal interlingua should include the concepts like ELDER-BROTHER and YOUNGER-BROTHER.

Neural Machine Translation

- Neural Machine Translation (also known as Neural MT, NMT, Deep Neural Machine Translation, Deep NMT, or DNMT) is a state-of-the-art machine translation approach that utilizes neural network techniques to predict the likelihood of a set of words in sequence. This can be a text fragment, complete sentence, or with the latest advances an entire document.
- Unlike statistical machine translation, which consumes more memory and time, neural machine translation, NMT, trains its parts end-to-end to maximize performance.
- NMT uses deep neural networks and artificial intelligence to train neural models

- Unlike the traditional phrase-based translation system which consists of many small sub-components that are tuned separately, neural machine translation attempts to build and train a single, large neural network that reads a sentence and outputs a correct translation.
- NMT makes use of vector representations for words. This means that words are transcribed into a vector defined by a unique magnitude and direction.
- Compared to phrase-based models, this framework is much simpler.
- Rather than separate component like the language model and translation model, NMT uses a single sequence model that produces one word at a time.
- As shown in the Fig. 6.2.4, the NMT uses a bidirectional recurrent neural network, also called an encoder, to process a source sentence into vectors for a second recurrent neural network, called the decoder, to predict words in the target language.

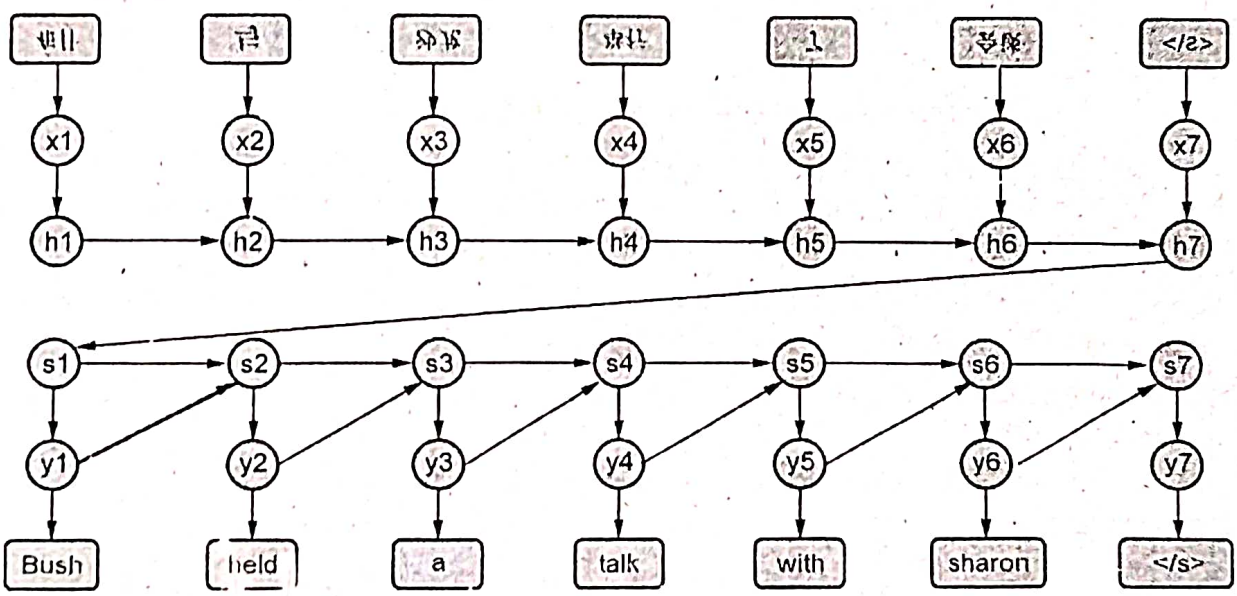


Fig. 6.2.4

Encoder and Decoder Architecture for MT

- The encoder-decoder recurrent neural network architecture with attention is currently the state-of-the-art on some benchmark problems for machine translation.
- This architecture is used in the heart of the Google Neural Machine Translation system, or GNMT, used in their Google Translate service.
- The following description will cover encoder-decoder architecture :
  - Encoder
    - The encoder is the feeding end of the system. It understands the sequence and reduces the dimension of the input sequence.

- The sequence is written in a fixed size known as the *context vector*.
- The context vector acts like input to the decoder, which generates an output sequence after the end token is reached.
- These sequence models are known as encoder-decoder models.
- This architecture can handle input and output sequences of variable length.

- Decoder
  - If LSTM is used for the encoder, the same is used for the decoder.
  - Decoder is more complex than the encoder network.
  - The decoder is in an "aware state". It knows what words you have generated so far and what the previous hidden state was.
  - The first layer of the decoder is initialized by using the context vector 'C' from the encoder network to generate the output.
  - Then a special token is applied at the start to indicate the output generation. It applies a similar token at the end.
  - The first output word is generated by running the stacked LSTM layers.
  - A *SoftMax* activation function applies to the last layer. Its job is to introduce non-linearity in the network. Now this word is passed through the remaining layers and the generation sequence is repeated.

- The parameters such as optimizers, cross-entropy loss, learning rate, etc., play an important role in improving the model's performance.
- Refer to the Fig. 6.2.5 below to understand the architecture of encoder decoder model.

