

# CSCE 771: Computer Processing of Natural Language

## Lecture 8: (NLP) Evaluation, Semantics

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PROF. BIPLAV SRIVASTAVA, AI INSTITUTE

12<sup>TH</sup> SEPTEMBER, 2024

***Carolinian Creed: “I will practice personal and academic integrity.”***

Acknowledgement: Used materials by  
Jurafsky & Martin,

# Organization of Lecture 8

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- Opening Segment

- Announcements

- Main Lecture



- Concluding Segment

- About Next Lecture – Lecture 9

## Main Section

- Review quiz
- Review last class/ parsing
- Introduce evaluation metrics in NLP context
- Semantics
- Review projects

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Sep 24 (Tu)	Language Model – PyTorch, BERT, {Resume data, two tasks} – <b>Guest Lecture</b>
Sep 26 (Th)	Language Model – Finetuning, Mamba - <b>Guest Lecture</b>
Oct 1 (Tu)	Language model – comparing arch, finetuning - <b>Guest Lecture</b>
Oct 3 (Th)	Language model – comparison of results, discussion, ongoing trends– <b>Guest Lecture</b>

# Announcements

GUEST LECTURES ON  
LANGUAGE MODELS

# QUIZ

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- Submit using Black board
- Includes resume exercise
- Due by next Monday, Sep 16, 2024

# Recap of Lecture 7

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- We discussed statistical parsing - Probabilistic grammars
  - assign a probability to a sentence or string of words
  - In a probabilistic context-free grammar (PCFG), every rule is annotated with the probability of that rule being chosen assuming conditional independence.
  - The probability of a sentence is computed by multiplying the probabilities of each rule in the parse of the sentence.
  - We looked at Stanford parser
- We had Quiz 1

# Review of Quiz 1

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- Submit using Black board
- Includes resume exercise
- Due by next Monday, Sep 16, 2024

**Bonus question for Quiz 1** [10 points] - as discussed in class.

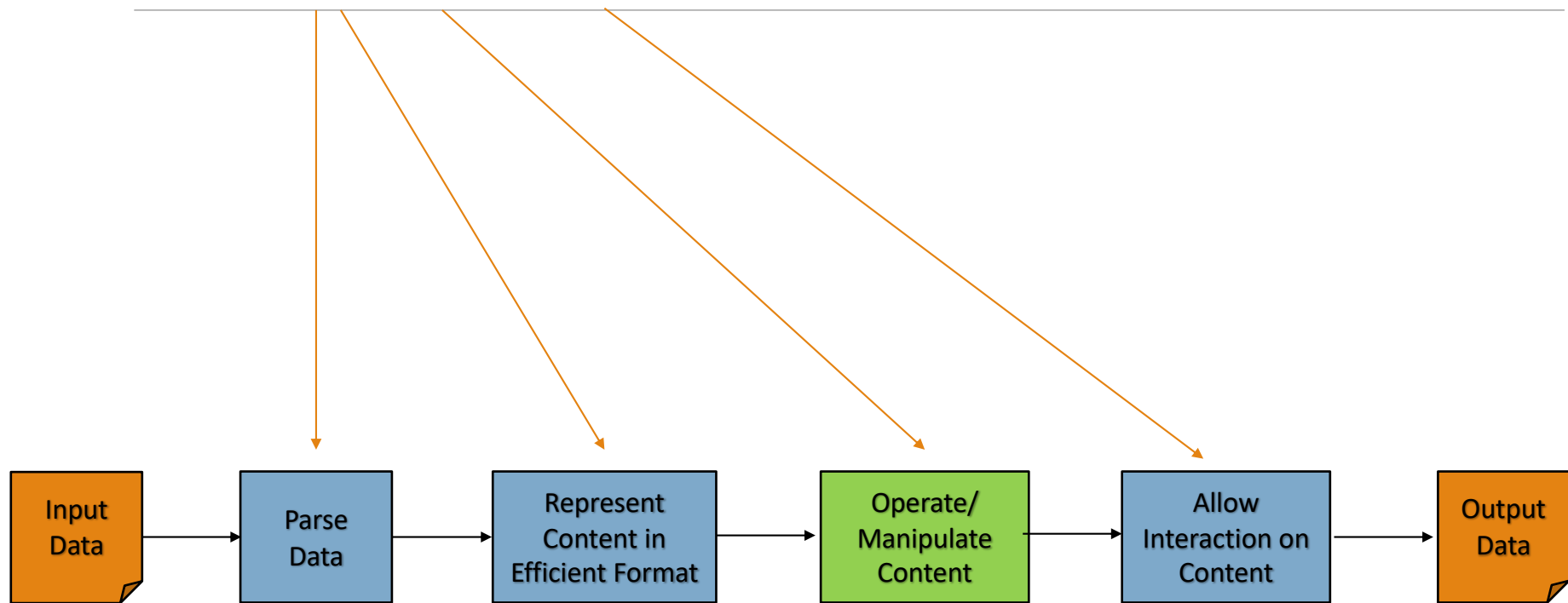
Represent resumes as vectors. Now show how the following will be done:  
Select a query **q** (document/resume) and then identify the document most similar to it from a corpus **C** containing **d** resumes, using **TF-IDF scores**?

