CSCE 771: Computer Processing of Natural Language
Lecture 7: Statistical Parsing, Quiz

PROF. BIPLAV SRIVASTAVA, AI INSTITUTE

10TH SEPTEMBER, 2024

Carolinian Creed: "I will practice personal and academic integrity."

Acknowledgement: Used materials by Jurafsky & Martin,

Organization of Lecture 7

- Opening Segment
  - Recap of Last Class
  - Announcements
- Main Lecture
- Concluding Segment
  - About Next Lecture – Lecture 8

Main Section

- Statistical Parsing
- Quiz 1

Recap of Lecture 6

- We discussed parsers
  - Shallow parsers
  - Dependency parsers

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

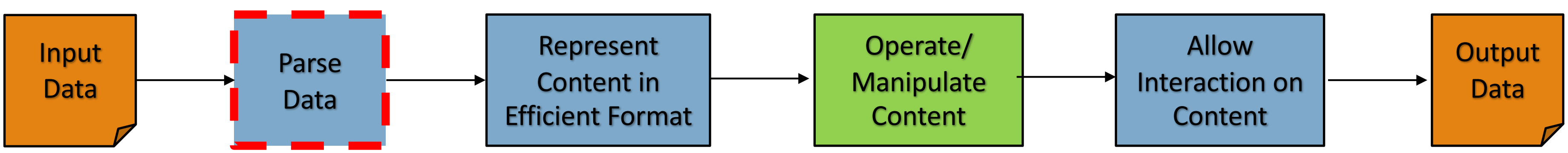
GUEST LECTURES ON LANGUAGE MODELS

Main Lecture

Statistical Parsing

Given a sentence X, predict the most **probable** parse tree Y

$$\underset{Y}{\operatorname{argmax}}\ P\ (Y|X)$$



Probabilistic CFG

N	a set of **non-terminal symbols** (or **variables**)
Σ	a set of **terminal symbols** (disjoint from N)
R	a set of **rules** or productions, each of the form $A \rightarrow \beta\ [p]$, where A is a non-terminal, β is a string of symbols from the infinite set of strings $(\Sigma \cup N)*$, and p is a number between 0 and 1 expressing $P(\beta\|A)$
S	a designated **start symbol**

p is the probability that non-terminal **A** will be expanded to the sequence **β**

$$\sum_{\beta} P(A \rightarrow \beta) = 1$$

A PCFG is said to be **consistent** if the sum of the probabilities of all sentences in the language equals 1

From Jurafsky & Martin

Probabilistic CFG Example

Grammar		Lexicon
$S \rightarrow NP\ VP$	[.80]	$Det \rightarrow that$ [.10] | a [.30] | the [.60]
$S \rightarrow Aux\ NP\ VP$	[.15]	$Noun \rightarrow book$ [.10] | $flight$ [.30]
$S \rightarrow VP$	[.05]	| $meal$ [.05] | $money$ [.05]
$NP \rightarrow Pronoun$	[.35]	| $flight$ [.40] | $dinner$ [.10]
$NP \rightarrow Proper\text{-}Noun$	[.30]	$Verb \rightarrow book$ [.30] | $include$ [.30]
$NP \rightarrow Det\ Nominal$	[.20]	| $prefer$ [.40]
$NP \rightarrow Nominal$	[.15]	$Pronoun \rightarrow I$ [.40] | she [.05]
$Nominal \rightarrow Noun$	[.75]	| me [.15] | you [.40]
$Nominal \rightarrow Nominal\ Noun$	[.20]	$Proper\text{-}Noun \rightarrow Houston$ [.60]
$Nominal \rightarrow Nominal\ PP$	[.05]	| NWA [.40]
$VP \rightarrow Verb$	[.35]	$Aux \rightarrow does$ [.60] | can [.40]
$VP \rightarrow Verb\ NP$	[.20]	$Preposition \rightarrow from$ [.30] | to [.30]
$VP \rightarrow Verb\ NP\ PP$	[.10]	| on [.20] | $near$ [.15]
$VP \rightarrow Verb\ PP$	[.15]	| $through$ [.05]
$VP \rightarrow Verb\ NP\ NP$	[.05]	
$VP \rightarrow VP\ PP$	[.15]	
$PP \rightarrow Preposition\ NP$	[1.0]	