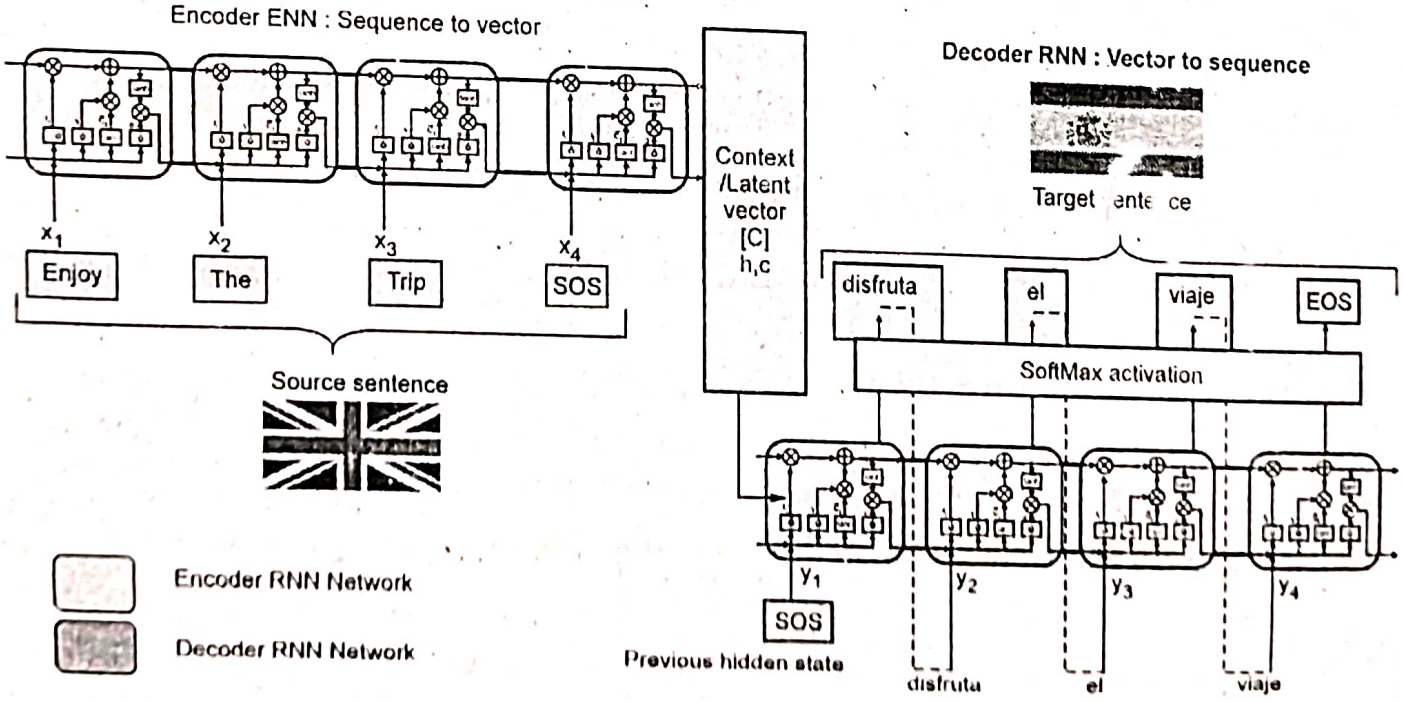


Fig. 6.2.5 Architecture of encoder decoder model

Applications of neural network translation

- One of the most popular translation systems in the world is Google translate.
- The system uses Google neural machine translation to enhance fluency and accuracy.
- The system not only applies a large data set for training its algorithms, its end-to-end design allows the system to learn over time and create better, more natural translations.
- Google neural machine translation can even process "zero-shot translations."
- For example, the translation from French to Spanish is a zero-shot translation because it is a direct translation.
- Previously, Google translate would translate the initial language into English, and then translate that English to the target language.

Review Questions

1. *Explain rule based techniques for MT.*
2. *Explain interleague based MT.*
3. *Explain neural MT.*

6.3 Statistical Machine Translation (SMT)

- In statistical MT the result is focussed and not the process like the classical MT approaches explained in section 6.2.
- When we wish to translate a sentence from one language to another it is always a challenging task to map all the culture specific concepts metaphors in languages, a word or a tense parallely to other language.
- All these constraints makes true translation of one language to other an very difficult or sometimes, impossible task.
- We can view MT task as a model to produce an output which maximises some value function representing importance of faithfulness and fluency.
- In statistical MT probabilistic models of faithfulness and fluency are built and later these are combined to choose most probable translation.
- Consider faithfulness and fluency as quality metric translation of source model sentence S to target language $\hat{T}$ is given as :

best - translation $\hat{T} = \text{argmax}_T$ faithfulness (T, S) fluency (T)

which resembles a noisy channel model.

- Let's consider following information for MT task,
- Let's consider a foreign language sentence $F = f_1, f_2, \ldots, f_m$ which will be converted to English.

- French and Spanish will be considered as foreign languages but target language is English every time.
- According to probabilistic modes the English sentence $\hat{E} = e_1, e_2, \ldots, e_l$ is best one if it has highest probability P(E | F).
- If we consider a noisy channel model then this can be rewritten using Bayes rule as

$$\hat{E} = \text{argmax}_E P(E \mid F) = \text{argmax}_E \frac{P(F \mid E)\, P(E)}{P(F)}$$

$$= \text{argmax}_E P(F \mid E)\, P(E)$$

- As in argmax denominator P(F) is a constant we can ignore it.
- So we get a noisy channel equation with two components : a translation model P(F | E) and language model P(E).

i.e.

$$\hat{E} = \underset{E \in \text{English}}{\text{argmax}} \quad \underbrace{P(F \mid E)}_{\text{Translation model}} \quad \underbrace{P(F)}_{\text{Language model}}$$

- Here the assumption is made that model generates corrupt version of English from foreign language input F. So our task is to find out the hidden sentence E which generated observation sentence F.
- This process is shown in Fig. 6.3.1.

