https://xkcd.com/208/

CS 2731
Introduction to Natural Language Processing

Session 2: Words and tokens

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Overview: Words and tokens

- Course logistics
- JupyterHub CRCD setup
- Words and corpora
- Morphemes
- Unicode
- Regular expressions
- Other text preprocessing
- Coding activity: preprocessing Airbnb listings

Course logistics

- Reading for today was Jurafsky & Martin sections 2-2.4, 2.6-2.7, 2.10
- I will release Homework 0 today unless we all get set up in class with CRCD JupyterHub fine
- Please remind me of your name before asking or answering a question (just this class session)

CRCD JupyterHub setup

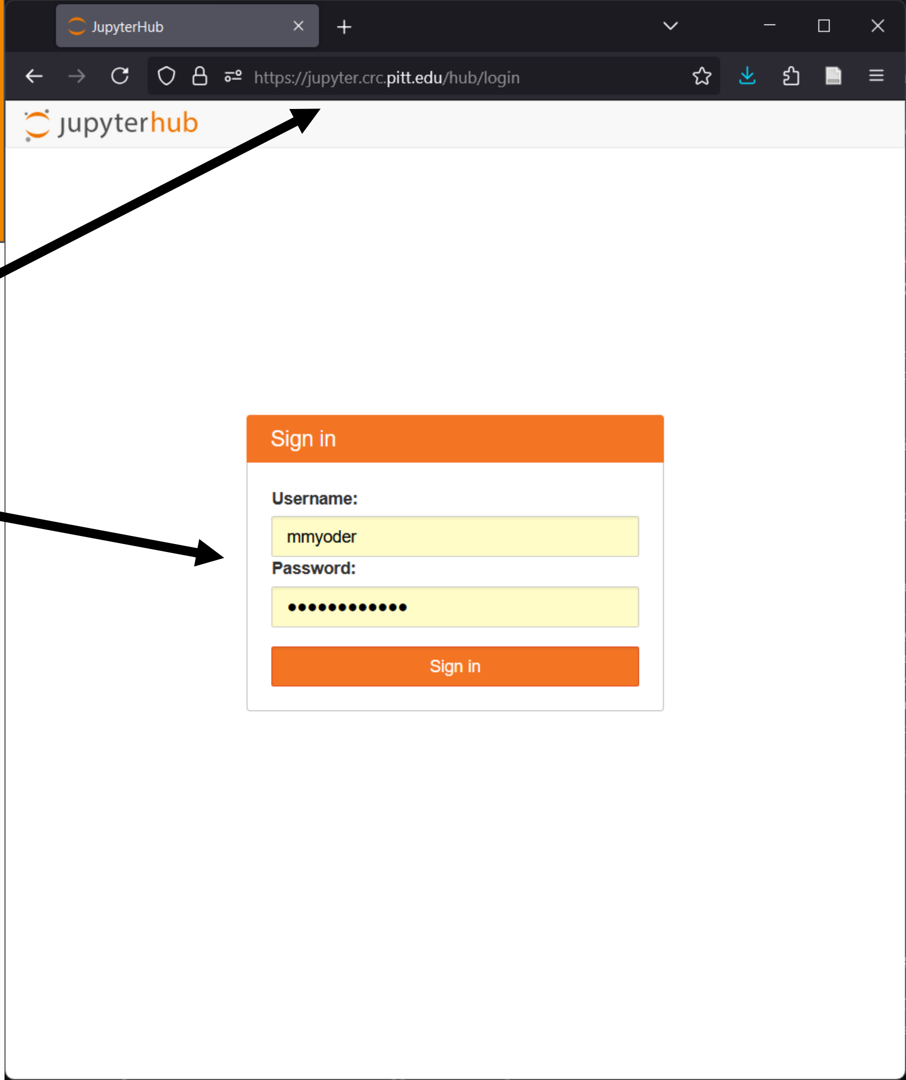
CRCD and JupyterHub

- CRCD (Center for Research Computing and Data) is a Pitt center providing computing services on various clusters
- They maintain a JupyterHub where people can run Jupyter Notebooks on their servers
- What we will be using the CRCD for:
    - Working through code examples in class
    - Writing code to submit as part of homework assignments
    - Running code and storing data for your projects (if you want to)

