

CSCE 771: Computer Processing of Natural Language

Lecture 9: Semantics, ML Basics (Review)

PROF. BIPLAV SRIVASTAVA, AI INSTITUTE

17TH SEPTEMBER, 2024

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

Acknowledgement: Used materials by
Jurafsky & Martin, 2nd edition

Organization of Lecture 9

- Opening Segment
 - Announcement

- Main Lecture



- Concluding Segment
 - Reading material:
 - About Next Lecture – Lecture 10

Main Section

- Semantics
 - Shallow: similarity, relatedness; frames
 - Propbank
 - Deep: AMR
 - ConceptNet
- ML Basics
 - Supervised learning

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

Announcements

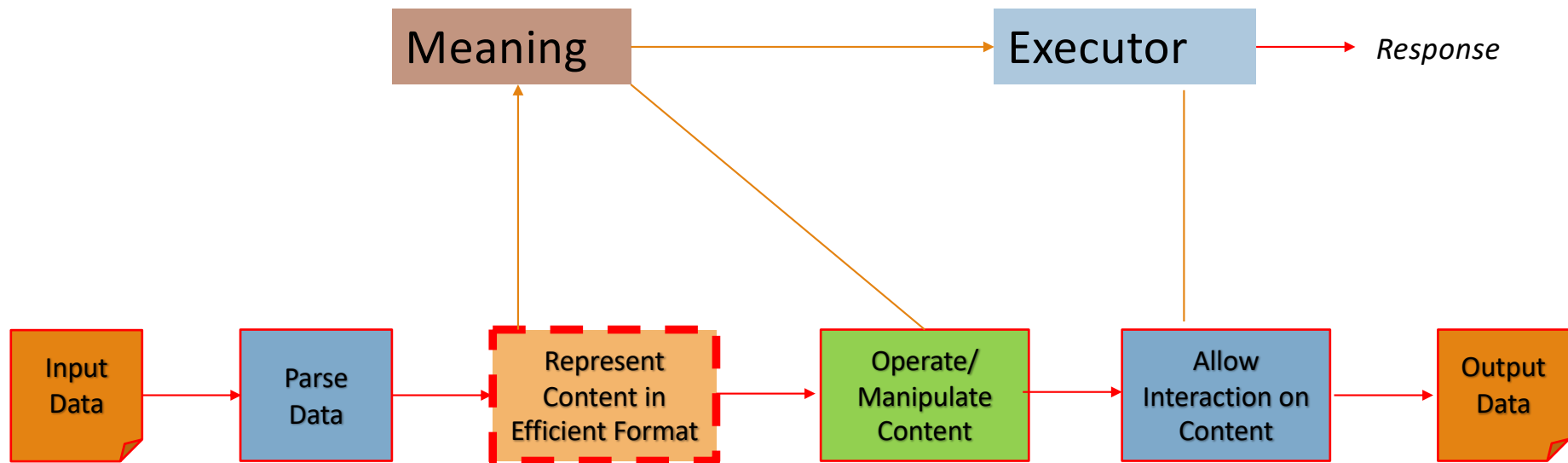
GUEST LECTURES ON
LANGUAGE MODELS

QUIZ 1

- Submit using Black board
- Includes resume exercise
- Was due Monday, Sep 16, 2024

Main Lecture

Semantics, Parsing and Representation



Semantics

- ***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:

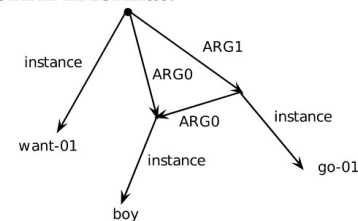


Figure 1: Equivalent formats for representing the meaning of “The boy wants to go”.