# Main Lecture

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# NLP Evaluation

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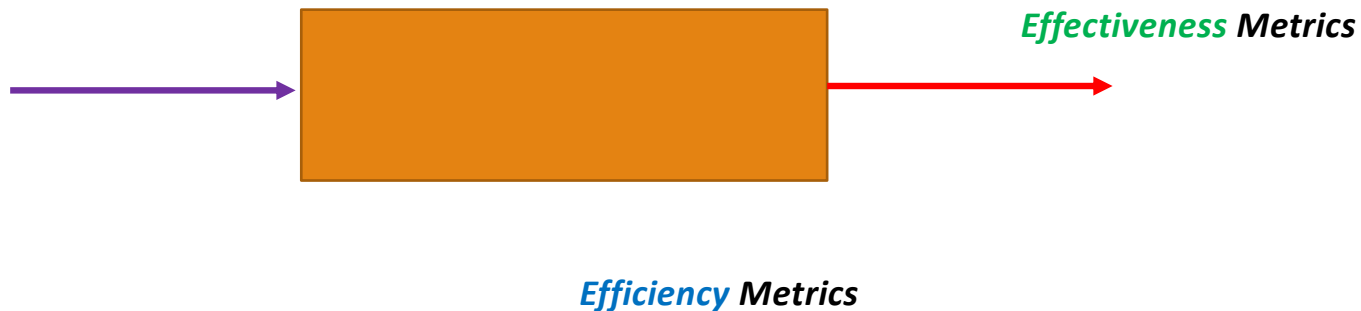
# Metric Types

- **Effectiveness**: what the user of a system sees, primarily cares about

**Extrinsic** evaluation (esp. downstream applications)

- **Efficiency**: what the executor in a system sees, primarily cares about

**Intrinsic** evaluation



# Example: Detecting Spam in Email

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- **Effectiveness**: what the user of a system sees, primarily cares about
  - *How many spams identified?*
  - *How many spams missed?*
- **Efficiency**: what the executor in a system sees, primarily cares about
  - *How fast were spams detected?*
  - *How much memory was used per million emails processed ?*

# Metrics: Accuracy, Precision, Recall

Actual Class	Predicted class	
	Class = Yes	Class = No
Class = Yes	True Positive	False Negative
Class = No	False Positive	True Negative

**Accuracy** =  
$$\frac{(TP+TN)}{(TP+FP+FN+TN)}$$

**Precision** =  
$$\frac{(TP)}{(TP+FP)}$$

**Recall** =  
$$\frac{(TP)}{(TP+FN)}$$

**F1 Score: Harmonic Mean**  
$$\frac{1}{F1} = \frac{1}{Precision} + \frac{1}{Recall}$$

$$F1 = \frac{2 * (Recall * Precision)}{(Recall + Precision)}$$

# Evaluating Parsers - PARSEVAL

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Degree to which the constituents in the hypothesis parse tree look like the constituents in a hand-labeled, gold-reference parse like PENN TreeBank