Logging in to your CRCD JupyterHub account

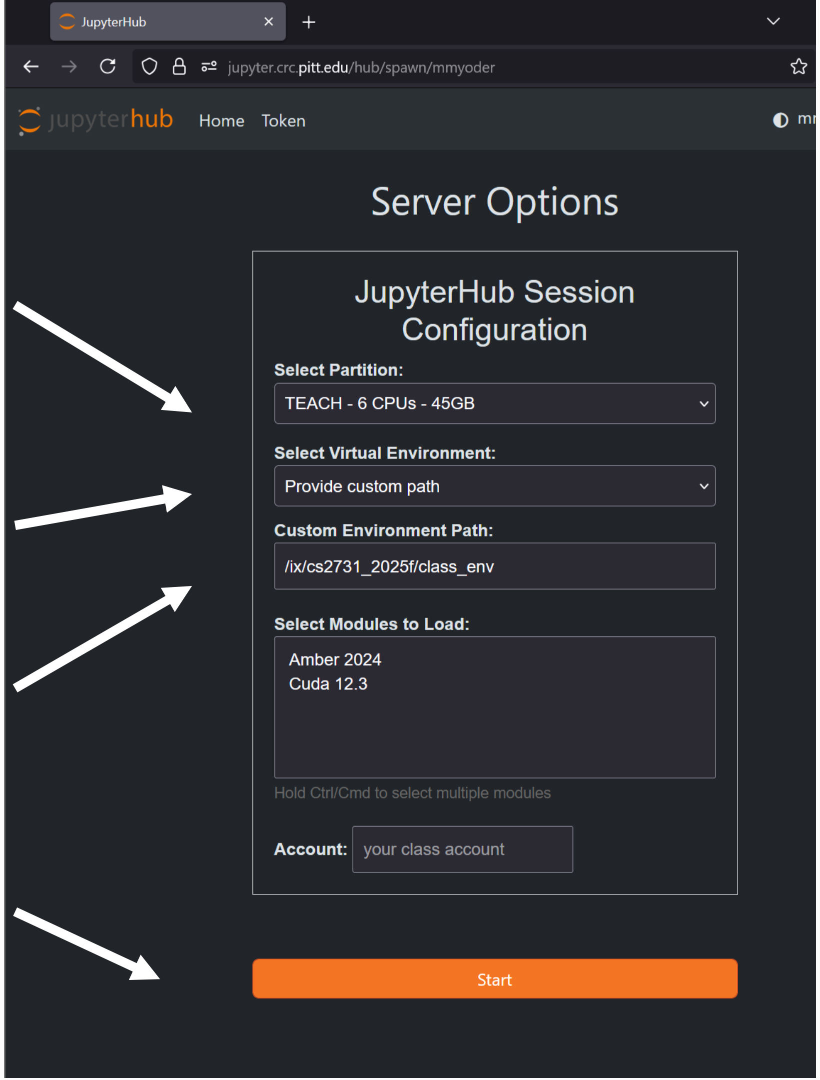
1. Go to **jupyter.crc.pitt.edu** in a web browser
2. Log in with your Pitt credentials

Note that if you are off-campus, you have to log in to the Pitt VPN first through the GlobalProtect app. Instructions: https://services.pitt.edu/TDClient/33/Portal/KB/ArticleDet?ID=293



Starting a Jupyter Notebook on the CRCD JupyterHub

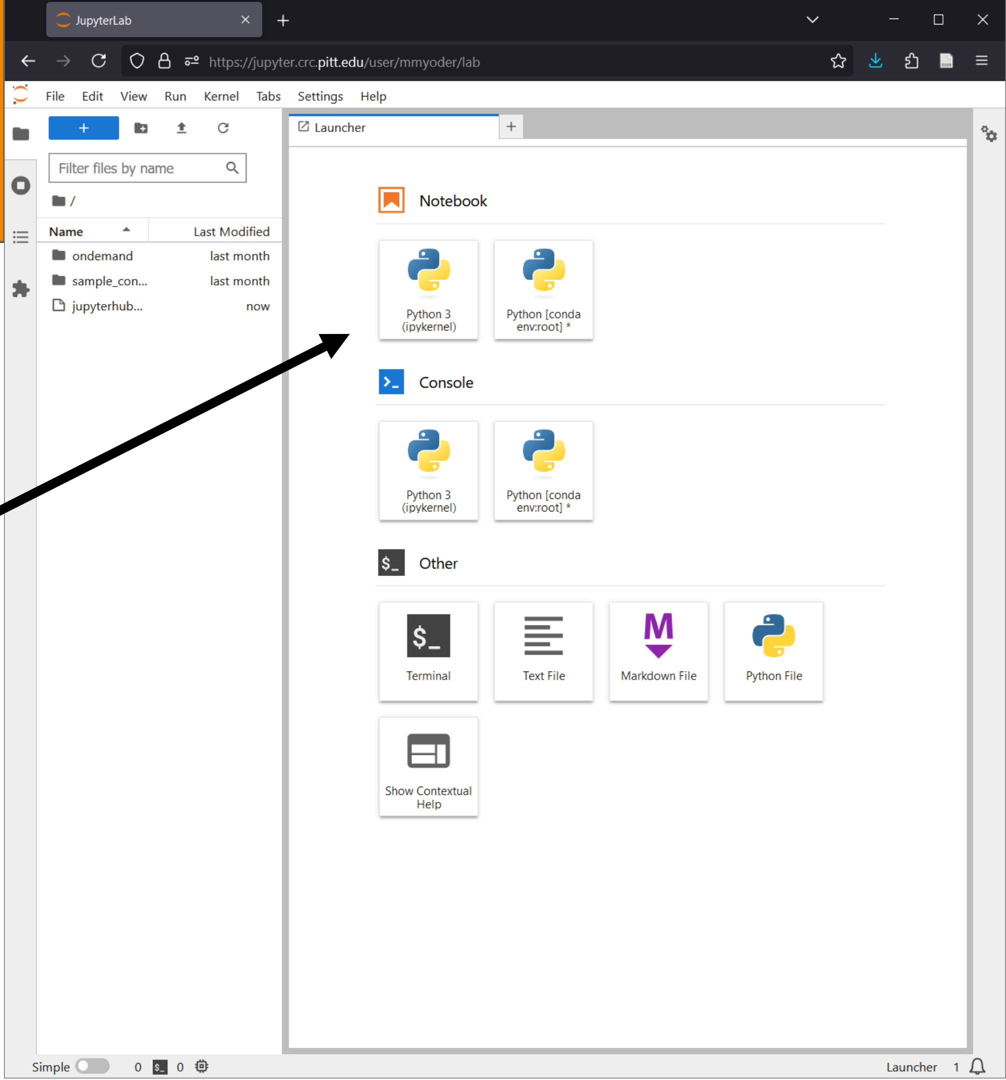
1. Partition: **TEACH – 6 CPUs – 45 GB**
   We might use the GPU options later on in the course
2. Under **Select Virtual Environment**, select **Provide custom path**
3. **Custom Environment Path**: /ix/cs2731_2025f/class_env
4. Click **Start**
5. Wait for the server to start up