Frames, Slots: Frame Semantics

- Examples
 - "John sold a car to Mary"
 - "Mary bought a car from John"
 - "Mary paid John a undisclosed amount to get his car"
- To understand a word, one needs to understand the knowledge related to the word
 - In example: sell, buy, pay
- Capture knowledge in structures called **semantic frames** which have placeholders called slots (variables)
 - During parsing of sentences, values are filled
- **Frame semantics** is a theory of linguistic meaning developed by Charles J. Fillmore; related notion is semantic parsing

PropBank FrameSet

- A repository of formalized predicates
<https://proppbank.github.io/>

```
<roleset id="care.01"  
    name="having an opinion, feeling tenderly/strongly  
for/about">  
<roleset id="care.02"  
    name="liking/desiring/wanting">  
<roleset id="care.03"  
    name="tending, taking care of">  
<roleset id="care.04"  
    name="being cautious, taking care to">
```

Example: Care

<https://github.com/proppbank/proppbank-frames/blob/main/frames/care.xml>

Hindi – भेजा - *Beja*

Credits: <https://verbs.colorado.edu/propbank/framesets-hindi/Beja-v.html>

Example: Hindi Propbank

Roleset id: Beja.01 , to send, transport, ship something

Arg0: the one who sends something

Arg2: the recipient to whom something is sent

Arg1: the thing that is sent

Roleset id: Beja.02 , to send, transport, ship something

Arg0: the one who sends something

Arg2-gol: the place where something is sent

Arg1: the thing that is sent

Roleset id: Beja.03 , to make someone send something to someone

Argc: the causer- the one who makes someone send something

Arga: the intermediate causer

Arg0: the agent- the one who sends something

Arg2: the one to whom something is sent

Arg1: the thing that is sent

Roleset id: Beja.04 , to make someone send something to someplace

Argc: the causer- the one who makes someone send something

Arga: the intermediate causer

Arg0: the agent- the one who sends something

Arg2-gol: the place where something is sent

Arg1: the thing that is sent

Abstract Meaning Representation (AMR)

- Example: “The boy wants to go”
- AMR concepts are
 - English words (“boy”),
 - PropBank framesets (“want-01”), or
 - special key-words.
- Keywords include special entity types (“date-entity”, “world-region”, etc.), quantities (“monetary-quantity”, “distance-quantity”, etc.)
- logical conjunctions (“and”, etc).
- AMR uses approximately 100 relations

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:

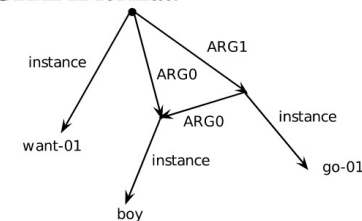


Figure 1: Equivalent formats for representing the meaning of “The boy wants to go”.

PENMAN

Notation

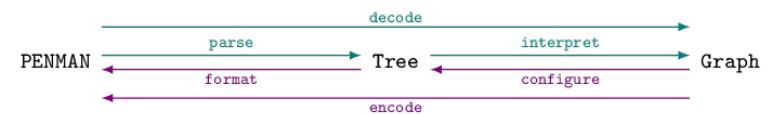
```

; |----- Variable (this one is the graph's top)
; | |----- Instance relation
; | |-----
; | |-----
(d / drive-01
; |-----
; |----- Concept (node label)
; |----- Indicates the node's concept
; |----- Edge relation
; |-----
:ARG0 (h / he)
; |-----
; |----- Role (edge label)
:manner (c / care-04
; |----- Attribute relation
; |-----
:polarity -))
; |-----
; |----- Atom (or "constant")

```

<node> ::= '(' <id> '/' <node-label> <edge>* ')'
<edge> ::= ':'<edge-label> (<const> | <id> | <node>)

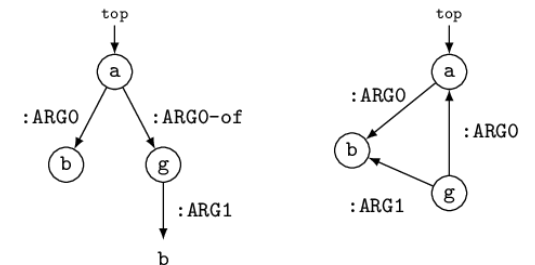
Credit: <https://penman.readthedocs.io/en/latest/notation.html>



```

(a / alpha
 :ARG0 (b / beta)
 :ARG0-of (g / gamma
 :ARG1 b))