Overall measure is by F1 score

$$F_1 = \frac{2PR}{P + R}$$

**labeled recall:** =  $\frac{\text{\# of correct constituents in hypothesis parse of } s}{\text{\# of correct constituents in reference parse of } s}$

**labeled precision:** =  $\frac{\text{\# of correct constituents in hypothesis parse of } s}{\text{\# of total constituents in hypothesis parse of } s}$

From Jurafsky & Martin

# Average Performance With Multiple Classes

- Setting

- Class A: 1 TP and 1 FP
- Class B: 10 TP and 90 FP
- Class C: 1 TP and 1 FP
- Class D: 1 TP and 1 FP

$$\text{Precision} = \frac{(\text{TP})}{(\text{TP} + \text{FP})}$$

- Average precision = ?

- Macro and micro average

- A macro-average will compute the metric independently for each class and then take the average (hence treating all classes equally)
- A micro-average will aggregate the contributions of all classes to compute the average metric.

A macro-average will then compute:  $Pr = \frac{0.5 + 0.1 + 0.5 + 0.5}{4} = 0.4$

A micro-average will compute:  $Pr = \frac{1 + 10 + 1 + 1}{2 + 100 + 2 + 2} = 0.123$

**Source and credit:** <https://datascience.stackexchange.com/questions/15989/micro-average-vs-macro-average-performance-in-a-multiclass-classification-settin>

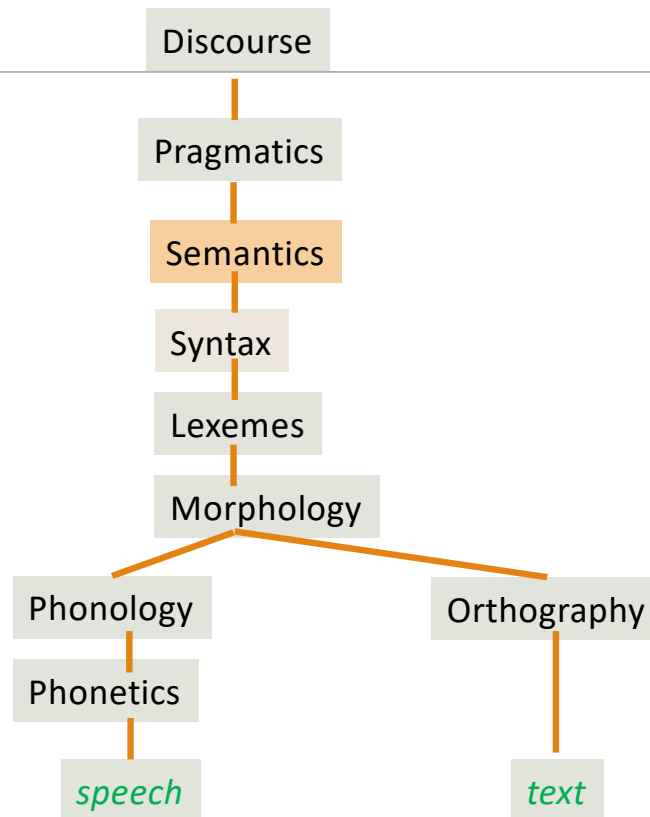
# Code Sample – Metrics Calculation

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**Notebook:**

<https://github.com/biplav-s/course-nl-f22/blob/main/sample-code/l8-review-evalmetrics/Metric%20Calculations.ipynb>

