

Syntactic Parsing:

↳ Morphology is based on independent words, while syntax deals with combinations of words.

↳ Morphology is often irregular (aberrant/funulant)

↳ Some sentences are syntactically/grammatically correct but have no semantic meaning.

⇒ constituents.

↳ group of words that give meaning when they go together.

↳ one phrase can have multiple phrases.

↳ noun phrase / preposition phrase / clause.

CFG

↳ terminal → vocab

↳ Det → Determiner

↳ Parsing → using parse tree

bottom up ↳ top down.

↳ CFG requires lots of knowledge & rules.

Top Parser:

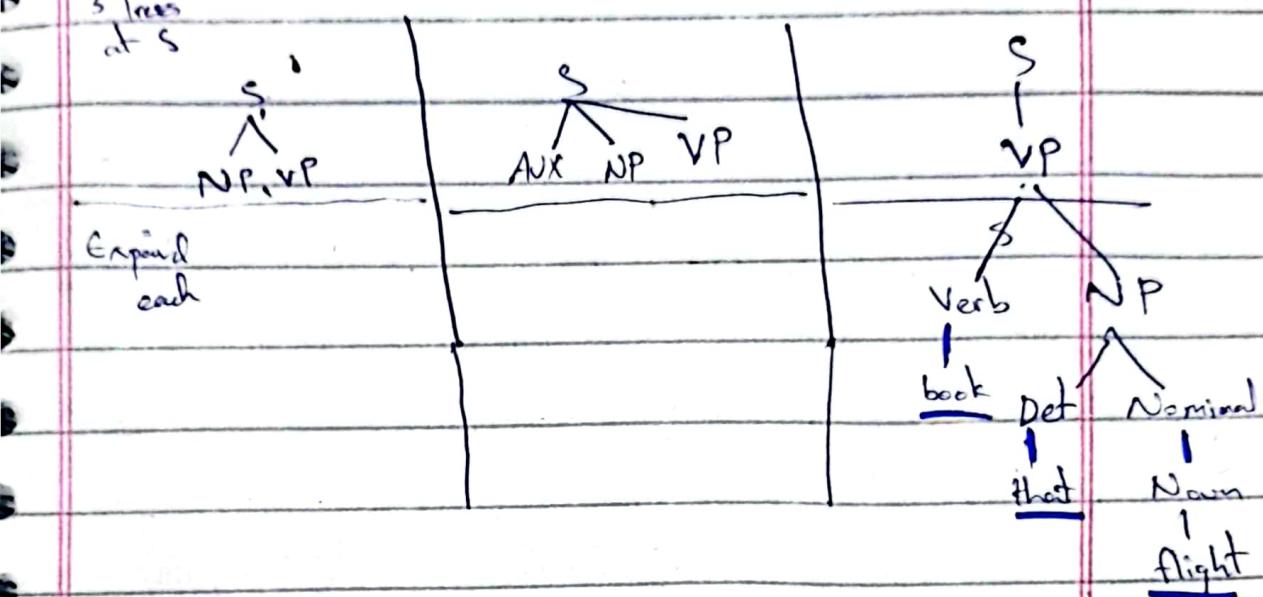
Example:

(Top Down Parsing).