```



Credit: <https://penman.readthedocs.io/en/latest/structures.html>

Sample Code – PENMAN/ AMR

Sample code:

<https://github.com/biplav-s/course-nl-f22/blob/main/sample-code/I9-semantics/PENMAN%20Notation%20-%20AMR.ipynb>

AMR Tools/ Libraries

- Libraries
 - Spacy: <https://spacy.io/universe/project/amrlib>
 - IBM Research: <https://github.com/IBM/transition-amr-parser>
- Tools
 - AMR Eager: <https://bollin.inf.ed.ac.uk/amreager.html>

AMR Demo

<http://amparser.coli.uni-saarland.de:8080/>

AM Parser Demo

On this page, you can try out the AM Parser. This is a compositional neural parser which can parse English sentences into graph-based semantic representations. You can find more details in our ACL 2019 paper, or have a look at the source code on Github.

Sentence

The boy wants to go

Select graph formalisms into which the sentence will be parsed:

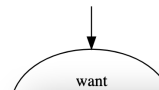
☒ DM ☒ PAS ☒ PSD ☒ EDS ☒ AMR-2017

Parse

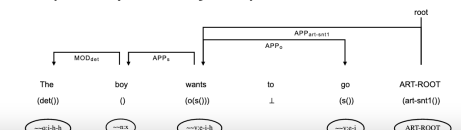
Parses

Parsing time: 3.2s, visualization time: 9.3s.

DM



DM (AM dependency tree)



Exercise: 5 mins

- Try your sentences online
- Look at output in different formats

Semantic Parsing

- Shallow semantic parsing
 - Also called: slot-filling or frame semantic parsing
 - "show me flights from **Boston** to **Dallas**"
- Deep semantic parsing
 - "show me flights from **Boston** to **anywhere** that has flights to **Dallas**"
 - Reference to quantifiers

Applications

- Paraphrasing
- Machine comprehension
- Question-answering
- Dialog

References:

- ACL 2020 Tutorial on Semantic Parsing
- https://en.wikipedia.org/wiki/Semantic_parsing

Semantic Parsing

Language to Meaning



Task-specific parsing

Example Task

Database Query

What states
border Texas?



Oklahoma
New Mexico
Arkansas
Louisiana

Source:
ACL 2020 Tutorial on Semantic Parsing

Resources: Semantic Parsing Libraries

- Open Sesame
 - Given English sentence, predicts FrameNet frames
 - <https://github.com/swabhs/open-sesame>
- AMRLib
 - Python library for AMR parsing, generation and visualization simple
 - <https://github.com/bjascob/amrlib>

Review: Lexical Meaning – Common Terms

- **Synonym:** same/ similar meaning
 - start-begin, finish-end, far-distant
- **Antonym:** opposite meaning
 - Far – near, clever - stupid, high - low, big – small
- **Homonym:** identical in spelling and pronunciation
 - bear, bank, ...
- **Homophones:** sounds identical but are written differently
 - site-sight, piece-peace.
- **Homograph:** written identically but sound differently
 - Potato, tomato, lead, wind, minute
- **Polysemy:** a word or phrase which has two (or more) different meanings (i.e., senses)
 - Duck, sharp

Source: Mausam

More Terms

- **Affective meanings** or **connotation**: word's meaning that are related to a writer or reader's emotions, sentiment, opinions, or evaluations
 - Positive evaluation: good, happy
 - Negative evaluation:
- **Sentiment**: Positive or negative evaluation expressed through language
 - Scherer's Typology of Affective States

