

WHenever I learn a new skill I concoct elaborate fantasy scenarios where it lets me save the day.

OH NO! THE KILLER MUST HAVE FOLLOWED HER ON VACATION!



BUT TO FIND THEM WE'D HAVE TO SEARCH THROUGH 200 MB OF EMAILS LOOKING FOR SOMETHING FORMATTED LIKE AN ADDRESS!



IT'S HOPELESS!

EVERYBODY STAND BACK.



I KNOW REGULAR EXPRESSIONS.



CS 2731

# Introduction to Natural Language Processing

Session 2: Words and tokens

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August 27, 2025

# Overview: Text normalization

- 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)

# CRCDD JupyterHub setup

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# CRCD and JupyterHub

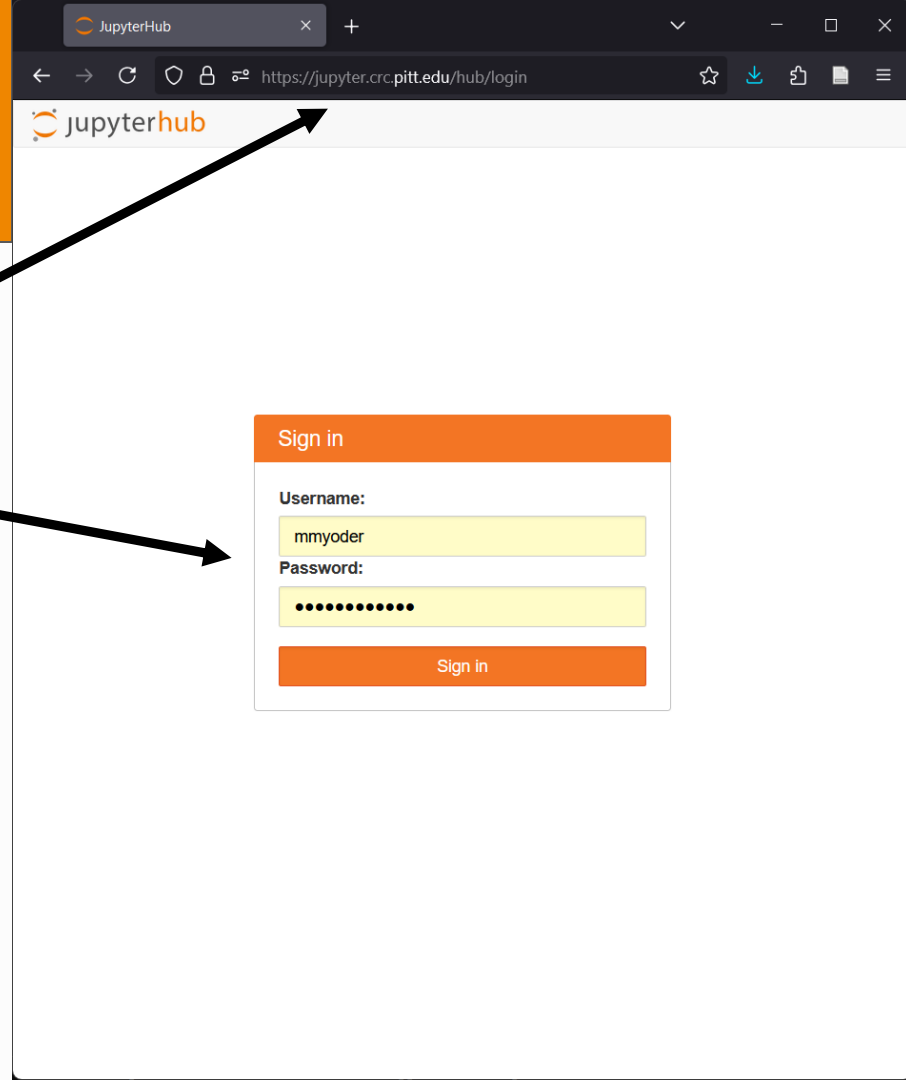
- CRCD (Center for Research Computing and Data) is a Pitt center providing computing services on various clusters
- They maintain a JupyterHub where people can run Jupyter Notebooks on their servers
- What we will be using the CRCD for:
  - Working through code examples in class
  - Writing code to submit 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:**  
`/ihome/myoder/mmyoder/cs2731_env`
4. Click **Start**
5. Wait for the server to start up