Question: is the *PCFG in example consistent?*

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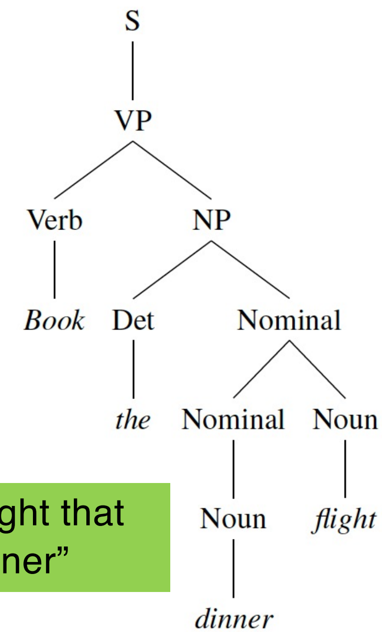
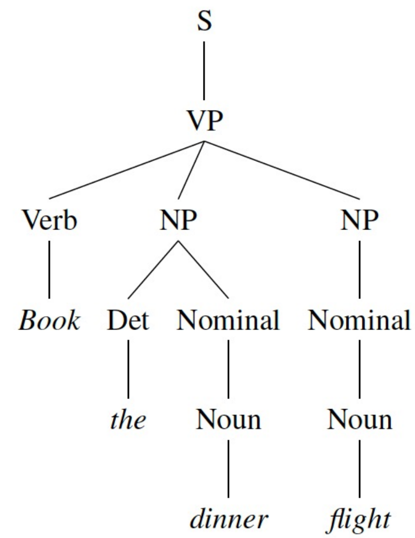
Example



“Book a flight that serves dinner”



“Book a flight on behalf of ‘the dinner’

Interpretations of
“***Book the dinner flight***”

Rules			P	Rules			P
S	→	VP	.05	S	→	VP	.05
VP	→	Verb NP	.20	VP	→	Verb NP NP	.10
NP	→	Det Nominal	.20	NP	→	Det Nominal	.20
Nominal	→	Nominal Noun	.20	NP	→	Nominal	.15
Nominal	→	Noun	.75	Nominal	→	Noun	.75
				Nominal	→	Noun	.75
Verb	→	book	.30	Verb	→	book	.30
Det	→	the	.60	Det	→	the	.60
Noun	→	dinner	.10	Noun	→	dinner	.10
Noun	→	flight	.40	Noun	→	flight	.40

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Decisions with PCFG

Probability of parse tree T, given sentence S, is

$$P(T,S) = \prod_{i=1}^{n} P(RHS_i|LHS_i)$$

Definition:
Yield of a parse tree = String of words allowed by parse tree

Of all parse trees with a yield of S, the disambiguation algorithm for parsing picks the parse tree that is most probable given S:

$$\hat{T}(S) = \underset{T s.t. S = \text{yield}(T)}{\text{argmax}} P(T|S) \quad \longrightarrow \quad \hat{T}(S) = \underset{T s.t. S = \text{yield}(T)}{\text{argmax}} P(T)$$

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Interpretations of
"***Book the dinner flight***"

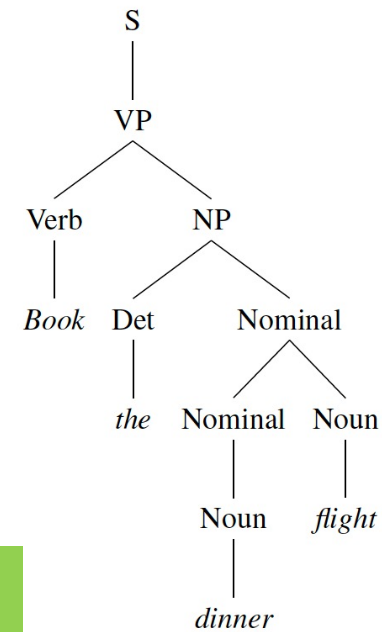
"Book a flight that serves dinner"