Welcome to your JupyterLab

Files are here

You can launch a new Jupyter Notebook by clicking Python 3 (ipykernel) under Notebook



Words and corpora

How many words in this phrase?

they lay back on the San Francisco grass and looked at the stars and their

- How many?
  - 15 tokens (or 14 if you count "San Francisco" as one)
  - 13 types (or 12) (or 11?)
- **Type**: a unique word in the vocabulary
- **Instance (token)**: an instance of a word type in running text
- **Lemma**: same stem, part of speech, rough word sense
  - cat and cats = same lemma
- **Wordform**: the full inflected surface form
  - cat and cats = different wordforms

Slide adapted from Jurafsky & Martin

How many words in a corpus?

Corpus: a (machine-readable) collection of texts

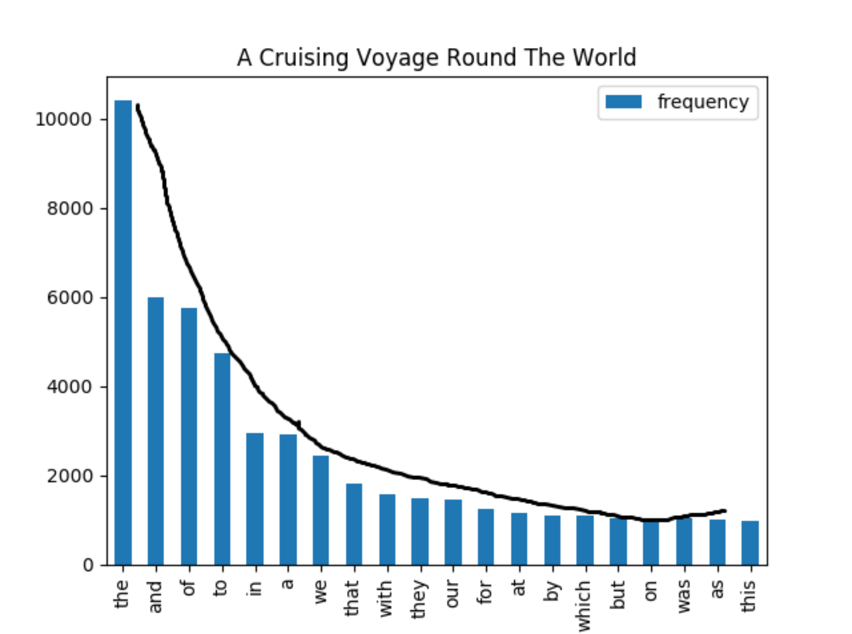
N = number of word instances

V = vocabulary = set of types, |*V*| is size of vocabulary

	Instances = N	Types = |V|
Switchboard phone conversations	2.4 million	20 thousand
Shakespeare	884,000	31 thousand
COCA	440 million	2 million
Google N-grams	1 trillion	13+ million

Slide adapted from Jurafsky & Martin

Word frequencies: Heap’s Law



The Lexical Learner blog

- Word (type) frequency is inversely proportional to word frequency rank

$$\text{frequency} \propto \frac{1}{(\text{rank} + b)^a}$$

- "Long tail" of infrequent words
- Similar to Zipf’s Law

Corpora vary along dimensions like

- Texts don't appear out of nowhere!
- **Language**: 7097 languages in the world
- **Variety**, like African American Language varieties.
  - AAE Twitter posts might include forms like "*iont*" *(I don't)*
- **Code switching**, e.g., Spanish/English, Hindi/English:

  Por primera vez veo a @username actually being helpful! It was beautiful:)

  [For the first time I get to see @username actually being helpful! it was beautiful:)]

  dost tha or ra- hega ... dont wory ... but dherya rakhe

  [“he was and will remain a friend ... don’t worry ... but have faith”]

- **Genre:** newswire, fiction, scientific articles, Wikipedia
- **Author Demographics**: writer's age, gender, ethnicity, SES
- Corpus datasheets [Bender & Friedman 2018, Gebru+ 2020] ask about this information

Slide adapted from Jurafsky & Martin

Morphemes

Morphemes

- Morphemes: small meaningful units that make up words
  - **Roots**: The core meaning-bearing units
  - **Affixes**: Parts that adhere to roots

un-think-able; kitten-s

- Affixes can add grammatical meaning (inflections, 2nd column) or modify semantic meaning (derivations, 3rd column)

<root>	<root>ing	<root>er
run	running	runner
think	thinking	thinker
program	programming	programmer
kill	killing	killer

Slide adapted from Jurafsky & Martin, David Mortensen

Dealing with complex morphology is necessary for many languages

- e.g., the Turkish word:
  Uygarlastiramadiklarimizdanmissinizcasina
  '(behaving) as if you are among those whom we could not civilize'

  Uygar 'civilized' + las 'become'
  + tir 'cause' + ama 'not able'
  + dik 'past' + lar 'plural'
  + imiz '1pl' + dan 'abl'
  + mis 'past' + siniz '2pl' + casina 'as if'

Slide adapted from Jurafsky & Martin

Unicode

Unicode

a method for representing written text in

- any character (more than 150,000!)
- any script (168 to date!)
- of the languages of the world
  - Chinese, Arabic, Hindi, Cherokee, Ethiopic, Khmer, N'Ko,...
  - dead ones like Sumerian cuneiform
  - invented ones like Klingon
  - plus emojis, currency symbols, etc.