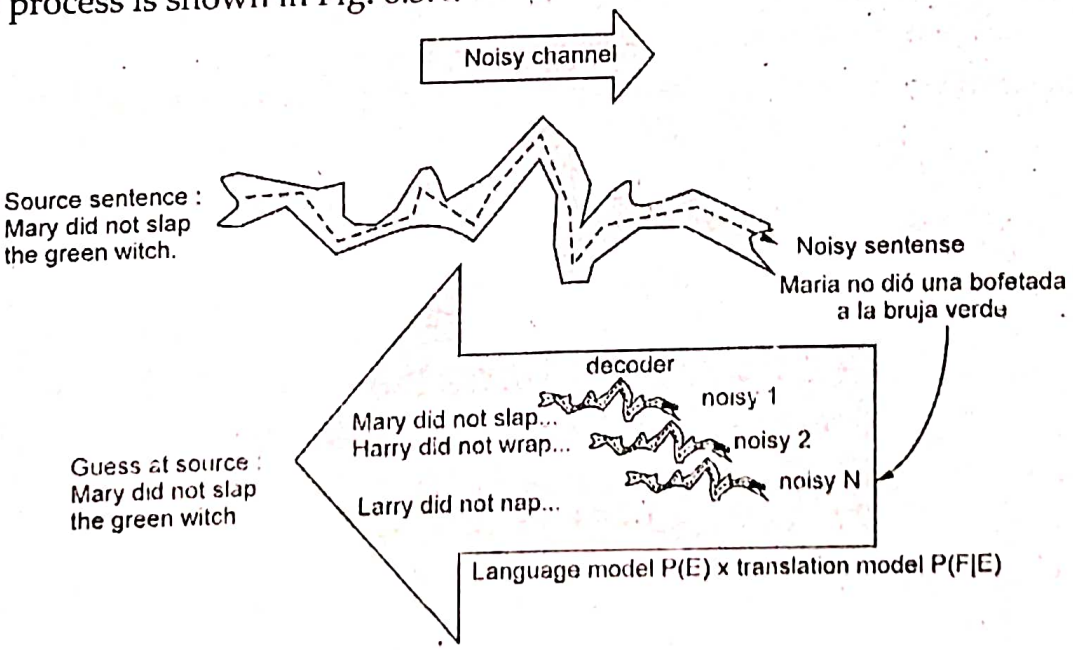


Fig. 6.3.1 The noisy channel model of statistical MT. To translate Spanish (source language) to English (target language), we instead think of "sources" and "targets" backwards. We build a model of the generation process from an English sentence through a channel to a Spanish sentence. Now given a Spanish sentence to translate, we pretend it is the output of an English sentence going through the noisy channel and search for the best possible "source" English sentence

- In statistical MT model there are three components for translating fresh sentence F to English sentence E :
  1) A language model to compute P(E).
  2) A translation model to compute P(F | E).
  3) A decoder which produces most probable E from given F.
- The first component was discussed in detail earlier.
- In the next sections we focus on translation model and decoding algorithms.

The phrase-based translation model P(F|E) :

- The task of phrase based translation model is assigning a probability that English sentence E generates foreign sentence F.
- Instead of focusing on translation of individual word, modern statistical MT focuses on behavior of phrases.
- Phrase based statistical MT model uses phrases as well as single words as fundamental units of translation.
- This can be understood from the example in Fig. 6.3.2

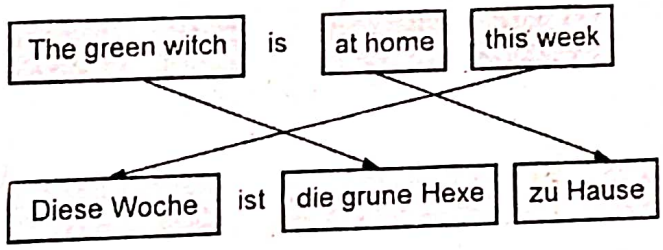


Fig. 6.3.2 Complex reorderings necessary when translating from English to German. German often puts adverbs in initial position that English would more naturally put later. German tensed verbs often occur in second position in the sentence, causing the subject and verb to be inverted

- The phrase based translation model follows three steps :
  1) In the first step English source words are grouped into phrases $\bar{e}_1, \bar{e}_2 - \bar{e}_I$.
  2) In the second step each English phrase $\bar{e}_i$ is translated to Spanish phrase $\bar{f}_i$.
  3) In the third step each of the Spanish phrase is recorded.
- Phrase based translation uses probability model based on translation probability and distortion probability where :

Factor ϕ $(\bar{f}_i \mid \bar{e}_i) \rightarrow$ translation probability of generating Spanish phrase $\bar{f}_i$ from English phrase $\bar{e}_i$.

d $\rightarrow$ distortion probability for reordering of Spanish phrases.

Distortion is positional difference of word in Spanish sentence than in English. It is measure of distance between position of phrases.

Parameter of distortion is $d(a_i - b_{i-1})$

where

$a_i \rightarrow$ Start position of Spanish phrase generated by i^{th} English phrase $\bar{e}_i$

$b_{i-1} \rightarrow$ End position of Spanish phrase generated by $i-1^{th}$ English phrase $\bar{e}_i - 1$.

A small constant α can be raised to distortion.

$$\text{So, } d(a_i - b_{i-1}) = \alpha^{|a_i - b_{i-1} - 1|}$$

- Final model of phrase based MT is given as,

$$P(F \mid E) = \prod_{i=1}^{I} \phi(\bar{f}_i, \bar{e}_i)\, \alpha(a_i - b_{i-1})$$

- To understand this process consider following example shown in Fig. 6.3.3.

Position	1	2	3	4	5
English	Mary	did not	Slap	the	green witch
Spanish	Maria	no	dió una bofetada	a la	bruja verde

Fig. 6.3.3

- In this example the distortions are 1 and probability P(F | E) is computed as,

$$P(F \mid E) = P(\text{Maria, Mary}) \times d(1) \times P(\text{no} \mid \text{did not}) \times$$
$$d(1) \times P(\text{dió una bofetada} \mid \text{slap}) \times$$
$$d(1) \times P(\text{a la} \mid \text{the}) \times d(1) \times P(\text{bruja verde} \mid \text{green witch}) \times d(1)$$

- For using phrase based mode we need two more models :
  1. **Model of decoding** : For finding hidden English string from surface Spanish string
  2. **Model of training** : To learn parameters i.e. set of pl rase translation probabilities

$$\phi(\bar{f}_i \mid \bar{e}_i)$$

- The parameters for training and distortion constant α are set if we have large bilingual training set.