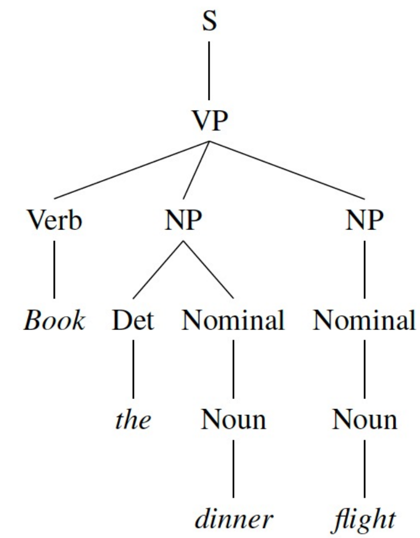
"Book a flight on behalf of 'the dinner'

choosing the parse with the highest probability

Example

Interpretations of
"***Book the dinner flight***"





"Book a flight that serves dinner"

"Book a flight on behalf of 'the dinner'"

✓

$$P(T_{left}) = .05 * .20 * .20 * .20 * .75 * .30 * .60 * .10 * .40 = \mathbf{2.2 \times 10^{-6}}$$
$$P(T_{right}) = .05 * .10 * .20 * .15 * .75 * .75 * .30 * .60 * .10 * .40 = \mathbf{6.1 \times 10^{-7}}$$

Rules			P	Rules			P
S	→	VP	.05	S	→	VP	.05
VP	→	Verb NP	.20	VP	→	Verb NP NP	.10
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Verb	→	book	.30	Verb	→	book	.30
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Noun	→	dinner	.10	Noun	→	dinner	.10
Noun	→	flight	.40	Noun	→	flight	.40

From Jurafsky & Martin

Assumptions/ Issues with PCFG - 1

Issue: CFG rules impose an independence assumption on probabilities that miss rule dependencies

- Example:
  - **nouns** can be **subjects** as well as **objects**
  - A **pronoun** is a **noun**, but also is a **determiner noun.** **[Example: NP -> DT NN :28, NP -> PRP 0.25]**
  - **Subjects** are **more likely** to be **pronouns** than **objects**. **[**91% subjects are pronouns, 34% objects are pronouns in Switchboard dataset]
- Same rule's application can be contextual based on where the rule is being applied. Example, NP -> PRP
- Not being able to differentiate can cause incorrect parsing

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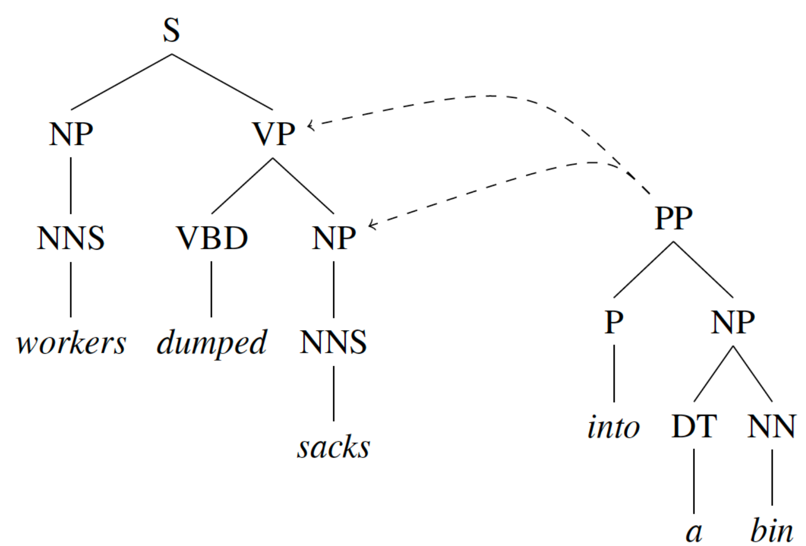
Assumptions/ Issues with PCFG - 2