Slide adapted from Jurafsky & Martin

ASCII: Some history for English

1960s American Standard Code for Information Exchange

- 1 byte per character
- Set of letters without diacritical marks (such as accent marks, etc)
- Encodings for special characters used by teletypes, too

Slide adapted from Jurafsky & Martin

Code Points

- Unicode assigns a unique ID, a **code point**, to each of its 150,000 characters
- 1.1 million possible code points
  - 0 – 0x10FFFF
- Written in hex, with prefix "U+"
  - a is U+0061 which = 0x0061

Slide adapted from Jurafsky & Martin

Some code points

0061	a	LATIN SMALL LETTER A
0062	b	LATIN SMALL LETTER B
0063	c	LATIN SMALL LETTER C
00F9	ù	LATIN SMALL LETTER U WITH GRAVE
00FA	ú	LATIN SMALL LETTER U WITH ACUTE
00FB	û	LATIN SMALL LETTER U WITH CIRCUMFLEX
00FC	ü	LATIN SMALL LETTER U WITH DIAERESIS
8FDB	进	
8FDC	远	
8FDD	违	
8FDE	连	
1F600	😀	GRINNING FACE
1F00E	🀎	MAHJONG TILE EIGHT OF CHARACTERS

A code point has no visuals; it is **not** a glyph!

Glyphs are stored in **fonts**: **a** *a* a a

But all of them are U+0061, abstract "LATIN SMALL A"

Slide adapted from Jurafsky & Martin

Encodings and UTF-8

- We don't stick code points directly in files
- We store **encodings** of characters
- The most popular encoding is UTF-8
- Most of the web is stored in UTF-8

Slide adapted from Jurafsky & Martin

Variable Length Encoding

- **UTF-8** (Unicode Transformation Format 8)
- UTF-8 encoding of `hello` is :
  - 68 65 6C 6C 6F
- Code points ≥128 are encoded as a sequence of 2, 3, or 4 bytes
  - First few bits say if its 2-byte, 3-byte, or 4-byte

Tokenization

Why tokenize?

- Using a deterministic series of tokens means systems can be compared equally
  - Systems agree on the length of a string
- Eliminates the problem of unknown words

Slide adapted from Jurafsky & Martin

Space-based tokenization

- A very simple way to tokenize
- For languages that use space characters between words
  - Arabic, Cyrillic, Greek, Latin, etc., based writing systems
- Segment off a token between instances of spaces

Slide adapted from Jurafsky & Martin

Issues in Tokenization

- Can't just blindly remove punctuation:
  - m.p.h., Ph.D., AT&T, cap’n
  - prices ($45.55)
  - dates (01/02/06)
  - URLs (http://www.pitt.edu)
  - hashtags (#nlproc)
  - email addresses (someone@cs.colorado.edu)
- Clitic: a word that doesn't stand on its own
  - "are" in we're, French "je" in j'ai, "le" in l'honneur
- When should multiword expressions (MWE) be words?
  - New York, rock ’n’ roll

Slide adapted from Jurafsky & Martin

Tokenization in languages without spaces between words

- Many languages (like Chinese, Japanese, Thai) don't use spaces to separate words!
- How do we decide where the token boundaries should be?

Slide adapted from Jurafsky & Martin

Word tokenization in Chinese

- Chinese words are composed of characters called "hanzi" (or sometimes just "zi")
- Each one represents a meaning unit called a morpheme
- Each word has on average 2.4 of them.
- But deciding what counts as a word is complex and not agreed upon.

Slide adapted from Jurafsky & Martin

How to do word tokenization in Chinese?

姚明进入总决赛 “Yao Ming reaches the finals”

3 words?
姚明 进入 总决赛
YaoMing reaches finals

5 words?
姚 明 进入 总 决赛
Yao Ming reaches overall finals

7 characters? (don't use words at all):
姚 明 进 入 总 决 赛
Yao Ming enter enter overall decision game

Slide adapted from Jurafsky & Martin

Word tokenization / segmentation

- In Chinese NLP it's common to just treat each character (zi) as a token.
    - So the **segmentation** step is very simple
- In other languages (like Thai and Japanese), more complex word segmentation is required.
    - The standard algorithms are neural sequence models trained by supervised machine learning.

Slide adapted from Jurafsky & Martin

Subword tokenization & BPE

Another option for text tokenization

- **Use the data** to tell us how to tokenize.
- **Subword tokenization** (because tokens can be parts of words as well as whole words)
- Many modern neural NLP systems (like BERT) use this to handle unknown words
- 2 parts:
    - A token learner that takes a raw training corpus and induces a vocabulary (a set of tokens).
    - A token segmenter that takes a raw test sentence and tokenizes it according to that vocabulary

Slide adapted from Jurafsky & Martin

Byte Pair Encoding [BPE, Sennrich+ 2016] token learner

Let vocabulary be the set of all individual characters

= {A, B, C, D,..., a, b, c, d....}

Repeat:

- Choose the two symbols that are most frequently adjacent in the training corpus (say 'A', 'B')
- Add a new merged symbol 'AB' to the vocabulary
- Replace every adjacent 'A' 'B' in the corpus with 'AB'.