book that flight

3 Trees
at S

Expand
each



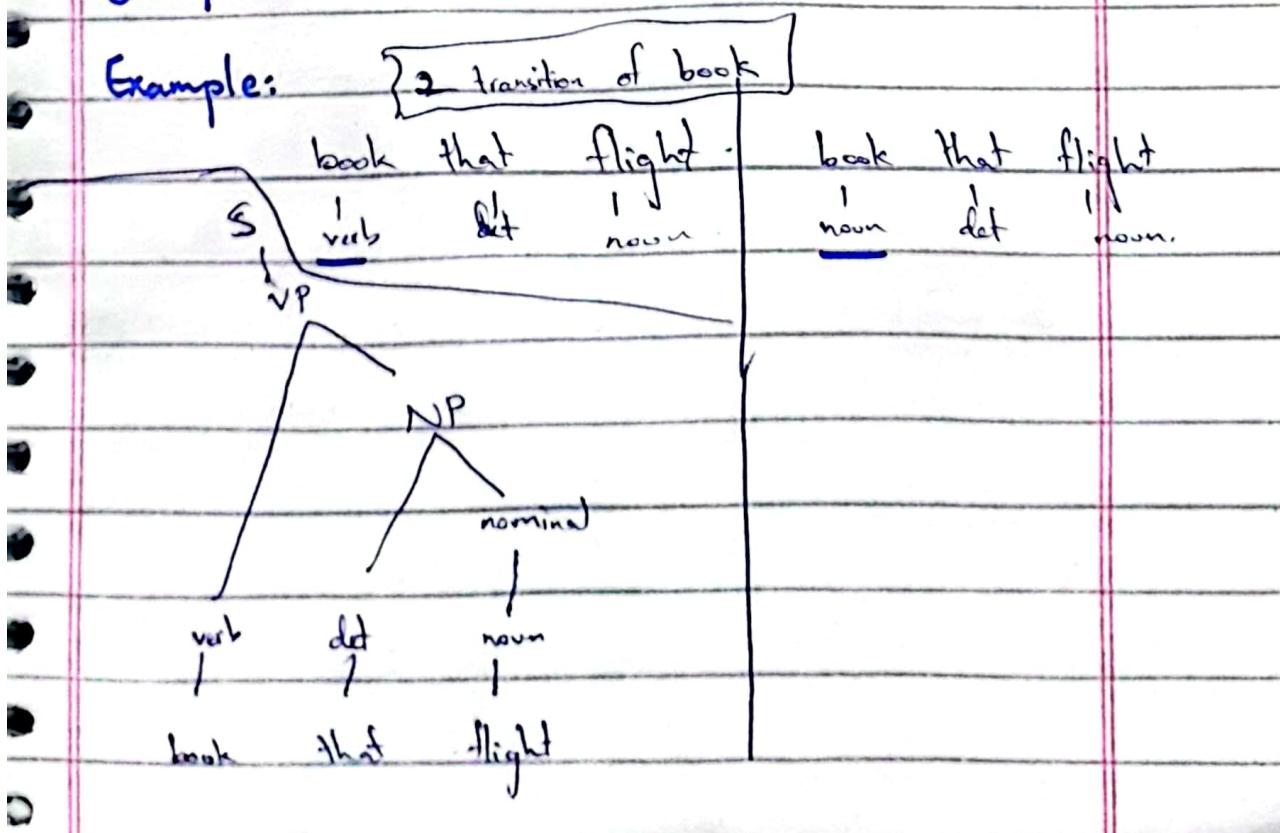
If one sentence has more than one possible parse trees \Rightarrow ambiguous sentence.

Bottom Up Parsing:

Reading

Example:

{ 2 transition of book }



In bottom up, start with terminal & check production rules.

↳ check pairs else single words.

↳ shift reduce parsing. (bottom up parsing)

↳ for training parser, manually annotated corpus is required

↳ Semantic ambiguity leads toward semantic ambiguity.

↳ Pantreebank.

NLP-15 (08/11/24)

↳ If multiple parse trees, which one to use?

↳ Use probability.

↳ require probability of each production rule.

↳ probabilistic CFG

↳ prob sum of each non-terminal is 1.