Issue: Lack of sensitivity to lexical dependencies

Example: *worker dumped sacks into a bin*

"into a bin" prepositional phrase can be attached to either the VP or NP leading to different meanings

- When attached to VP, sacks are in location "into a bin"
- When attached to NP, "sacks into a bin" are dumped - nonsensical



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Improvement: Probabilistic Lexicalized CFGs

- Augment PCFG with a lexical head for each rule.
- The probability of a rule is conditional on the lexical head

VP -> VBD NP P *is modified to*

VP(dumped,VBD) -> VBD(dumped,VBD) NP(sacks,NNS) PP(into,P)

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Calculating Probability from Treebank

$$P(\alpha \to \beta|\alpha) = \frac{\text{Count}(\alpha \to \beta)}{\sum_{\gamma}\text{Count}(\alpha \to \gamma)} = \frac{\text{Count}(\alpha \to \beta)}{\text{Count}(\alpha)}$$

Probability of each expansion of a non-terminal:

- counting the number of times an expansion occurs
- normalizing for all expansions

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Evaluating Parsers - PARSEVAL

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

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

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

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

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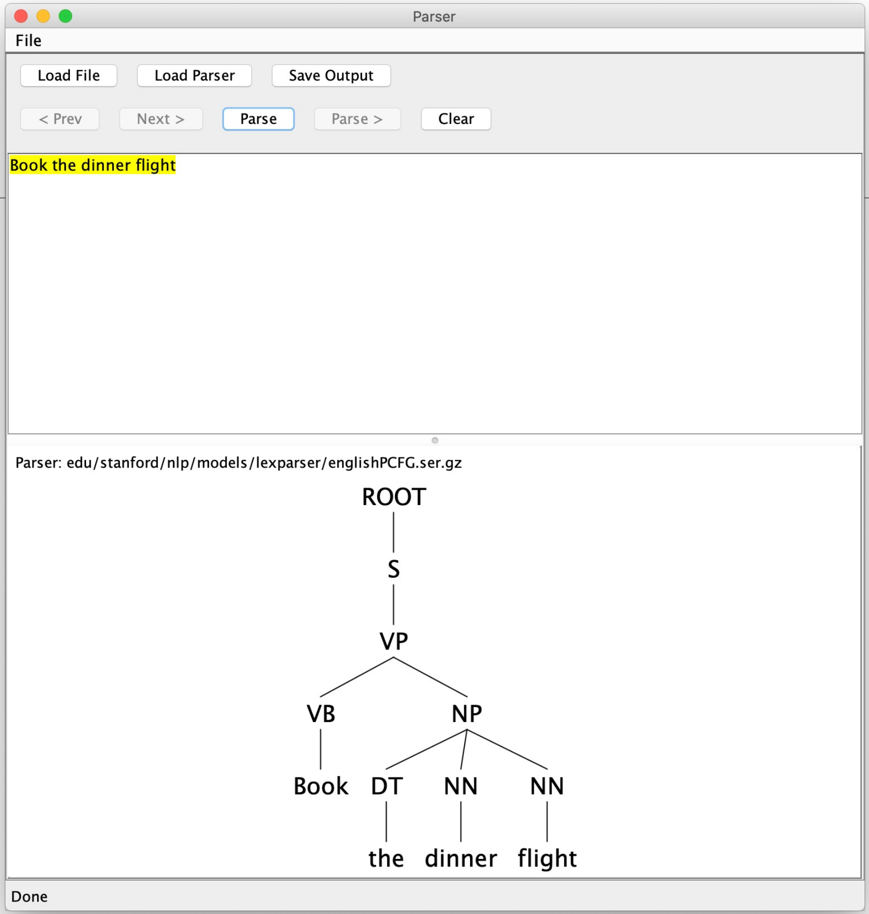
Output from a Popular Parser: Stanford Parser