Source: Jurafsky & Martin

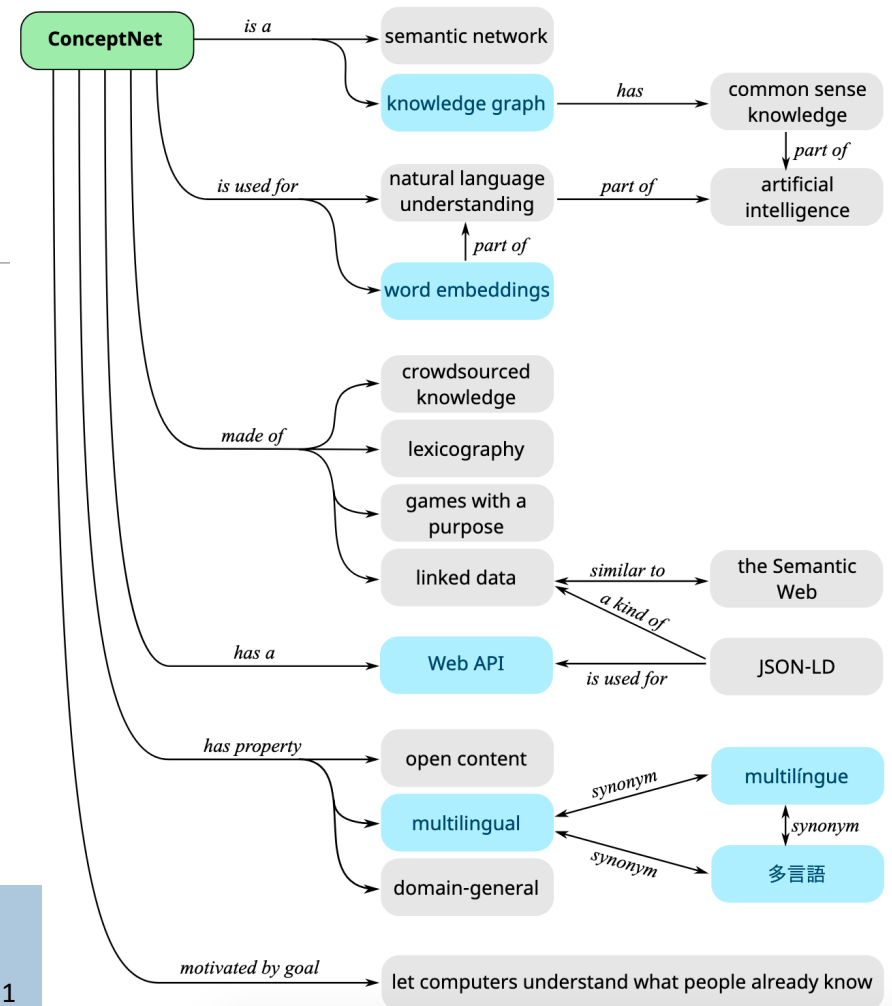
ConceptNet

- NLP focused graph knowledge graph that connects words and phrases of natural language with labeled edges.
- Concepts collected from experts, crowd-sourcing, and games with a purpose
- Supports multiple languages
- Provides "loose" semantics - relatedness

Details: <http://conceptnet.io/>,

<https://github.com/commonsense/conceptnet5/wiki>,

Paper: <https://www.aaai.org/ocs/index.php/AAAI/AAAI17/paper/viewFile/14972/14051>



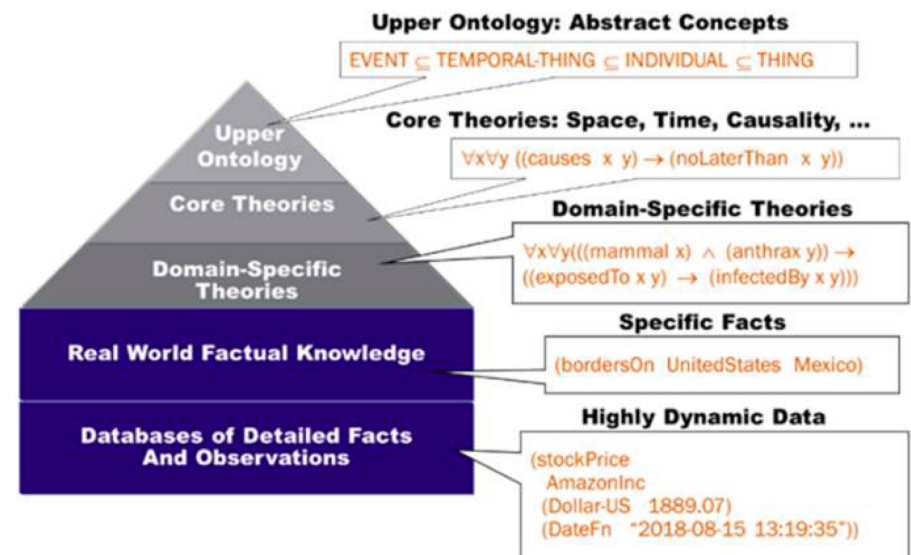
Demonstration - ConceptNet

Examples:

- Concepts:
 - Word: <http://conceptnet.io/c/en/word> ,
 - duck: <http://conceptnet.io/c/en/duck>
- Relationships:
 - <http://conceptnet.io/s/resource/wordnet/rdf/3.1>

Project CYC

- A large ontology to capture the world and human common sense
 - Doug Lenat lead team of computer scientists, computational linguists, philosophers, and logicians
 - Identify and formally axiomatize the tens of millions of rules about world
 - 35+ years effort by Cycorp
- Reasoners on the ontology to make decisions
 - 1000+ specialized reasoners



Details: <https://www.cyc.com/>

Source: Cyc White Paper

Cyc Details

- Ontology of about 1.5 million general concepts (e.g., taxonomically “placing” terms like eyes, sleep, night, person, unhappiness, hours, posture, being woken up, etc.);
- More than 25 million general rules and assertions involving those concepts
 - *“Most people sleep at night, for several hours at a time, lying down, with their eyes closed, they can be awakened by a loud noise but don’t like that, “*
- Domain-specific extensions to the common sense ontology and knowledge base
 - healthcare, intelligence, defense, energy, transportation and financial services.
- Promoting synergistic use of ontology and learning based approaches (now)

Source: White Paper – Cyc Technology Overview

Machine Language Basics (Review)

Machine Learning – Insights from Data

- Descriptive analysis
 - Describe a past phenomenon
 - **Methods:** classification, clustering, dimensionality reduction, anomaly detection, neural methods
- Predictive analysis
 - Predict about a new situation
 - **Methods:** time-series, neural networks
- Prescriptive analysis
 - What an agent should do
 - **Methods:** simulation, reinforcement learning, reasoning
- New areas
 - Counterfactual analysis
 - Causal Inferencing
 - Scenario planning

Machine Learning – Label Based View

- Label **available** – Supervised Learning
 - Example: Classification
- Label **unavailable** – Unsupervised Learning
 - Example: Clustering

Common Textual Data Processing Steps for ML

- Input: strings / documents/ corpus
- Processing steps (task dependent / optional - *)
 - Parsing
 - Word pre-processing
 - Tokenization – getting tokens for processing
 - Normalization* - making into canonical form
 - Case folding* – handling cases
 - Lemmatization* – handling variants (shallow)
 - Stemming* – handling variants (deep)
 - Semantic parsing – representations for reasoning with meaning *
 - Embedding – creating vector representation*

Impt: Contextual Word Embeddings

- Words as discrete
- Words with distributional assumptions:
 - Context: given a word, its nearby words or sequences of words
 - Words used in similar ways are likely to have related meanings; i.e., words used in the same (similar) context have related meanings
 - No claim about meaning except relative similarity v/s dis-similarity of words

TF-IDF based Word Representation -1

- Given N documents
- Term frequency (TF):** for term (word) t in document d
= $tf(t, d)$

Variants to reduce bias due to document length

Sources:

- (a) sci-kit documentation
- (b) Wikipedia: <https://en.wikipedia.org/wiki/Tf%E2%80%93idf>

Variants of term frequency (tf) weight

weighting scheme	tf weight
binary	0, 1
raw count	$f_{t,d}$
term frequency	$f_{t,d} / \sum_{t' \in d} f_{t',d}$
log normalization	$\log(1 + f_{t,d})$
double normalization 0.5	$0.5 + 0.5 \cdot \frac{f_{t,d}}{\max_{\{t' \in d\}} f_{t',d}}$
double normalization K	$K + (1 - K) \frac{f_{t,d}}{\max_{\{t' \in d\}} f_{t',d}}$

TF-IDF based Word Representation -2

- Given N documents
- Term frequency (TF): for term (word) t in document d
= $tf(t, d)$
- **Inverse document frequency IDF(t)**

$$= \log [N / DF(t)] + 1$$

DF(t) = **document frequency**, the number of documents in the document set that contain the term t.