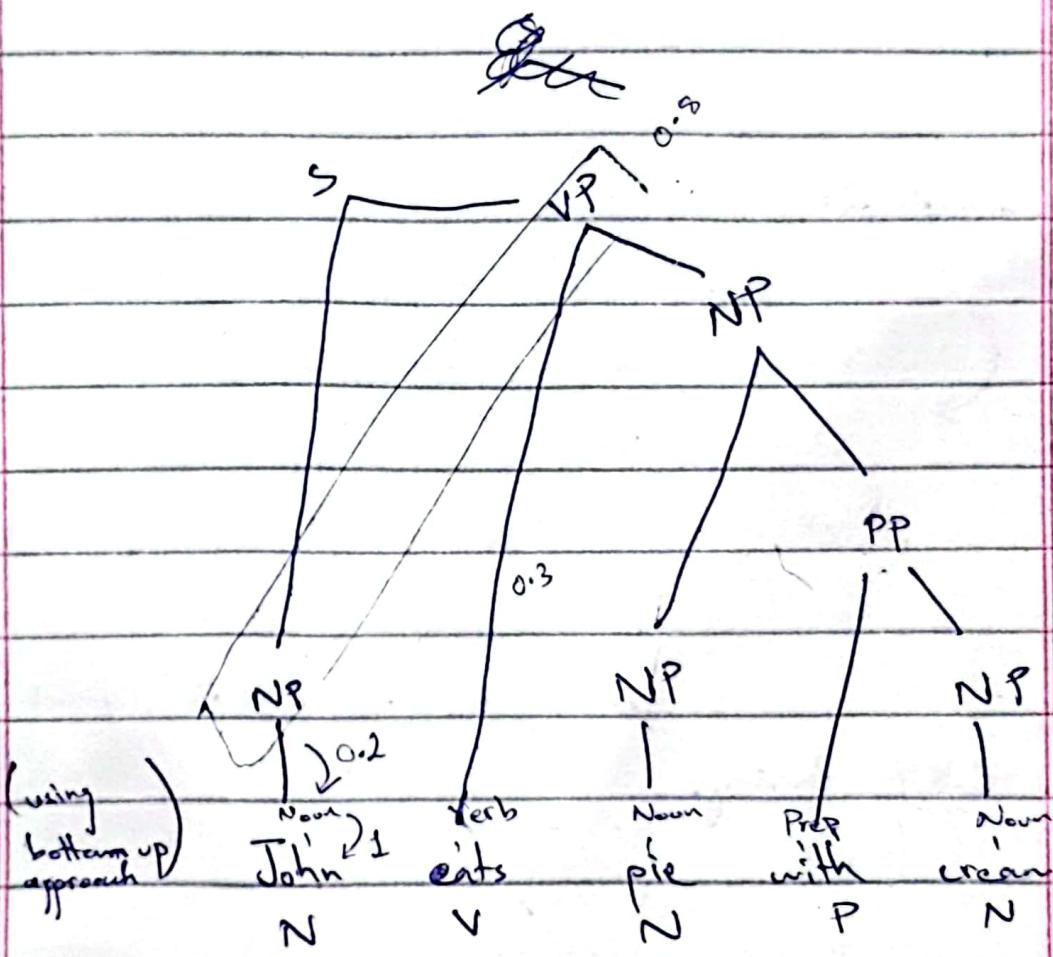
$$\rightarrow \text{prob}(1) = \frac{\text{count}(S \text{ noun } S)}{\text{count}(\text{starting with } S)}$$

$$\rightarrow \text{prob}(2) = \frac{\text{count}(\text{only Noun as NP})}{\text{count}(NP)}$$

~~NP VP~~

Example:

→ John eats pie with cream.



↳ computing prob of parse tree.

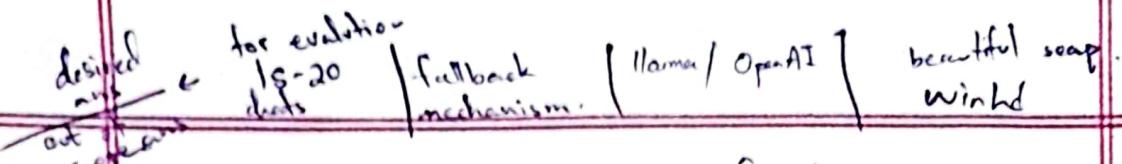
$$S \rightarrow NP VP \quad 0.8$$

$$NP \rightarrow Noun \quad 0.2$$

NP -

$$\text{prob} = (0.8 * 0.2 * 1) * (0.3 * 1.0)$$

Workflow \rightarrow flow diagram + written flow.



\hookrightarrow CFG must be converted to CNF

NO more than 2 siblings \hookrightarrow on right side.