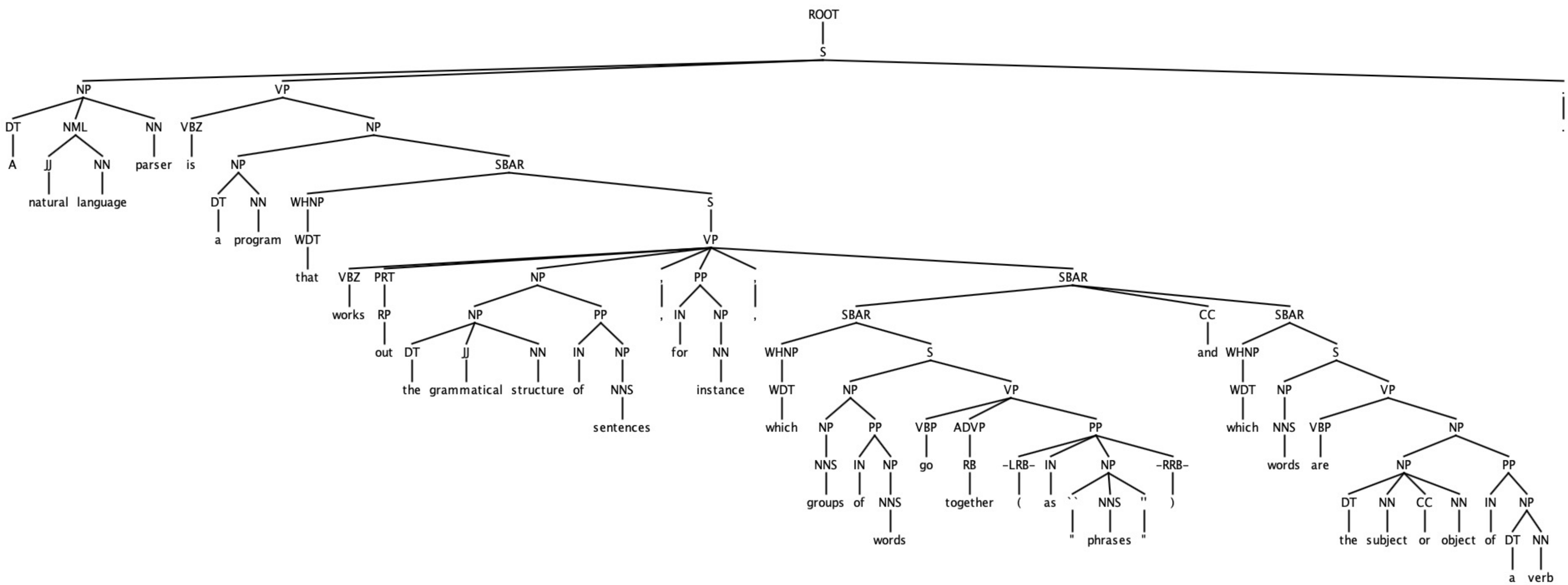


Demonstrations in multiple languages

https://nlp.stanford.edu/software/lex-parser.shtml

Stanford Parser Example - 2

A natural language parser is a program that works out the grammatical structure of sentences, for instance, which grou of words go together (as "phrases") and which words are the subject or object of a verb.



Lecture 7: Concluding Comments

- We have completed 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.
- Probabilistic lexicalized CFGs:
  - PCFG model is augmented with a lexical head for each rule.

Concluding Segment

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

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QUIZ

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

About Next Lecture – Lecture 8

Lecture 8: Evaluation, Semantics

- Review quiz
- Introduce evaluation metrics in NLP context
- Discussion on semantics

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, Evaluation - Metrics		Code: scikit f1 score package, Code: ConceptIO
10	Sep 19 (Th)	Towards Language Model: Vector embeddings, Embeddings, CNN/ RNN		Code: embedding, genism word vector, tf-idf