- The training set should have pairing of each Spanish sentence with English to understand which Spanish sentence phrase is translated by English sentence phrase.
- This mapping is called as phrase alignment.
- With large training set with sentence labelled with phrase alignment, the number of times each phrase pair occurred is counted and normalized to get probabilities as,

$$\phi(\bar{f}, \bar{e}) = \frac{\text{count}(\bar{f}, \bar{e})}{\Sigma \bar{f}\ \text{count}(\bar{f}, \bar{e})}$$

- Each phrase pair $(\bar{f}, \bar{e})$ along with probability $\phi(\bar{f}, \bar{e})$ is stored in phrase translation table.
- One more way of extracting exact phrases as word alignment.
- Example of word alignment is shown in Fig. 6.3.4 and word alignment matrix in Fig. 6.3.5.

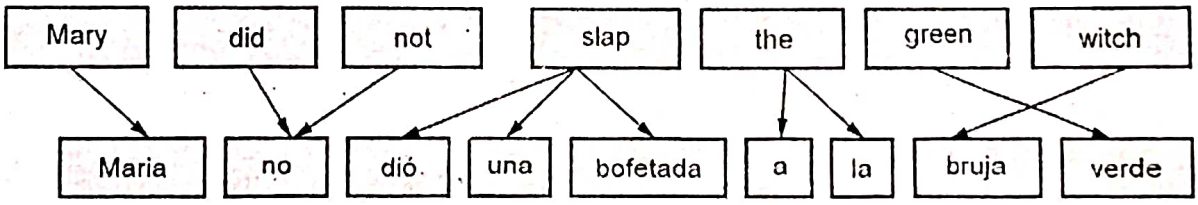


Fig. 6.3.4 A graphical model representation of a word alignment between the English and Spanish sentences.

	Maria	no	dió	una	bofetada	a	la	bruja	verde
Mary									
did									
not									
slap									
the									
green									
witch									

Fig. 6.3.5 An alignment matrix representation of a word alignment between the English and Spanish sentences.

Alignment in MT :

- Word alignment is the basic concept used in statistical translation model.
- A word alignment is a mapping between the source words and the target words in a set of parallel sentences.
- To understand word alignment consider the example shown in Fig. 6.3.6.

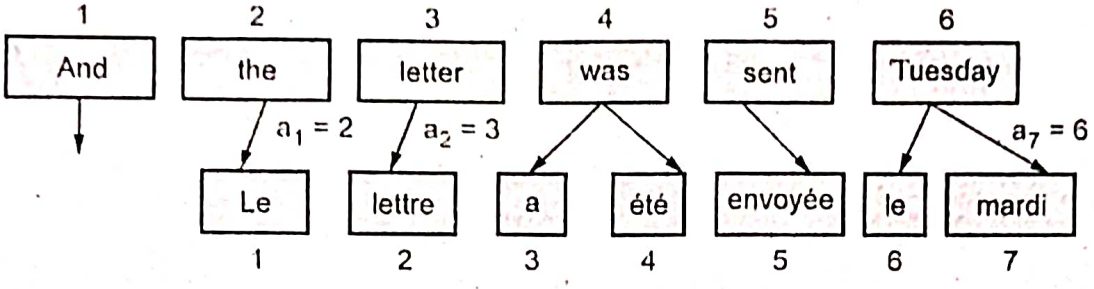


Fig. 6.3.6 An alignment between an English and a French sentence. Each French word aligns to a single English word.

- In this section we will discuss IBM models for word alignment.
- IBM models consider that each French word comes from exactly one English word.
- By this assumption we can assign index number of the English word that the French word comes from.
- So the alignment in Fig. 6.3.6 can be given as A = 2, 3, 4, 4, 5, 6, 6

Review Question

1. *Explain statistical MT.*

6.4 Cross Lingual IR

- Humans have the unique ability to express themselves through different mediums of communication like : Oral, written, through images and pictures, through gestures and sign language, etc.
- Out of these, oral and written communication in natural language facilitates the fastest way of conveying the ideas, so they are very popular.
- Written communication is advantageous as it preserves the information manually as well as electronically.
- Around 7000 languages exist in the world, out of which very few are used across the globe.
- English language has the greatest internet presence, even though it is not the most spoken language in the world.
- With the advancements in technology, a humongous amount of e-text is getting generated across the world.

- The e-text may contain :
  1. Documents in different languages
  2. Multilingual documents
  3. Images with captions in different languages.
- People with linguistic diversity have started using their mother tongue for searching the documents present in various domains and languages.
- While using search engines, query based information retrieval is a common way.
- With this context in simple words Cross-Lingual Information Retrieval (CLIR) is retrieving information in one language based on the query written in another language.
- The users can search document databases in multiple languages and retrieve information in a form that is useful to them, even though they don't have linguistic competence in the target languages.
- CLIR is important for countries like India where a very large fraction of people are not conversant with English and thus don't have access to the vast store of information on the web.
- Searching distributed, unstructured, heterogeneous, multilingual data is the goal of CLIR system.