Example:

$$X \rightarrow ABC \rightarrow X \rightarrow AX_2.$$

$$X_2 \rightarrow BC.$$

\hookrightarrow new production rule added.

\hookrightarrow new symbol added to vocab.

Example 2:

$$\sqrt{VP} \rightarrow VBD \ NP \ PP \ PP$$

$$\xrightarrow{\quad} X_2 \rightarrow NP \ PP.$$

$$X_3 \rightarrow X_2 \ PP.$$

$$VP \rightarrow VBD \ X_3.$$

NLP-16

(10/11/24)

CKY Parsing:

\hookrightarrow bottom up parser.

\hookrightarrow grammar should be in CNF.

\hookrightarrow fill table with unaries.

\hookrightarrow if prob, add also.

A_0 , A_B

\hookrightarrow Ambiguity is handled by probability.

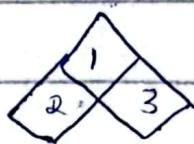
\hookrightarrow top cell has atleast one rule

starting with S else not valid.

↳ reduce the rules

$$\begin{array}{ll} V \rightarrow \text{people} & 0.1 \\ VP \rightarrow V & 0.1 \\ \text{reduced as} & \\ VP \rightarrow V & 0.1 * 0.1 \end{array}$$

$$NP \rightarrow N \quad 0.3 * 0.7$$



↳ cell 1 will have combinations of 2 & 3

↳ discard invalid combinations.

$$S \rightarrow NP VP \quad (0.9 * 0.35 * 0.06)$$

Examples:

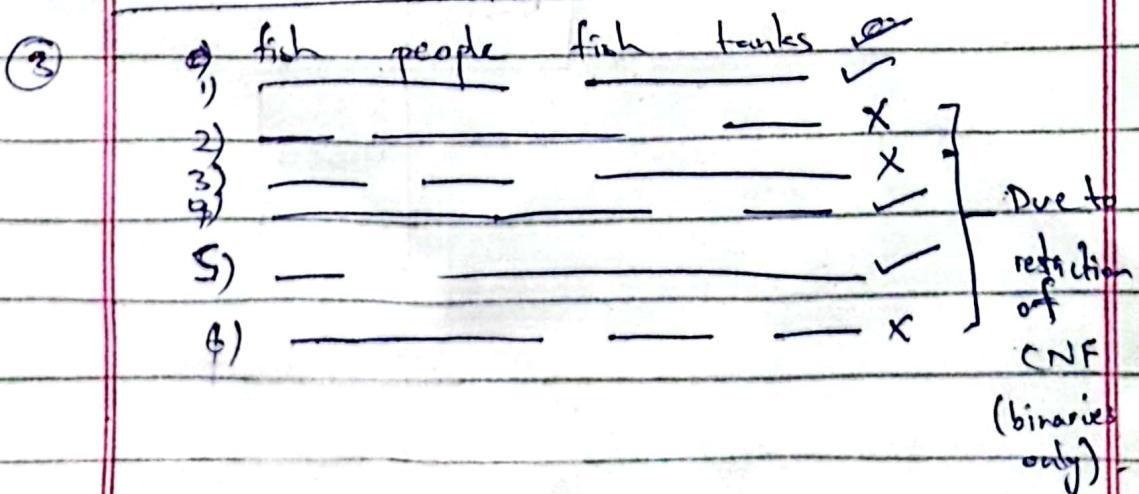
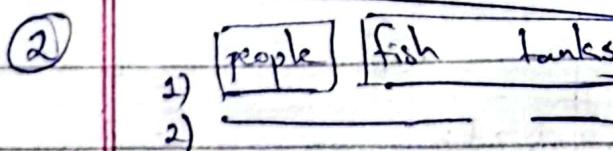
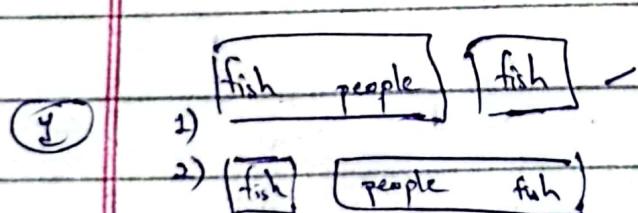
fish People Fish Tank