Until *k* merges have been done.

Slide adapted from Jurafsky & Martin

Byte Pair Encoding (BPE) token learner

Iteratively merge frequent neighboring tokens to create longer tokens.

Start with all characters
Repeat:

- Choose most frequent neighboring pair ('A', 'B')
- Add a new merged symbol ('AB') to the vocabulary
- Replace every 'A' 'B' in the corpus with 'AB'.

Until *k* merges

Vocabulary

[A, B, C, D, E]

[A, B, C, D, E, AB]

[A, B, C, D, E, AB, CAB]

Corpus

A B D C A B E C A B

AB D C AB E C AB

AB D CAB E CAB

Slide adapted from Jurafsky & Martin

BPE token learner

Original (very fascinating 🙄) corpus:

low low low low low lowest lowest newer newer newer newer newer newer wider wider wider new new

Split on whitespace, add end-of-word tokens _

corpus	
5	l o w _
2	l o w e s t _
6	n e w e r _
3	w i d e r _
2	n e w _

vocabulary

_, d, e, i, l, n, o, r, s, t, w

Slide adapted from Jurafsky & Martin

BPE token learner

- Merge e r to er

corpus		vocabulary
5	l o w _	_, d, e, i, l, n, o, r, s, t, w, er
2	l o w e s t _	
6	n e w er _	
3	w i d er _	
2	n e w _	

- Merge er _ to er_
- Merge n e to ne

Slide adapted from Jurafsky & Martin

BPE token learner

The next merges are:

Merge	Current Vocabulary
(ne, w)	_, d, e, i, l, n, o, r, s, t, w, er, er_, ne, new
(l, o)	_, d, e, i, l, n, o, r, s, t, w, er, er_, ne, new, lo
(lo, w)	_, d, e, i, l, n, o, r, s, t, w, er, er_, ne, new, lo, low
(new, er_)	_, d, e, i, l, n, o, r, s, t, w, er, er_, ne, new, lo, low, newer_
(low, _)	_, d, e, i, l, n, o, r, s, t, w, er, er_, ne, new, lo, low, newer_, low_

Slide adapted from Jurafsky & Martin

BPE token segmenter algorithm

- On the test data, run each merge learned from the training data:
  - Greedily, in the order we learned them
- So merge every e r to er, then merge er _ to er_, etc.
- Result:
  - Test set "n e w e r _" would be tokenized as a full word
  - Test set "l o w e r _" would be two tokens: "low er_"

Slide adapted from Jurafsky & Martin

Regular expressions (regex)

Regular expressions

- A formal language for specifying text strings
- How can we search for any of these?
    - woodchuck
    - woodchucks
    - Woodchuck
    - Woodchucks

Regular Expressions: Disjunctions (OR)

- Letters inside square brackets []

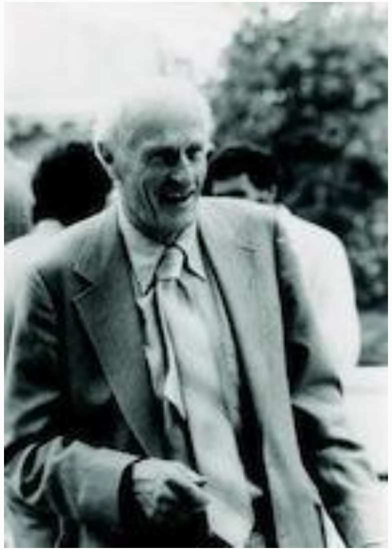
Pattern	Matches
`[wW]oodchuck`	Woodchuck, woodchuck
`[1234567890]`	Any digit

- Ranges `[A-Z] [a-z] [0-9]`
- Negations `[^A-Z]`
  - Carat means negation only when first in []
- Sequence disjunctions with pipe |
  - `groundhog|woodchuck`

Slide adapted from Jurafsky & Martin

Regular Expressions wildcards: *+.

Pattern	Matches	
`oo*h`	0 or more of previous char	oh ooh oooh ooooh
`o+h`	1 or more of previous char	oh ooh oooh ooooh
`beg.n`	Any char	begin begun begun beg3n



Stephen C Kleene

Slide adapted from Jurafsky & Martin

Regular expression example

- Find all instances of the word “the” in a text.

```
the
```

- Misses capitalized examples

```
[tT]he
```

- Incorrectly returns "other" or "theology"

```
[^a-zA-Z][tT]he[^a-zA-Z]
```

Slide adapted from Jurafsky & Martin

Errors

The process we just went through was based on fixing two kinds of errors:

1. Matching strings that we should not have matched (there, then, other)

   False positives (Type I errors)

2. Not matching things that we should have matched (The)

   False negatives (Type II errors)

Slide adapted from Jurafsky & Martin

Simple Application: ELIZA

- Early NLP system that imitated a Rogerian psychotherapist [Weizenbaum 1966]
- Uses pattern matching to match phrases

  `“I need X”`

- and translates them into, e.g.