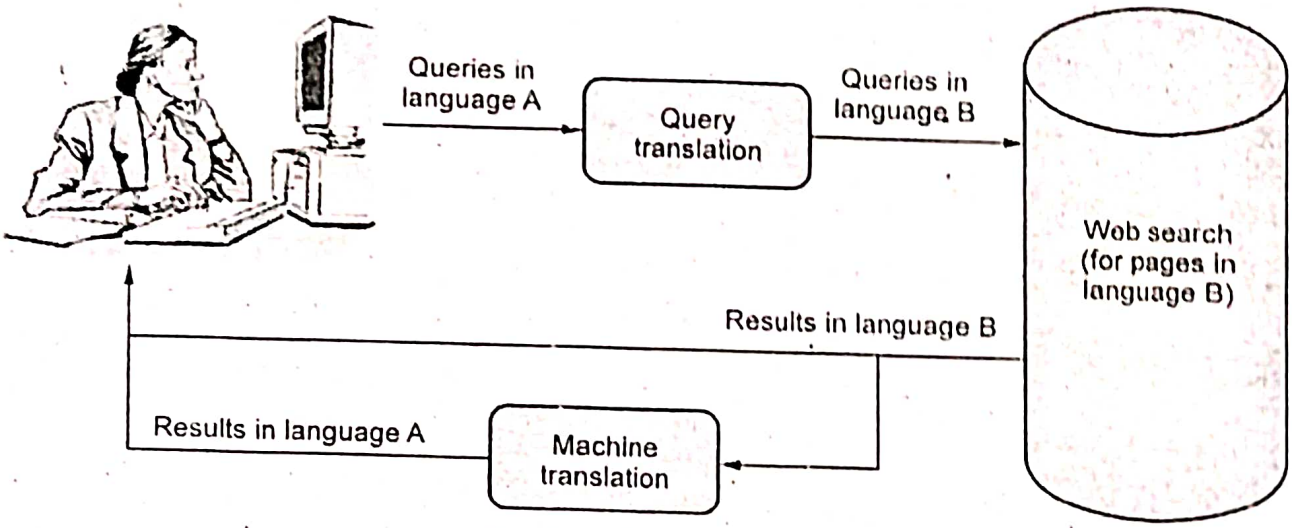


Fig. 6.4.1 CLIR system

- As shown in the Fig. 6.4.1, a user can enter a query in any language. For example, Hindi. If the relevant information is present in language B (For example English), the query is first translated to language B. After the web search the retrieved information in language B is again translated to language A, and results are displayed to the user.

Different approaches of CLIR are :

1. **Query translation approach :**
   - As shown in the Fig. 6.4.2, the query is translated to the target document language.
   - This is the most appropriate approach, as the query is shorter and fast to translate than a complete document.
   - One disadvantage can be, query translation can suffer from translation ambiguity due to the limited context.