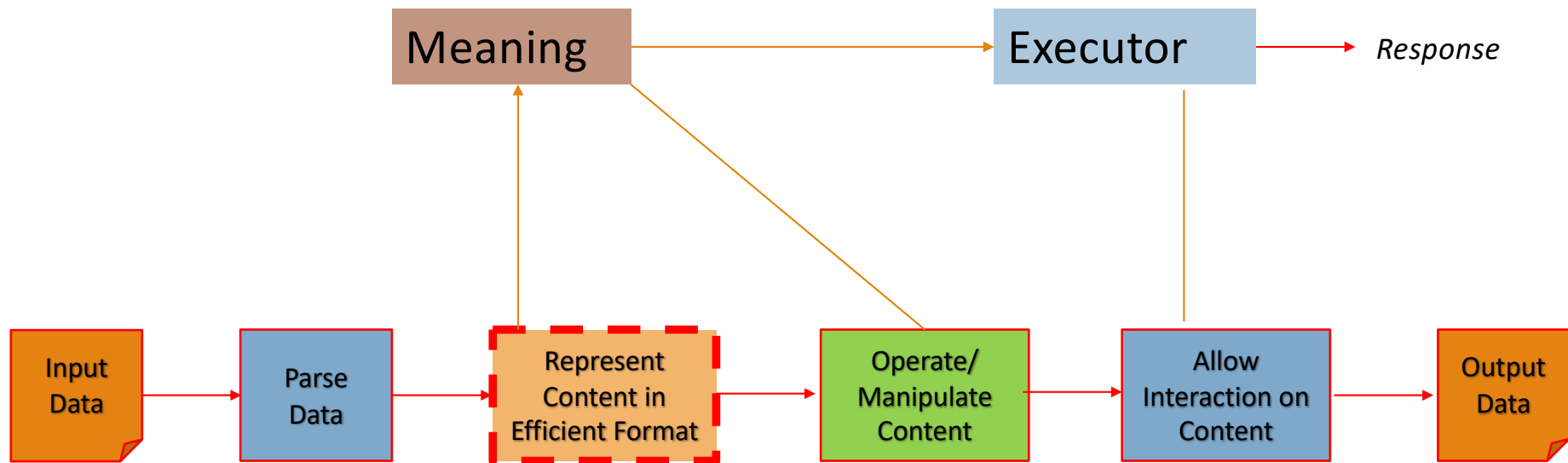
# Semantics



- **Discourse:** study of group of sentences
- **Pragmatics:** how context contributes to meaning of sentences
- **Semantics:** meaning of words and combinations of words
- **Syntax:** rules for combining and using words/ phonemes.
- **Lexemes:** a set of words that are related through inflection (fly: verb, fly: noun)
- **Morphology**—rules that govern morphemes - the minimal meaningful units of language (lemmas and affixes)
- **Orthography:** convention for writing a language. E.g., spelling
- **Phonology:** organization of speech sound (i.e., phoneme)
- **Phonetics:** study of how sound is made and received

# Semantics, Parsing and Representation

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# Semantics

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- ***lexical semantics***: studies word meanings and word relations, and
- ***formal semantics***: studies the logical aspects of meaning, such as sense, reference, implication, and logical form
- ***conceptual semantics***: studies the cognitive structure of meaning

Source: Jurafsky & Martin,  
Wikipedia (<https://en.wikipedia.org/wiki/Semantics>)

# From Text to Meaning

- Shallow semantics
  - Input: text
  - Output: *lexical semantics*
- Deep semantics
  - Input: text
  - Output: *formal semantics*

Source: Abstract Meaning Representation for Sembanking,  
<https://amr.isi.edu/a.pdf>

## LOGIC format:

$\exists w, b, g:$   
 $\text{instance}(w, \text{want-01}) \wedge \text{instance}(g, \text{go-01}) \wedge$   
 $\text{instance}(b, \text{boy}) \wedge \text{arg0}(w, b) \wedge$   
 $\text{arg1}(w, g) \wedge \text{arg0}(g, b)$

## AMR format (based on PENMAN):

(w / want-01  
:arg0 (b / boy)  
:arg1 (g / go-01  
:arg0 b))

## GRAPH format:

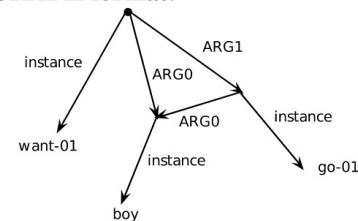


Figure 1: Equivalent formats for representing the meaning of “The boy wants to go”.