The screenshot shows the JupyterHub interface in a web browser. The browser address bar shows the URL `jupyter.crc.pitt.edu/hub/spawn`. The page title is "JupyterHub". The navigation bar includes "Home" and "Token". The main content area is titled "Server Options" and contains a "JupyterHub Session Configuration" form. The form has the following fields:

- Select Partition:** A dropdown menu with "TEACH - 6 CPUs - 45GB" selected.
- Select Virtual Environment:** A dropdown menu with "Provide custom path" selected.
- Custom Environment Path:** A text input field containing the path `/ihome/myoder/mmyoder/cs2731_env`.
- Select Modules to Load:** A list box containing "Amber 2024" and "Cuda 12.3". Below the list box, it says "Hold Ctrl/Cmd to select multiple modules".
- Account:** A text input field containing the text "your class account".

At the bottom of the form is a large orange button labeled "Start".

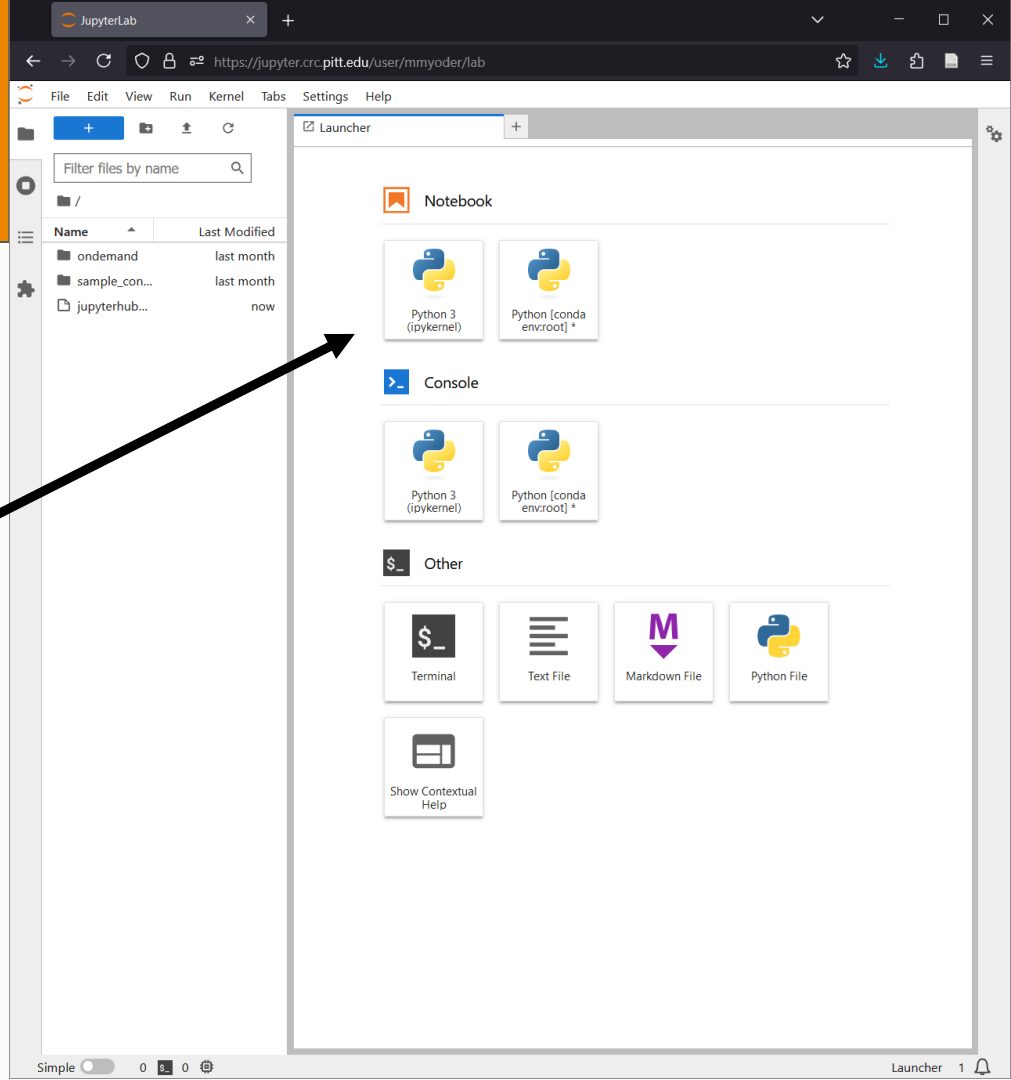
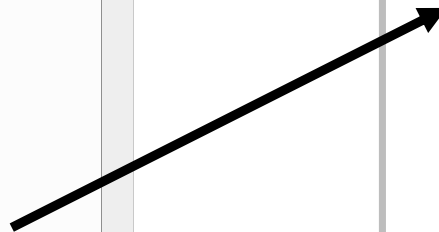