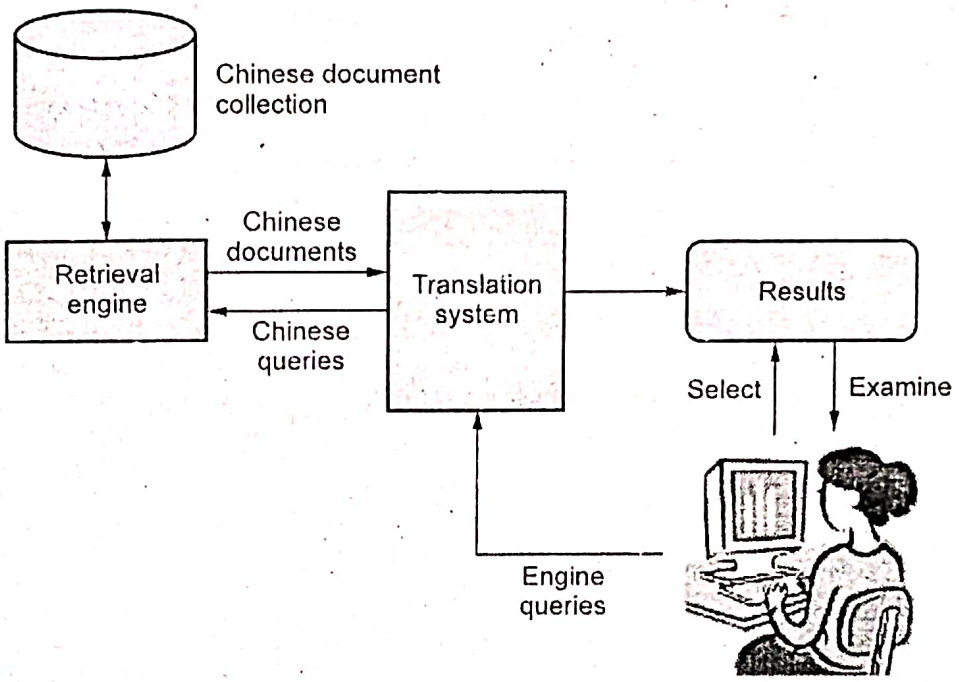


Fig. 6.4.2

2. **Document translation approach :**

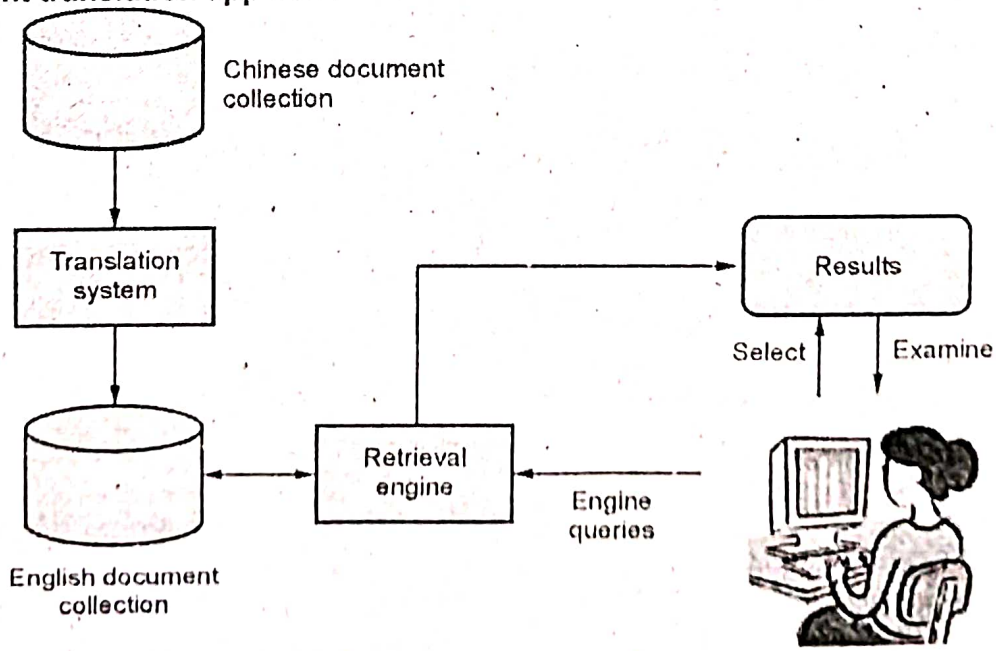


Fig. 6.4.3

- As shown in the Fig. 6.4.3, the documents in target language are translated to source language.
- Document translation can provide more accurate translation due to richer contexts.
- Advantage of document translation is, it's easy for the user to understand the document easily once it is retrieved.

3. **Interlingua based approach :**
   - In this the documents and the query are both translated into some common third Interlingua (like UNL).
   - This approach generally requires huge resources as the translation needs to be done online.

Challenges in CLIR :

1. **Translation ambiguity :**
   - Due to ambiguities in various phases of NLP, more than one translation is possible of the source sentence.
   - **For example :** Word "Pooja" can have two meanings, it can be the name of a girl or the second meaning can be worshipping.
2. **Phrase identification :**
   - In some languages like Japanese the words are not separated by white spaces. This may lead to the incorrect translation.
3. **Dictionary coverage :**
   - The linguistic resources in the dictionary can prove as a constraint in performance of the system.
   - Out-of-Vocabulary (OOV) problems.
   - Daily new words are added to the language, which may not be recognized by the system.
   - Apart from traditional CLIR systems, recently cross-lingual word embeddings and neural network based information retrieval systems are becoming increasingly popular.
   - Cross-lingual word embeddings can represent words in different languages in the same vector space by learning a mapping from monolingual embeddings.
   - Neural network based information retrieval can produce better representations for documents and queries. In this case the ranking is done directly from relevant labels.

Review Question

1. *Explain challenges of CLIR.*

6.5 Discourse Processing

cohesion

- Typically a high level text documents like for ex. Academic articles are divided into different sub sections like Abstract, Introduction, Methodology, Result and Conclusion.
- Automatic detection of all these types is a difficult problem.
- To address this problem the algorithms for discourse segmentation are used.
- The unsupervised discourse segmentation algorithms are based on concept of cohesion.
- Cohesion is linking of different textual units by using linguistic devices.
- Lexical cohesion is the cohesion which exists in two units which is indicated by relations between words in those units.

  For ex. : Consider the sentence

  Peel, core and slice – the pears and apples.

  Add the fruit to skilled.
- In this sentence lexical cohesion between these two sentences is shown by hypernyn relation between fruit and words pears and apples.

Reference resolution

- To understand the concept of reference resolution, lets consider following example.
- "Lakshmi is studying in 10^{th} standard. She is a very good singer and participated in many music programs. The performance of this 16 years old is also excellent in academics."
- In the above passage there is mention of one person named Lakshmi.
- The linguistic expressions like her, she are used to denote an individual is known as reference.
- Reference resolution is a task to determine what entities are referred to by which linguistic expressions.
- Referring expression (for ex. she) is a haliral language expression used to perform reference.
- The referred entity is called as reference (for ex. Lakshmi).
- Reference to an entity which is previously introduced in discourse is called anaphora and the referring expression is called as anaphoric. For ex. Pronoun, she and 16 years old are anaphoric.

- Two referring expressions used to refere same entity are said to corefer.
- So typically the task of reference resolution involve two tasks :
  1. Coreference resolution
  2. Pronominal anaphora resolution
- Coreference resolution is the task to find out referring expressions referring to same entity.
- Pronominal anaphora resolution is the task to find out antecedent for single pronoun.

  For ex. : antecedent of she is Lakshmi. We need to find out the given a pronoun she, its antecedent is Lakshmi.
- Pronominal anaphora resolution can be considered as subtask of coreference resolution.
- There are various algorithms which can be used for this purpose. Some of them are :
  1. Hobbs algorithm
  2. Centering algorithm
  3. Log linear algorithm

6.6 Dialogue and Conversational Agent

- The most fundamental use of any language is to communicate with other number by establishing a dialogue.
- Typically conversational agent establishes dialogue in the form of speech rather than text so they are also called as spoken dialogue system on spoken language systems.
- Conversation is a complex joint activity which is characterized by following properties :

1) Turns and Turn taking

- In any dialogue, speakers take turns to converse
- This turn taking behaviour is studied under field of Conversation Analysis (CA).
- Turn taking behaviour follows turn taking rules which are applied at the places where speaker shift occurs, known as Transition Relevance Place or TRP
- Turn taking rule at each TRP states :

  a. If in a turn current speakers select A as next speaker, A must speak.

  b. If next speaker is not selected, any other speaker can take next turn.

  c. Current speaker will continue if no one takes next turn.

2) Language as action : Speech acts

- The basis of this property is utterance is a kind of action.

  For ex :

  I second your opinion

  In this sentence the verb second perform the action which changes state of the world.

  These verbs are called performing verbs and the actions they perform are called as speech as acts.

  Speech acts are used to describe illocutionary acts.

3) Language as joint action : Grounding

- It is based on the fact that speakers and hearer establish common ground.
- By doing this hearer ground 'speaker's utterances indicating that hearer has understood speakers meaning and intention.