# First Order Predicate Logic (FOPL)

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Quick Review

# Concepts

## Quick Review

**Constants:** a, b, student123, teacher94

- Name of a specific object.

**Variables:** X, Y.

- Refer to an object without naming it.

**Predicates:** Father, Before

- Relationships between objects. May be many and may not be unique. Objects are specified as arguments (arity of a predicate).

**Functions:** father-of

- Mapping from objects to objects. Mapping must be present and be unique. Objects are specified as arguments (arity of a predicate).

**Terms:** dad-of(organism33), leftLeg(John)

- A logical expression that refers to an object

**Atomic Sentences:** in(dad-of(dog33), food6)

- Can be true or false
- Correspond to propositional symbols P, Q

Objects  
Relations  
Functions

Adapted from:

a) Dan Weld's AI course (CSE 573, Univ. of Washington)

b) Russell & Norvig, AI: A Modern Approach

# FOPL - Syntax

## Quick Review

BNF (Backus-Naur Form) grammar  
of sentences in FOPL

Source: Russell & Norvig, AI: A Modern Approach

$$\begin{aligned} \text{Sentence} \rightarrow & \text{AtomicSentence} \\ & | \text{Sentence} \text{ Connective } \text{Sentence} \\ & | \text{Quantifier Variable}, \dots \text{Sentence} \\ & | \neg \text{Sentence} \\ & | (\text{Sentence}) \end{aligned}$$

$$\text{AtomicSentence} \rightarrow \text{Predicate}(\text{Term}, \dots) \quad \text{Term} = \text{Term}$$

$$\begin{aligned} \text{Term} \rightarrow & \text{Function}(\text{Term}, \dots) \\ & | \text{Constant} \\ & \backslash \text{Variable} \end{aligned}$$

$$\text{Connective} \rightarrow \Rightarrow \mid \wedge \vee \mid \Leftrightarrow$$

$$\text{Quantifier} \rightarrow \forall \mid \exists$$

$$\text{Constant} \rightarrow A \mid X \mid \text{John} \mid \dots$$

$$\text{Variable} \rightarrow a \mid x \mid s \mid \dots$$

$$\text{Predicate} \rightarrow \text{Before} \mid \text{HasColor} \mid \text{Raining} \mid \dots$$

$$\text{Function} \rightarrow \text{Mother} \mid \text{LeftLegOf} \mid \dots$$

# Connectives and Quantifiers

**Logical connectives:** and, or, not,  $\Rightarrow$

**Quantifiers:**

- $\forall$  : For all
- $\exists$  : There exists

Examples:

1. All students:  $\forall$  **students**
2. All students are university members:  
 $\forall x$  **Student(x)  $\Rightarrow$  UniversityMember(x)**  
*(For all x, if x is a student, then x is a UniversityMember)*
3. A phone:  $\exists x$  **Phone(x)**
4. John has a phone:  
 $\exists x$  **Phone(x)  $\wedge$  Owns(John,x)**  
*(There exists a phone such that John owns it.)*

# From Text to Meaning

- Deep semantics
  - Input: text
  - Output: *formal semantics*

Source: Abstract Meaning Representation for Sembanking,  
<https://amr.isi.edu/a.pdf>

## LOGIC format:

$\exists w, b, g:$   
 $\text{instance}(w, \text{want-01}) \wedge \text{instance}(g, \text{go-01}) \wedge$   
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## AMR format (based on PENMAN):

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(w / want-01
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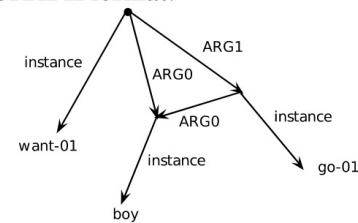


Figure 1: Equivalent formats for representing the meaning of “The boy wants to go”.