} In computer
we use
matrix

$N \rightarrow \text{fish}$			
$V \rightarrow \text{fish}$			
	0.5 $N \rightarrow \text{people}$		
	0.1 $V \rightarrow \text{people}$		
		$N \rightarrow \text{fish}$	
		$V \rightarrow \text{fish}$	
			$N \rightarrow \text{tanks}$
			$V \rightarrow \text{tanks}$

fish people fish tanks

①	fish	people	fish	tanks
	N → fish 0.2 V → fish 0.6 NP → N 0.2 0.6 NP → V 0.1 0.6 S → VP 0.1 * 0.6 0.1	VP → VNP *	N → fish 0.2 V → people 0.5 NP → N NP → V S → NP	✓
fish				②
people				
			N → fish 0.2 V → fish 0.6	
				N → tanks 0.2 V → tanks 0.3



Embeddings:

- ↳ numbers are fast for processing. (by arranging in order then assign num)
- ↳ one hot encode \Rightarrow does not give info about similar/opposite semantic words.
- ↳ Word Embeddings provide similarity & has low dimensions.
 - ↳ min / distance b/w similar words.
 - ↳ corpus required (words in d/f contexts)
 - ↳ low dimension \rightarrow data loss (low acc.)
 - ↳ high dimension \rightarrow no data loss (high acc.).
 - ↳ BERT \Rightarrow attention mechanism.
 - ↳ train embedding from scratch / or train/fine-tune for specific context.
- ↳ m \Rightarrow multilingual. (mBERT)
 - ↳ predict next word depending upon basic information.
 - ↳ center word prediction
 - ↳ prev info + next info used.
 - ↳ possible words from corpus.
 - ↳ work with lowest vector distance.
 - ↳ <is> <ss> —
(for starting) -

↳ In CBOW, embedding is bi-product of model.

NLP-18

(19/11/21)

Words to Vector.

CBOW → basic purpose \Rightarrow center word (pred)

↳ biproduct \Rightarrow embeddings.

num/4 \rightarrow value can't go beyond 1.

\Rightarrow input vector size \Rightarrow vocab size.

* $(V \times 1)$ (col) * $(1 \times V)$ (row)

Embedding \leftarrow $N \times V \Rightarrow 100 \times 20$,
Dimension \downarrow I
Size vocab size.

\Rightarrow Batch

↳ usually 2^{Power} , for faster computation.

↳ does not greatly impact on accuracy.

ReLU

↳ $\max(0, \text{val})$

Softmax.

↳ convert nums to probabilities.

$(0-1) \Rightarrow \text{sum} = 1$.

↳ $\frac{\exp(\text{value})}{\text{sum of values}}$.

$$y_i = \frac{e^{z_i}}{\sum_{j=1}^V e^{z_j}}$$

- ↳ If pred vs actual are not same weights & bias are updated \Rightarrow back prop.
- ↳ KNN \Rightarrow not fixed activation function (ReLU) cross-entropy.
- ↳ CBOW \Rightarrow shallow network ($2W + 2$ Bias).

NLP - 19 (22/11/24)

- ↳ stop training when loss not decreasing.
 - \hookrightarrow manually / flags in code.
- ↳ CBOW \rightarrow prediction (main) embeddings (byproduct).
- ↳ extract embeddings from hidden layer.
 $w_1 \rightarrow$ col matrix , $w_2 \rightarrow$ row matrix
 \hookrightarrow transpose to add.
 $N \times V \rightarrow$ dimensions.

BERT Model:

- \hookrightarrow attention layer.
- \hookrightarrow mostly for embedding only (byproduct).
- \hookrightarrow for classification, need to add layer to end.

→ for training from scratch.

↳ large data + time req.

→ Extrinsic Evaluation:

↳ after using in external task.

→ Intrinsic Evaluation:

↳ without using in external task.

NLP - 19

(29/11/24)

Question Answering:

↳ oldest nlp task.