  `“What would it mean to you if you got X?`

Slide adapted from Jurafsky & Martin

Simple Application: ELIZA

Men are all alike.
IN WHAT WAY

They're always bugging us about something or other.
CAN YOU THINK OF A SPECIFIC EXAMPLE

Well, my boyfriend made me come here.
YOUR BOYFRIEND MADE YOU COME HERE

He says I'm depressed much of the time.
I AM SORRY TO HEAR YOU ARE DEPRESSED

Slide adapted from Jurafsky & Martin

How ELIZA works

```
.* I’M (depressed|sad) .* → I AM SORRY TO HEAR YOU ARE \1

.* all .* → IN WHAT WAY?

.* always .* → CAN YOU THINK OF A SPECIFIC EXAMPLE?/
```

Slide adapted from Jurafsky & Martin

Other text preprocessing (normalization)

Case folding (lowercasing)

- Applications like IR: reduce all letters to lowercase
  - Since users tend to use lowercase
  - Possible exception: upper case in mid-sentence?
    - e.g., *General Motors*
    - *Fed* vs. *fed*
    - *SAIL* vs. *sail*
- For sentiment analysis, MT, information extraction
  - Case is helpful (*US* versus *us* is important)

Slide adapted from Jurafsky & Martin

Lemmatization

Represent words as their **lemma**: their shared root, dictionary headword form:

- *am, are, is* → *be*
- *car, cars, car's, cars'* → *car*
- Spanish quiero (‘I want’), quieres (‘you want’)

  → querer ‘want'
- *He is reading detective stories*

  → *He be read detective story*

Stemming

- Reduce terms to stems, chopping off affixes crudely

This was not the map we found in Billy Bones's chest, but an accurate copy, complete in all things-names and heights and soundings-with

→

Thi wa not the map we found in Billi Bone s chest but an accur copi complet in all thing name and height and sound with

$$\begin{aligned}
\text{ATIONAL} &\rightarrow \text{ATE} \quad \text{(e.g., relational} \rightarrow \text{relate)} \\
\text{ING} &\rightarrow \epsilon \quad \text{if stem contains vowel (e.g., motoring} \rightarrow \text{motor)} \\
\text{SSES} &\rightarrow \text{SS} \quad \text{(e.g., grasses} \rightarrow \text{grass)}
\end{aligned}$$

Slide adapted from Jurafsky & Martin

Stopword removal

- Do we want to keep "function words" like *the*, *of*, *and*, *I*, *you*, etc?
- Sometimes no (information retrieval)
- Sometimes yes (authorship attribution)

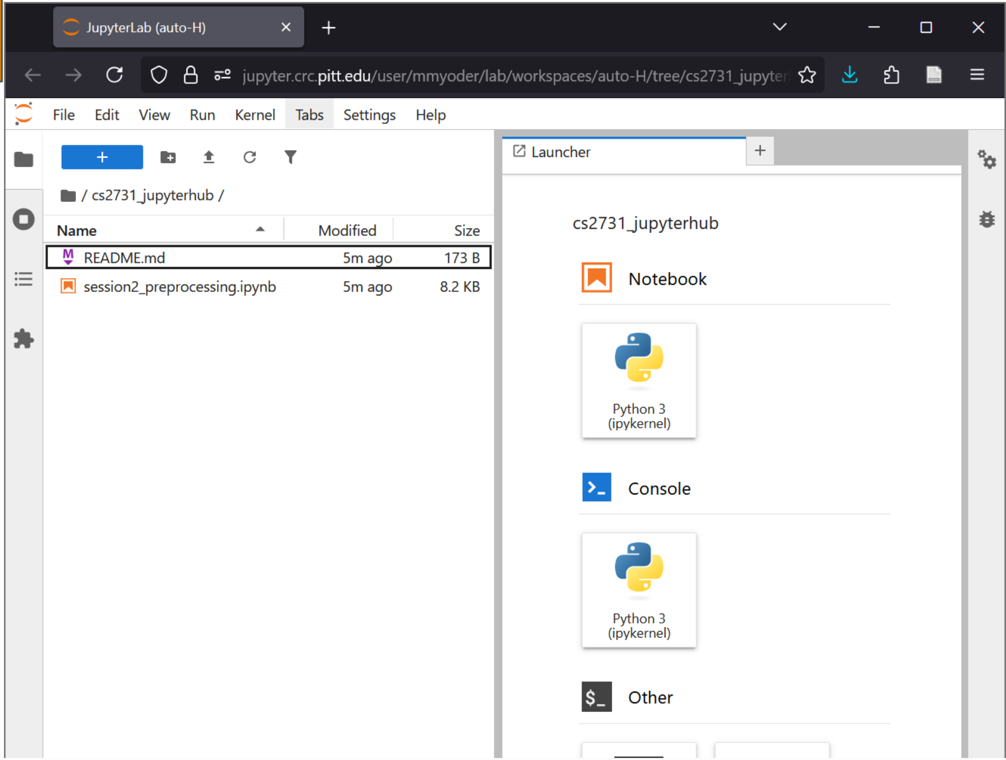
Conclusion: Words and tokens

- Word types are unique words
- Morphemes are the smallest meaning-bearing units within words
- Unicode represent characters for many languages and scripts in code points which can be encoded into bytes with UTF-8
- Tokenization: splitting texts into sequences of words
    - Subword tokenization finds tokens based on frequencies of sequences of characters in data
- Regular expressions match flexible sequences of characters
- Lemmatization: normalizing words to their dictionary roots
- Stemming: chopping off affixes of words to reduce them to stems
- Stopwords are function words like “the”, “a”, “and”, “of”, etc that are often ignored in NLP applications