# Exercise: Asking LLM for Semantics

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- shallow
- deep



# Review: Common Definitions

- **Corpus** (plural corpora): a computer-readable corpora collection of text or speech.
- **Lemma**: A lemma is a set of lexical forms having the same stem, the same major part-of-speech, and the same word sense. [Example: Cat and cats have same lemma.](#)
- **Word form**: The word form is the full inflected or derived form of the word. [Example: Cat and cats have different word forms.](#)
- **Word type**: Types are the number of distinct words in a corpus. if the set of words is  $V$ , the number of types is the word token vocabulary size  $|V|$ .
- **Word tokens**: The total number  $N$  of running words in the sentence / document of interest.
- **Code switching**: use multiple languages in a code switching single communicative act – [Example: Hindlish \(Hindi English\), Spanish \(Spanish English\)](#)

“They picnicked by [the](#) pool, then lay back on [the](#) grass and looked at [the](#) stars.”

- 16 tokens, 14 word types

Source: Jurafsky & Martin

# Lexical Semantics

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- Lemma
  - Sing, Mouse
- Word form
  - Sing, sang, sung
  - Mouse, mice
- Word sense
  - Mouse: a rodent
  - Mouse: an electronic pointing device

A lemma having many senses is called **Polysemous**

# Synonymous and Similar Words

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- **Synonym** - one word has a sense whose meaning is identical to a sense of another word
  - Two words are **synonymous** if they are **substitutable** one for the other in any sentence **without changing the truth conditions of the sentence, the situations in which the sentence would be true**
  - **Propositional meaning** – synonym words have the same propositional meaning (truth preserving)
- **Principle of contrast** – An assumption in linguistics is that difference in linguistic form (e.g., word form) is always associated with at least some difference in meaning
  - Water and H<sub>2</sub>O are truth preserving but used in different context
  - Synonym words are used for approximate synonymy. Then, how similar are the words?

Source: Jurafsky & Martin

# Word Similarity - SimLex-999

- Captures similarity between word pairs, mining the opinions of 500 annotators via Amazon Mechanical Turk on a scale of 1 to 10

**Note:** *similarity*, rather than *relatedness* or *association*

- Contains
  - 666 Noun-Noun pairs,
  - 222 Verb-Verb pairs
  - 111 Adjective-Adjective pairs

vanish	disappear	9.8
behave	obey	7.3
belief	impression	5.95
muscle	bone	3.65
modest	flexible	0.98
hole	agreement	0.3

Source: Jurafsky & Martin

- **Usage:** Evaluation of learning based approaches for finding word similarity by correlation

[SimLex-999: Evaluating Semantic Models with \(Genuine\) Similarity Estimation](#). 2014. Felix Hill, Roi Reichart and Anna Korhonen. *Computational Linguistics*. 2015  
Website: <https://fh295.github.io/simlex.html>

## Meaning (Semantics) versus Structure (Lexical)

Pair	Simlex-999 rating	WordSim-353 rating
<i>coast - shore</i>	9.00	9.10
<i>clothes - closet</i>	1.96	8.00

Example courtesy: <https://fh295.github.io/simlex.html>

# Word Relatedness/ Association

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- **Semantic Field:** related words from the same particular domain and bear structured relations with each other.
  - Example 1: cup, coffee
  - Example 2: scalpel, surgeon
  - Usually determined by experts in a field
- **Word Association Test/ Task:** how word meaning is stored in memory
  - Have people respond to word associations as a game; e.g., say the first word that comes to mind when one says “Doctor”
  - Applications
    - Used in marketing
    - Also evaluation of learning procedures discovering meaning (e.g., word embedding)

Source: Jurafsky & Martin

## Sources:

- <https://psychology.jrank.org/pages/656/Word-Association-Test.html>,
- Establishing the Reliability of Word Association Data for Investigating Individual and Group Differences , Tess Fitzpatrick, David Playfoot, Alison Wray, Margaret J. Wright *Applied Linguistics*, Volume 36, Issue 1, February 2015, Pages 23–50, <https://doi.org/10.1093/applin/amt020>