↳ factoid / narrative.

↳ IR based (doc/content unstructured).

Knowledge based (any type of db).

Hybrid (both IR + Knowledge based)

↳ no context is maintained, all
questions are independent.

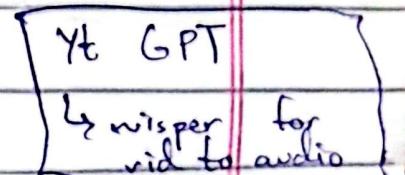
↳ context in chatbot.

Indexing:

- ↳ for fast searching (SOZAR, USEEN)
- ↳ which embeddings for vector conversion.
- ↳ for customised chatbot.
- ↳ if info is not factoid, answer retrieval becomes complex.
- ↳ MRR \Rightarrow for info retrieval.
- ↳ knowledge base

Langchain:

- ↳ focus on modularity.
- ↳ Krisma, Redis for db.
- ↳ data loaded in vector store.
- ↳ Doc loaders \Rightarrow structured + unstructured data.
Read from file.
- split \Rightarrow page, further split.
store in db.
- \Rightarrow Doc Split



- ↳ overlap required while chunk split.

Chatbot

sentences/word embeddings

embed query \Rightarrow loop on splits.

Q: How to use vector store?

2 divisions of chatbot

- 1) creation
- 2) usage

\Rightarrow May have repetition in top k.

1) Exact match easily detected.

2) Paraphrase check also.

\hookrightarrow top relevant & distinct.

max-marginal-relevance instead of
similarity-search.

\hookrightarrow meta-data-filter for specific pdf/doc.

Neural Machine Translation:

↳ Text/Speech

↳ speech → text → speech

speech → speech (^{Under} Research)

↳ seq learning ^{problem}, but input & output
are not aligned (length can vary)

↳ basic neural network ⇒ latest.

↳ NMT /OpenMT .

↳ Map variable length seq on
fixed length memory.

LSTM & GRU.

Encoder → learns embedding of source key.

Decoder → learns embedding of target key.

→ CBOW / FASTX / GLOB.

→ No of words ⇒ no of LSTM units.

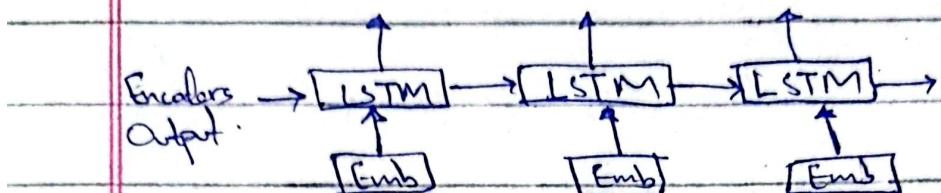
→ LSTM receives current word + previous
words (context) max 2/3 prev words.

→ Each LSTM decides

↳ reset / modify / retain .

⇒ Encoder has embeddings & 1 layer of LSTMs

⇒ Output of LSTM layer is given to decoder



Info bottleneck:

↳ only fixed amount of info to decoder.

↳ context from each LSTM or final LSTM only

Attention:

↳ context to each meaning.

↳ attention layer needs to be trained.

↳ when weighted sum is added, feedback is sent to encoder.

CBOW Model:

(Input) context vector \rightarrow output vector.

\hookrightarrow result (embeddings)

\Rightarrow Corpus for machine translation.

parallel corpus \Rightarrow source to target.

\Rightarrow Query \Rightarrow target text (translated).

Sentence translation rather than word.

translation (for learning alignment).

\Rightarrow Try to make don't form diagonal
in attention

\Rightarrow no preprocessing for emojis, digits
(auto learned).

\Rightarrow 2-3 people translate 1 sentence.
more than 1 person verify.

\Rightarrow Why padding?

for fix dimension of input vector.

Each token has unique (word to index).

\hookrightarrow embedding for encoder.

Softmax output \Rightarrow as weights.

Attention Layer:

↳ Determines

↳ softmax behaves differently.