4) Conversational structure :

- It focuses on structures of any conversation.
- The overall organization of conversation can be explained by following conversation :
- Consider following telephone conversation :

  Stage 1 : Enter a conversation

  Stage 2 : Identify speakers

  Stage 3 : Establish joint willingness to converse

  Stage 4 : Raise the first topic, typically done by the caller.
- As shown in the above example different structures exists in conversation.

5) Conversational implicature

- Implicature is particular class of licensed inferences.
- These inferences are drawn by hearer by set of maxims.

Review Question

1. *What are dialogue and conversational agent ?*

6.7 Natural Language Generation

- Natural-Language Generation (NLG) is a software process that produces natural language output.

- Common applications of NLG methods include the production of various reports, for example weather and patient reports image captions and chat bots.
- Automated NLG can be compared to the process humans use when they turn ideas into writing or speech.
- Psycholinguists prefer the term language production for this process, which can also be described in mathematical terms, or modeled in a computer for psychological research.

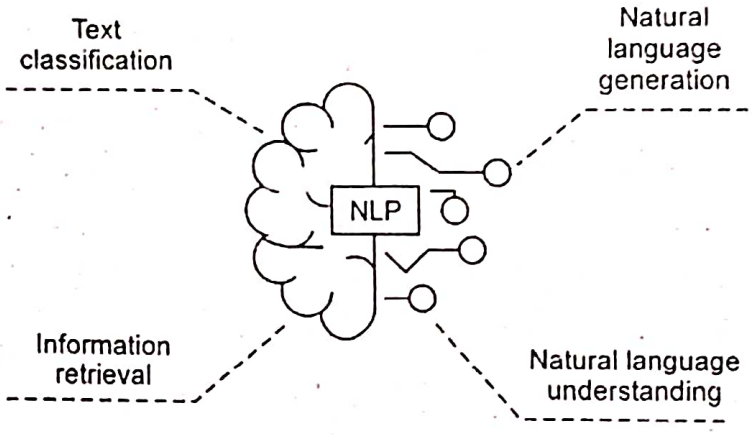


Fig. 6.7.1 Placing NLG in the context of NLP and NLU

- NLG systems can also be compared to translators of artificial computer languages, such as decompilers or transpilers, which also produce human-readable code generated from an intermediate representation.
- Human languages tend to be considerably more complex and allow for much more ambiguity and variety of expression than programming languages, which makes NLG more challenging.

NLP vs NLU vs. NLG

- Natural Language Processing (NLP) seeks to convert unstructured language data into a structured data format to enable machines to understand speech and text and formulate relevant, contextual responses. Its subtopics include natural language processing and natural language generation.
- Natural Language Understanding (NLU) focuses on machine reading comprehension through grammar and context, enabling it to determine the intended meaning of a sentence.
- Natural Language Generation (NLG) focuses on text generation, or the construction of text in English or other languages, by a machine and based on a given dataset.

Stages of NLG

- The process to generate text can be as simple as keeping a list of canned text that is copied and pasted, possibly linked with some glue text.
- The results may be satisfactory in simple domains such as horoscope machines or generators of personalised business letters.
- A sophisticated NLG system needs to include stages of planning and merging of information to enable the generation of text that looks natural and does not become repetitive.
- The typical stages of natural-language generation, as proposed by Dale and Reiterare as shown in Fig. 6.7.2 below.

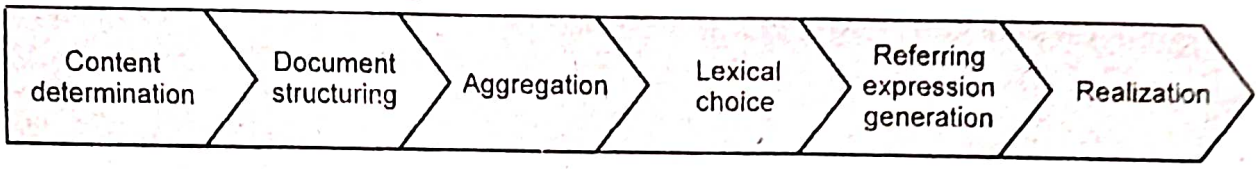


Fig. 6.7.2 Stages of NLG

- **Content determination :** Deciding what information to mention in the text.
- **Document structuring :** Overall organisation of the information to convey. For example, deciding to describe the areas with high pollen levels first, instead of the areas with low pollen levels.
- **Aggregation :** Merging of similar sentences to improve readability and naturalness. For instance, merging the two following sentences.
- **Lexical choice :** Putting words to the concepts. For example, deciding whether medium or moderate should be used when describing a pollen level of 4.
- **Referring expression generation :** Creating referring expressions that identify objects and regions. This task also includes making decisions about pronouns and other types of anaphora.
- **Realization :** Creating the actual text, which should be correct according to the rules of syntax, morphology and orthography. For example, using will be for the future tense of to be.

Alternative approach for NLG

- An alternative approach to NLG is to use "end-to-end" machine learning to build a system, without having separate stages as in Fig. 6.7.2.
- An NLG system can also be built by training a machine learning algorithm (often an LSTM) on a large data set of input data and corresponding (human-written) output texts.

- Long Short-Term Memory (LSTM) is an artificial recurrent neural network (RNN) architecture used in the field of deep learning.
- The end-to-end approach has perhaps been most successful in image captioning, that is automatically generating a textual caption for an image.