- **TF-IDF(t, d)** = $TF(t, d) * IDF(t)$,

Variants of inverse document frequency (idf) weight

weighting scheme	idf weight ($n_t = \{d \in D : t \in d\} $)
unary	1
inverse document frequency	$\log \frac{N}{n_t} = -\log \frac{n_t}{N}$
inverse document frequency smooth	$\log \left(\frac{N}{1 + n_t} \right) + 1$
inverse document frequency max	$\log \left(\frac{\max_{t' \in d} n_{t'}}{1 + n_t} \right)$
probabilistic inverse document frequency	$\log \frac{N - n_t}{n_t}$

Sources:

- (a) sci-kit documentation
- (b) Wikipedia: <https://en.wikipedia.org/wiki/Tf%E2%80%93idf>

TF-IDF Example Calculation

Github: <https://github.com/biplav-s/course-nl-f22/blob/main/sample-code/l5-wordrepresent/Word%20Representations%20-%20Vectors.ipynb>

Classification

Classifier Method Types

- Individual methods
 - Decision Tree
 - Naïve Bayes
- Ensemble
 - Bagging: Aggregate classifiers (“bootstrap aggregation” => bagging)
 - Random Forest
 - Samples are chosen with replacement (bootstrapping), and combined (aggregated) by taking their average
 - Gradient Boosting: aggregate to turn weak learners into strong learners
 - Boosters (aggregators) turn weak learners into strong learners by focusing on where the individual weak models (decision trees, linear regressors) went wrong
 - Gradient Boosting
 - XGBoost: “eXtreme Gradient Boosting.”

Source:

- Data Mining: Concepts and Techniques, by Jiawei Han and Micheline Kamber
- <https://towardsdatascience.com/getting-started-with-xgboost-in-scikit-learn-f69f5f470a97>

ML - Supervised

- By Example:
 - <https://github.com/biplav-s/course-nl/blob/master/I9-ml-review/Classification%20-%20Fake%20news.ipynb>
- Fake news dataset