↳ Encoder \Rightarrow learns representation of source lang

↳ Decoder \Rightarrow learns representation of target lang

↳ teacher forcing \Rightarrow Don't compute loss

in initial epochs (assume

(on pre
attention
decoder) output as correct), after
that start calculating
the loss.

↳ Attention layer requires input from

encoder + decoder & new weights

are ^{sent} ~~sent~~ to decoder

shift Right \Rightarrow Mark start/end of sentence
+ padding if required.

log Softmax \Rightarrow log probabilities

RNN has vanishing problem \Rightarrow LSTM
^{so}
is used

BLEU Score:

↳ for evaluating machine translation/
summarization etc.

(Bad) 0 - 1 (Good)

Bilingual Evaluation Understudy.

HT → Ground Truth / Gold Reference / Standard.

MT → Candidate

↳ based on precision.

↳ not subjective but quantitative measure.

↳ If word of candidate sentence is found in any reference, add 1 else 0. Then divide total by $\frac{\text{length}}{\text{count}}(\text{candidate})$.

↳ vanilla BLEU has prob, not good score.

↳ Modified BLEU, delete word from reference if matched with candidate.

Issues:

↳ no semantic meaning.

↳ no sentence structure

⇒ (opposite case ⇒ score is bad but good translation ⇒ reference grammar is diff from training data).

ROUGE: (Recall)

Recall Oriented Understry for Gisted Evaluation.

⇒ on unigram, bigram level etc.

max of 2 or 3 references.

↳ separate count for each reference
⇒ Opposite (ref is matched with candidate)

F-Measure:

$$2^* \text{BLEU}^* \text{ROUGE}$$

BLEU + ROUGE

$$\Rightarrow \frac{2^* 0.5 * 0.4}{0.5 + 0.4} = 0.44.$$

Next Topic

dictionaries don't have similarities

e.g. car vs bicycle

→ word sense vs synonyms (tall vs long).

→ wordnet ⇒ contains word simset

↳ Homophones:

only speaking is same.

↳ Homographs:

same spells only.

↳ Simset ⇒ used interchangeably.

⇒ Zeugma Test

for identifying word sense.

↳ use word in multiple sentences.

(Also merge them and check).

↳ If cannot be connotated \Rightarrow multiple sense.

\Rightarrow wordnet \Rightarrow (web+api+desktop version).

↳ for senses of words.

↳ not a corpus.

↳ It is a lexical resource.

↳ Hierarchy helps in making analogies.

MeSH (Medical Subject Headings).

→ Word Similarity: Thesaurus Method.

How to calculate for words?

→ 2 types of Algo.

1) Use lexical resources.

2) use ML & corpus

NLP-25

(19/22/24)

1) Thesaurus based (dict/wordnet)

↳ Path based similarity.

edges + 1 \Rightarrow pathlen.

simpath = $1/\text{pathlen}$.

(sometime not good in similarity as

dis-similar things can have good

score \Rightarrow can't threshold)

↳ Info content similarity

↳ every word has prob (instead of 1)

↳ prob from corpus

↳ descendant \Rightarrow subchilds also

sum of probs

$$N \quad \text{or } N = \frac{\text{no. of words}}{\text{in corpus}}$$

↳ log prob \Rightarrow to avoid

overflow issue

$$IC(c) = -\log P(c)$$

↳ lowest common subsumer (LCS)

1) convert all prob to log.

\Rightarrow only LCS or all words?

↳ use all common words

↳ high similarity value ~~at~~ at
works on low level of tree

L

↳ Lin Similarity:

only LCS used.

$$(A, B) = \frac{2 \log P(\text{LCS}(c_1, c_2))}{\log P(c_1) + \log P(c_2)}$$

\rightarrow wordnet required

The (extended) Levenshtein Algo

→ A thesaurus-based measure that looks

at glosses.

↳ uses dict.

↳ get desc of both words from

dict & find similarity using dict. description.

↳ 1st match phrase then words

$$1 + 2^2 = 5$$

word phrase

Embeddings or Cosine similarity.

(previously it was applied
on count now applied
on embeddings)

bLSTM

↳ bi-direction (future info also used).