NLG applications

- NLG makes data universally understandable making the writing of data-driven financial reports, product descriptions, meeting memos and more much easier and faster.
- It can take the burden of summarizing the data from analysts to automatically write reports that would be tailored to the audience.
- The main practical present-day applications of NLG are, therefore, connected with writing analysis or communicating necessary information to customers.
- NLG has more theoretical applications that make it a valuable tool not only in computer science and engineering, but also in cognitive science and psycholinguistics.
- Refer Fig. 6.7.3 for practical and theoretical applications of NLG

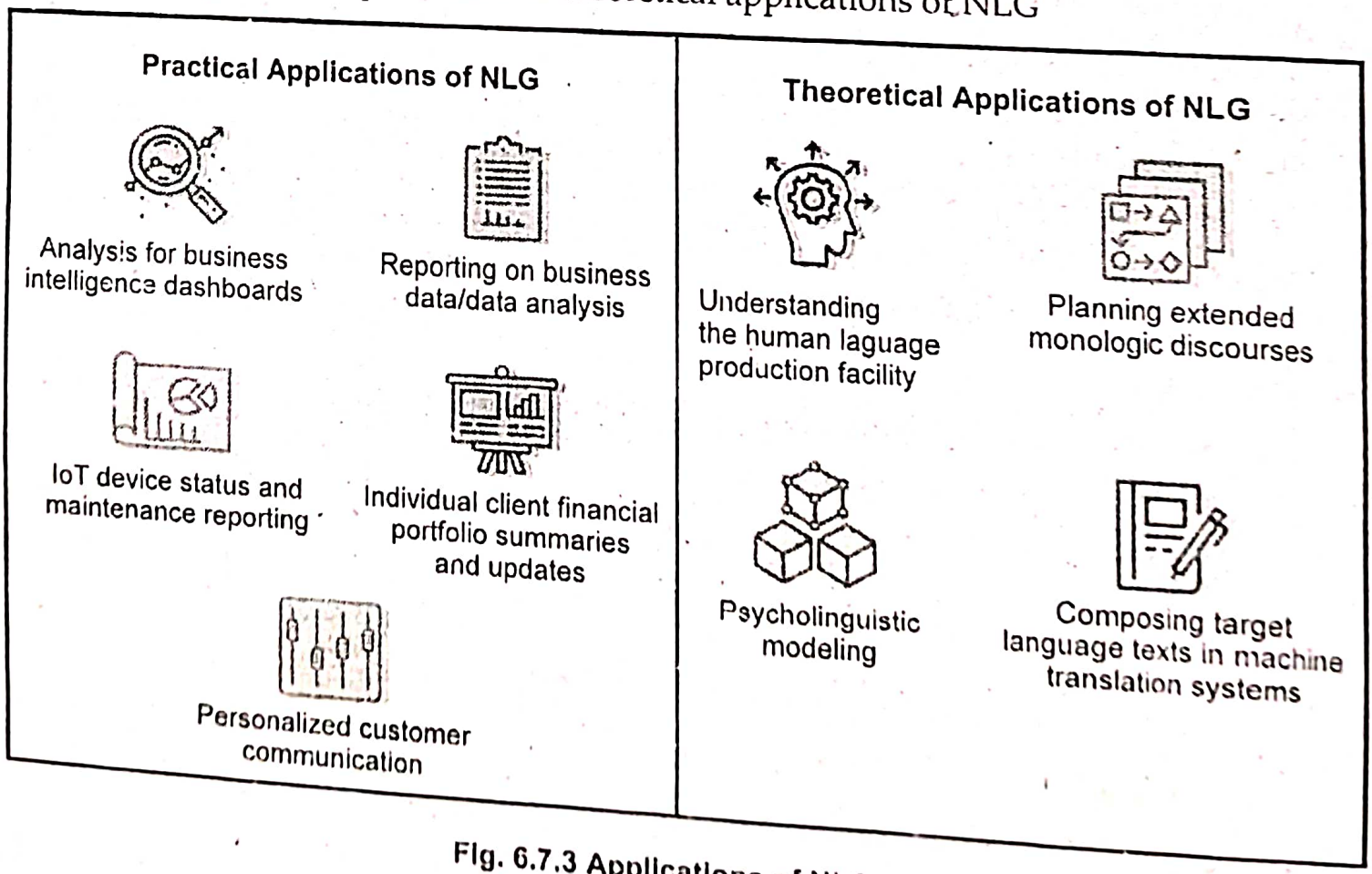


Fig. 6.7.3 Applications of NLG

NLG tools

- One can see that natural language generation is a complicated task that needs to take into account multiple aspects of language, including its structure, grammar, word usage and perception.
- Luckily, it won't build the whole NLG system from scratch as the market offers multiple ready-to-use tools, both commercial and open-source.
- Commercial NLG tools
  1. **Arria NLG PLC :** Is believed to be one of the global leaders in NLG technologies and tools and can boast the most advanced NLG engine and reports generated by NLG narratives.
  2. **AX semantics :** Offers eCommerce, journalistic and data reporting (e.g. BI or financial reporting) NLG services for over 100 languages. It is a developer-friendly product that uses AI and machine learning to train the platform's NLP engine.
  3. Yseop is known for its smart customer experience across platforms like mobile, online or face-to-face. From the NLG perspective, it offers a suite that can be consumed on-premises, in the cloud or as a service and offers Savvy, a plug-in for Excel and other analytics platforms.
  4. **Wordsmith :** It is an automated insights product that is an NLG engine that works chiefly in the sphere of advanced template-based approaches. It allows users to convert data into text in any format or scale. Wordsmith also provides a plethora of language options for data conversion.
- Open-Source NLG tools
  1. **Simplenlg :** Is the most widely used open-source realiser, especially by system-builders. It is an open-source Java API for NLG written by the founder of Arria. It has the least functionality but also is the easiest to use and best documented.
  2. **Natural OWL :** Is an open-source toolkit which can be used to generate descriptions of OWL classes and individuals to configure an NLG framework to specific needs, without doing much programming.

Review Questions

1. *How natural language is generated ?*
2. *Explain stages of NLG.*
3. *What are commercial NLG tools ?*

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