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

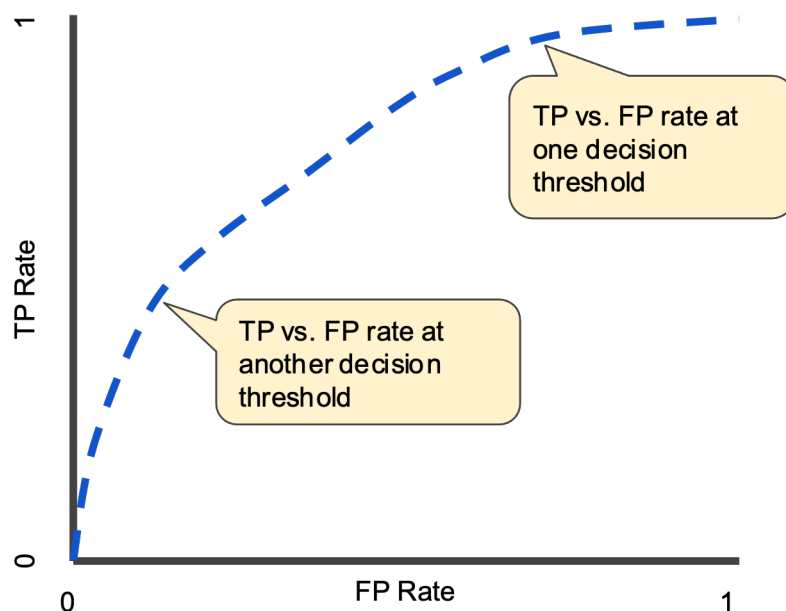
Recall =
$$\frac{(TP)}{(TP+FN)}$$

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

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

ROC – Receiver Operating Characteristic curve

An ROC curve plots TPR vs. FPR at different classification thresholds



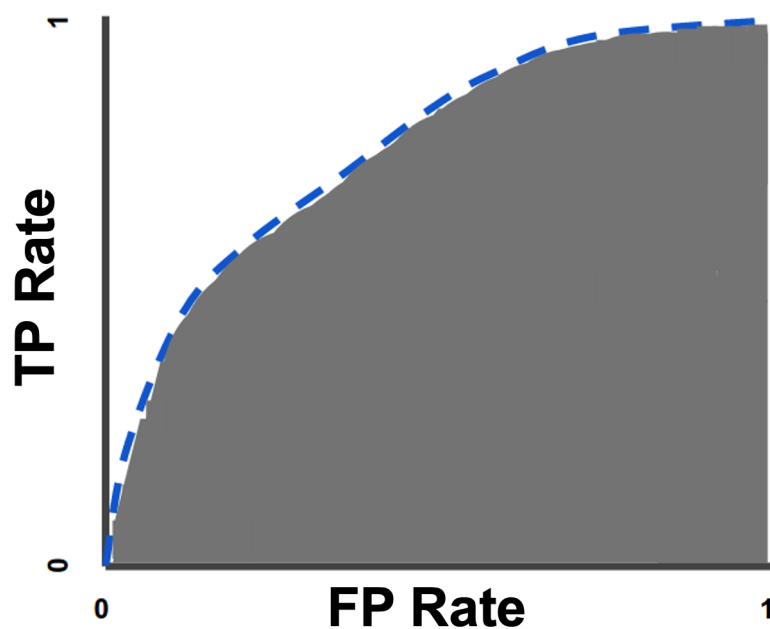
True Positive Rate = Recall =
$$\frac{(TP)}{(TP+FN)}$$

False Positive Rate =
$$\frac{(FP)}{(FP+TN)}$$

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

Source: <https://developers.google.com/machine-learning/crash-course/classification/roc-and-auc>

AUC – Area Under the ROC Curve



- Aggregate measure of performance across all possible classification thresholds.
- Interpretation: probability that the model ranks a random positive example more highly than a random negative example

Not helpful when the cost of false negatives vs. false positives are asymmetric

Source: <https://developers.google.com/machine-learning/crash-course/classification/roc-and-auc>

References

- Blogs: <https://blog.exsilio.com/all/accuracy-precision-recall-f1-score-interpretation-of-performance-measures/>
- Google: <https://developers.google.com/machine-learning/crash-course/classification/roc-and-auc>

AutoML – Automated Machine Learning

- Automate data preparation
- Automate feature selection
- Hyperparameter tuning
- Demo:
 - IBM Auto AI - <https://www.youtube.com/watch?v=ILCsbh9IKT0>

Lecture 9: Concluding Comments

- We reviewed how to give semantics to words and documents
- Can be human supervised or learning based or combined
- Can be generic or task-oriented

Concluding Segment

Course Project

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) and TA (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

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

- **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
 - Oct 8: in class
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About Next Lecture – Lecture 10

Lecture 10 Outline

- Machine Learning for NLP
 - Supervised learning
 - Unsupervised learning
 - Neural methods
- Language Models

7	Sep 10 (Tu)	Statistical parsing, QUIZ
8	Sep 12 (Th)	Evaluation, Semantics
9	Sep 17 (Tu)	Semantics, Machine Learning for NLP, Evaluation - Metrics
10	Sep 19 (Th)	Towards Language Model: Vector embeddings, Embeddings, CNN/ RNN
11	Sep 24 (Tu)	Language Model – PyTorch, BERT, {Resume data, two tasks} – Guest Lecture
12	Sep 26 (Th)	Language Model – Finetuning, Mamba - Guest Lecture
13	Oct 1 (Tu)	Language model – comparing arch, finetuning - Guest Lecture
14	Oct 3 (Th)	Language model – comparison of results, discussion, ongoing trends– Guest Lecture
15	Oct 8 (Tu)	PROJ REVIEW