Coding activity:
Preprocessing Airbnb listings

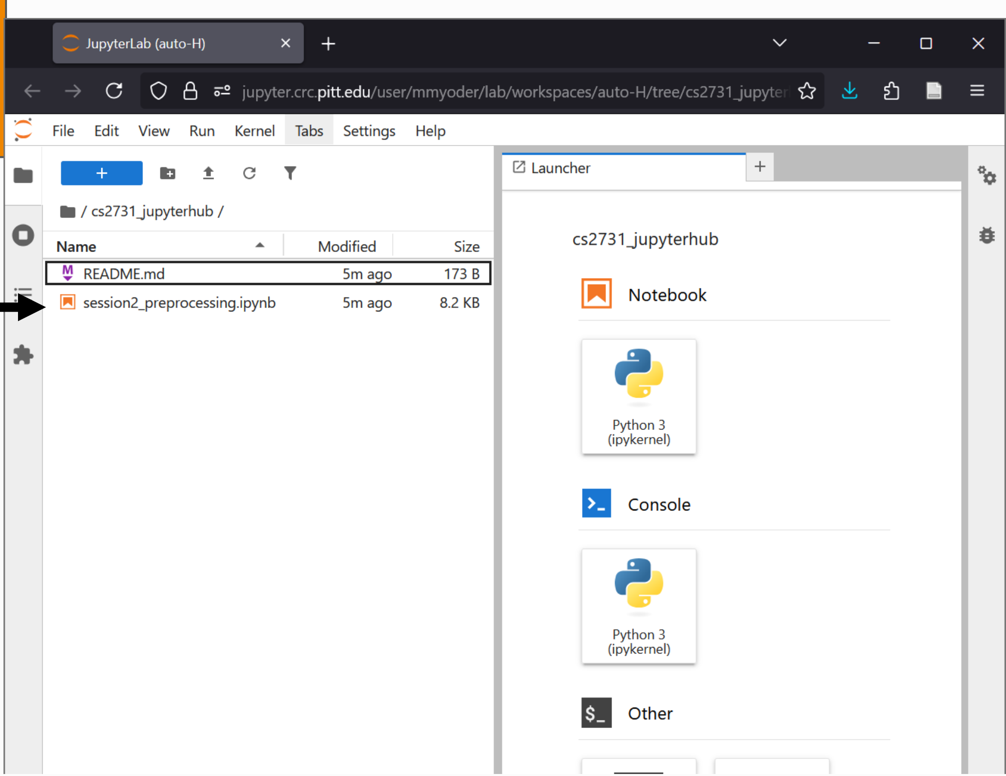
Load in-class notebooks

1. Go to this nbgitpuller link (also available on course website)
2. Log in with your Pitt username if necessary
3. Start a server with **TEACH – 6 CPUs, 48 GB**
4. Load custom environment at /ix/cs2731_2025f/class_env
5. This should pull a folder (cs2731_jupyterhub) into your JupyterLab