# Discovering Word Relatedness

- **Topic model:** a statistical notion of related words in a document. Hope is that meaningful topics will be from the same semantic field, but there is no guarantee
- Key idea
  - Topic: group of words
  - Counting words and grouping similar word patterns to infer topics within unstructured data.
  - Assumptions
    - Distributional hypothesis: similar topics make use of similar words
    - Statistical mixture hypothesis: documents talk about several topics
  - Perform unsupervised analysis/ clustering: given a corpus and number of topics (k), find k topics that are representative of key ideas in the corpus

## References:

- Blog: <https://monkeylearn.com/blog/introduction-to-topic-modeling/>
- Paper: <https://www.jmlr.org/papers/volume3/blei03a/blei03a.pdf>
- Tool: Gensim
  - Docs: [https://radimrehurek.com/gensim/auto\\_examples/index.html#documentation](https://radimrehurek.com/gensim/auto_examples/index.html#documentation)
  - Sample usage - <https://github.com/biplav-s/course-nl-f22/blob/07f1b1d68a044a8558894ee96611e27d3fc242a9/sample-code/l19-topic/ExploreTopics.ipynb>

# Course Project

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# Discussion: Course Project

**Theme:** Analyze quality of official information available for elections in 2024 [in a state]

- Take information available from
  - Official site: State Election Commissions
  - Respected non-profits: League of Women Voters
- Analyze information
  - State-level: Analyze quality of questions, answers, answers-to-questions
  - Comparatively: above along all states (being done by students)
- Benchmark and report
  - Compare analysis with LLM
  - Prepare report

- Process and analyze using NLP
  - Extract entities
  - Assess quality – metrics
    - Content – *Englishness*
    - Content – *Domain* -- election
  - ... other NLP tasks
  - Analyze and communicate overall

## Major dates for project check

- Sep 10: written – project outline
- Oct 8: in class
- Oct 31: in class // LLM
- Dec 5: in class // Comparative

Review current states chosen by others

# Project Discussion

1. Go to Google spreadsheet against your name
2. Enter the state you will focus on for course project

1. Create a private Github repository called “CSCE771-Fall2024-<studentname>-Repo”. Share with Instructor (biplav-s) and TA (vr25)
2. Create Google folder called “CSCE771-Fall2024-<studentname>-SharedInfo”. Share with Instructor ([prof.biplav@gmail.com](mailto:prof.biplav@gmail.com)) and TA ([rawtevipula25@gmail.com](mailto:rawtevipula25@gmail.com))
3. Create a Google doc in your Google repo called “Project Plan” and have the following by Friday (Aug 30, 2024)

## Timeline

1. Title: [Analyze quality of official information available for elections in 2024](#) in <state>
2. Data need:
  1. Official: state’s election commission
  2. LWV: <https://www.vote411.org/>
3. Methods:
4. Evaluation:
5. Milestones
  - Sep 10: written and feedback
  - Oct 8: in class
  - Oct 31: in class
  - Dec 5: in class

# Obtaining Election Data

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Here are a few things to do:

- A) **Official data** backed by laws: state election commission
  - a) Find the state's election commission
  - b) Find the Q/As they provide. They may be as FAQs or on different web pages.
  - c) Collect the Q/A programmatically

- B) **Secondary data** sources: non-profit
  - a) Find Q/As from Vote 411 which is supported by the non-profit: LWV.

For reference, for SC,

- A) Official - <https://scvotes.gov/voters/voter-faq/>
- B) Secondary - <https://www.vote411.org/south-carolina>

For extraction, one or more approaches:

- Manually annotating
- BeautifulSoup,
- Tika
- or other open source libraries.