Open Jupyter notebook

1. Double-click **session2_preprocessing .ipynb** on the left panel to open the notebook



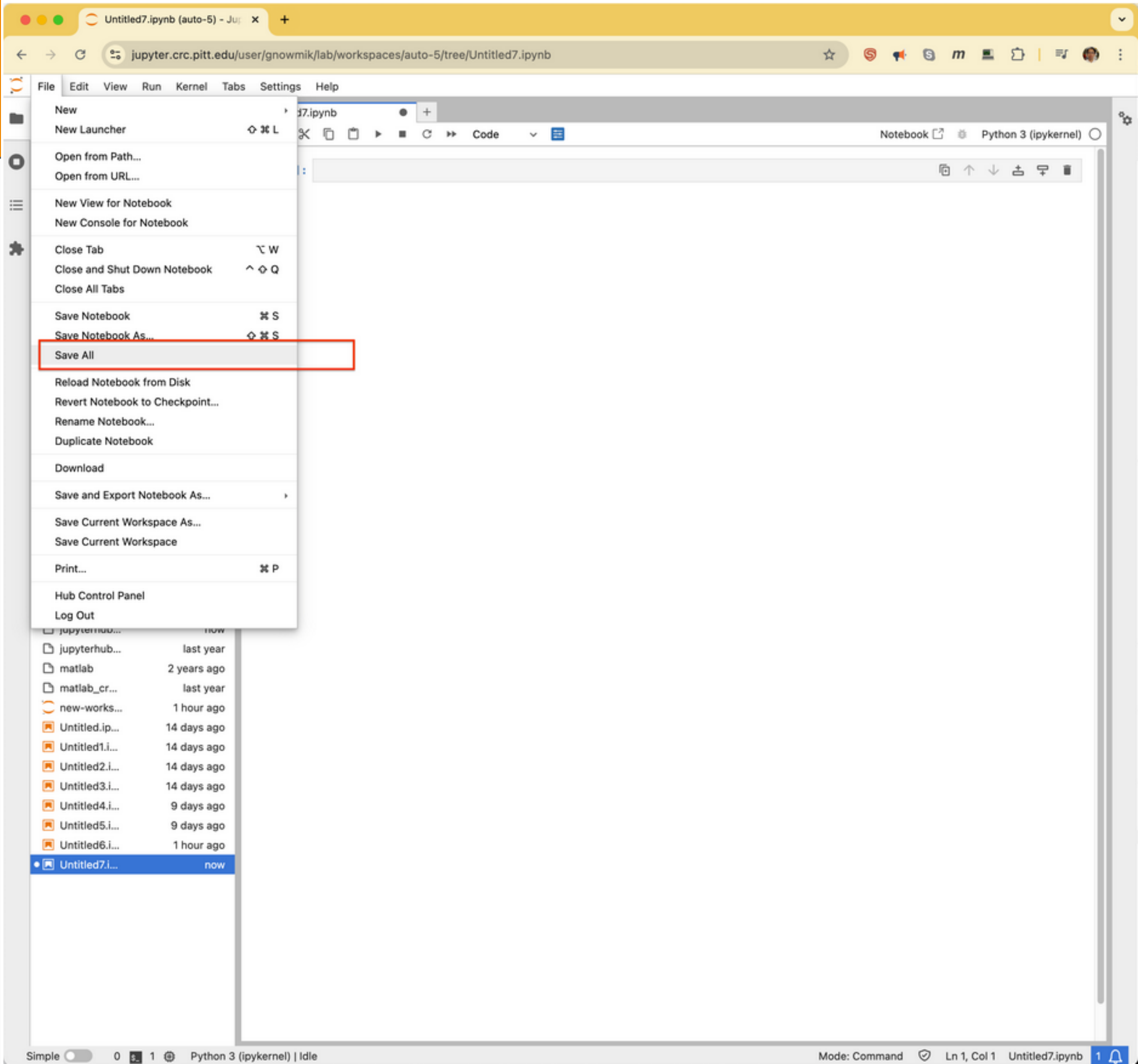
Jupyter Notebook basics

- Each block is called a “cell”
  - Has input and possibly output
  - Input can be Python code, Markdown or shell commands (after `!`)
- Modes
  - Command mode
    - Move, select, manipulate cells
    - Get into command mode by clicking anywhere outside of a cell
  - Edit mode
    - Edit content of a particular cell
- Running cells
  - Click “Run” button or do Ctrl+Enter (on Windows or Linux, Cmd+Enter on Mac) to run code or render Markdown
  - Any result will be shown in the output of the cell

Implementation

- Remove undesired text with regular expressions
- Lowercase
- Remove stopwords
- Tokenize with the NLTK package
- Stem the tokens with NLTK

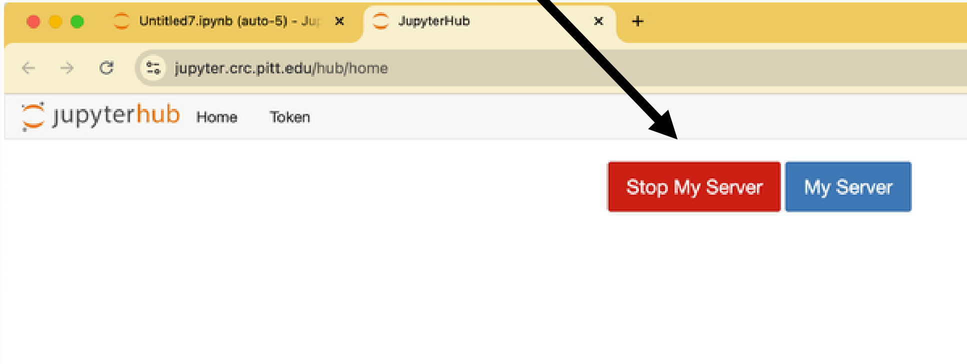
Saving your work

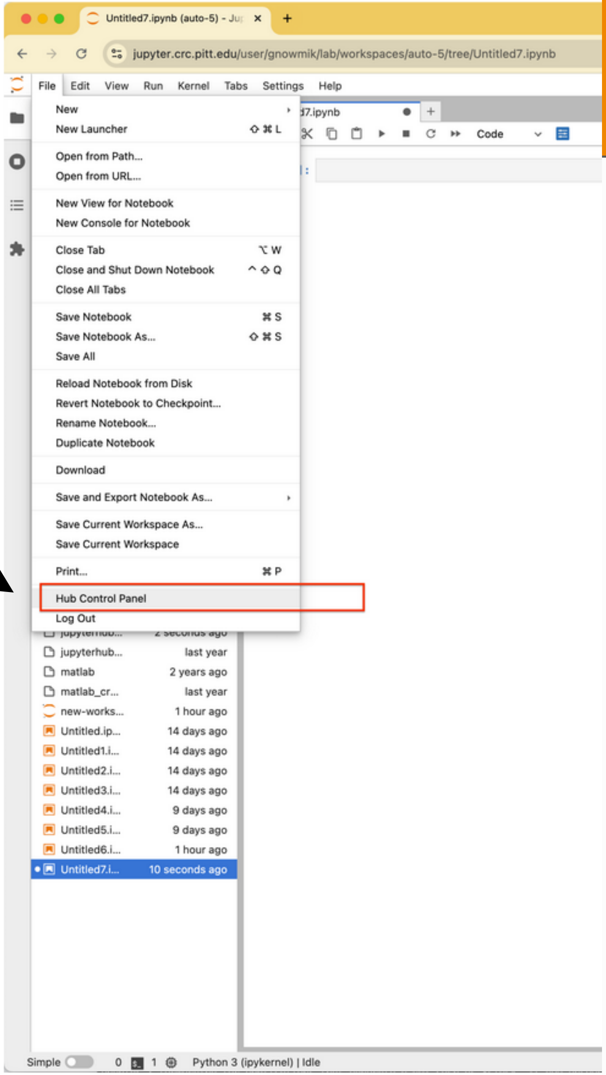


Ending your session

Be sure to save your work before ending the session

1. Select **File** > **Hub Control Panel**
2. Click **Stop My Server**





Questions?

Enjoy Labor Day holiday

No class on Monday