# Discussion: Course Project

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- **Expectations**

- Apply methods learned in class or of interest to a problem of interest
- Be goal oriented: aim to finish, be proactive, be innovative
- Do top-class work: code, writeup, presentation

- **Typical pitfalls**

- Not detailing out the project, assuming data
- Not spending enough time

- **What will be awarded**

- Results and efforts (balance)
- Challenge level of problem

Review current states chosen by others

# Course Project – Deadlines and Penalty Rubric

- Penalty
  - Missing milestones: [-10%]
  - Maximum: [-40%]
- Bonus possible
  - if two or more states considered
  -

## Timeline

1. Title: Analyze quality of official information available for elections in 2024 in <state>
2. Data need:
  1. Official: state's election commission
  2. LWV: <https://www.vote411.org/>
3. Methods:
4. Evaluation:
5. Milestones
  - Sep 10: written and feedback
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# Lecture 8: Concluding Comments

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- We looked at evaluation measures
  - accuracy, precision, recall, F1
  - Macro and micro averages
- We also started to look at semantics

# Concluding Segment

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# About Next Lecture – Lecture 9

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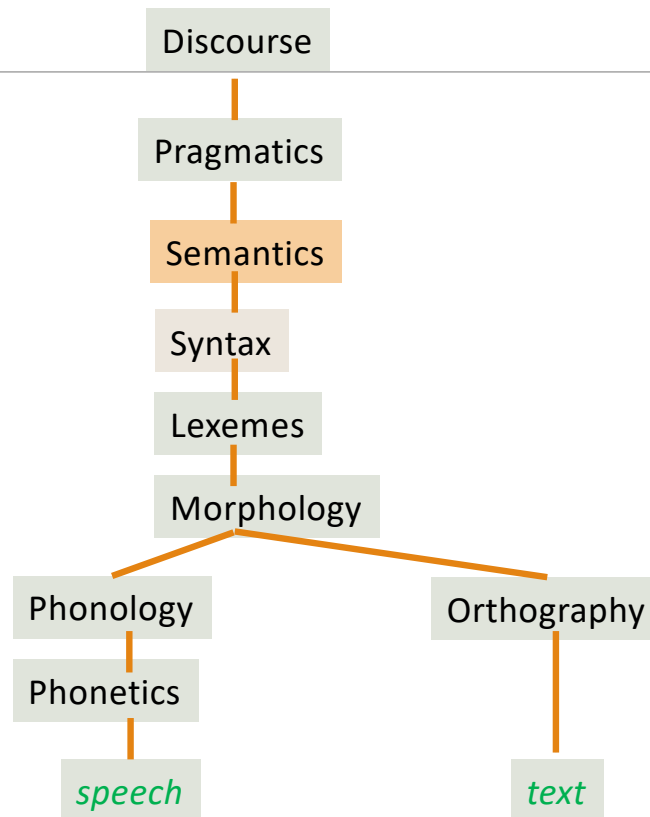
# Lecture 9: Semantics, ML

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- Complete semantics discussion
- Discuss ML for NLP

4	Aug 29 (Th)	NLP Tasks, Case Study – Business Application		
5	Sep 3 (Tu)	Parsing, Paper 1 discussion; project topics review		Practice exercise
6	Sep 5 (Th)	Project topics review, statistic Parsing		
7	Sep 10 (Tu)	Statistical parsing, QUIZ		Quiz 1, Project Check
8	Sep 12 (Th)	Evaluation, Semantics		Coding running example
9	Sep 17 (Tu)	Semantics, Machine Learning for NLP		Code: scikit fl score package, Code: ConceptIO
10	Sep 19 (Th)	Towards Language Model: Vector embeddings, Embeddings, CNN/ RNN		Code: embedding, genism word vector, tf-idf

# Summary of NLP Analysis



- **Discourse:** study of group of sentences
- **Pragmatics:** how context contributes to meaning of sentences
- **Semantics:** meaning of words and combinations of words
- **Syntax:** rules for combining and using words/ phonemes.
- **Lexemes:** a set of words that are related through inflection (fly: verb, fly: noun)
- **Morphology**—rules that govern morphemes - the minimal meaningful units of language (lemmas and affixes)
- **Orthography:** convention for writing a language. E.g., spelling
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