# Welcome to your JupyterLab

Files are here



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



# Words and corpora

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# 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

# How many words in a corpus?

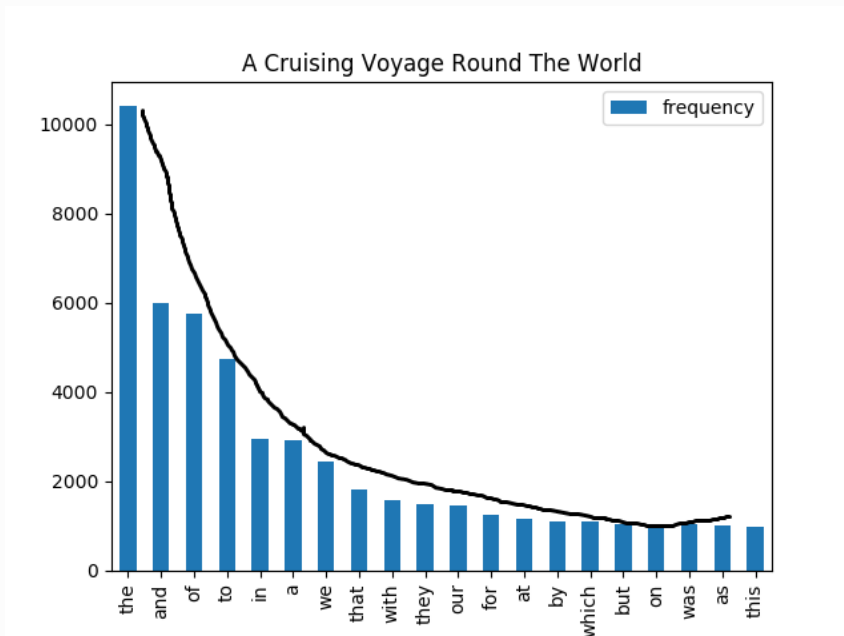
Corpus: a (machine-readable) collection of texts

$N$  = 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

# 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 worry ... 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

# Morphemes

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# 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



# 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'

# Unicode

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# 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.

# 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



# 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

# 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	连	
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** α a a

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

# 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

# Variable Length Encoding

- UTF-8 (Unicode Transformation Format 8)
- UTF-8 encoding of `hello` is :
  - `68 65 6C 6C 6F`
- Code points  $\geq 128$  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

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# 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

# 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

# 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](mailto: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](#)

# 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?

# 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.

# 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

# 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.



# Subword tokenization & BPE

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# 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

# 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.

# 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

# 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

# BPE token learner

- Merge **e r** to **er**

## 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, er

- Merge **er \_** to **er\_**
- Merge **n e** to **ne**

# 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—

# 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\_"



# Regular expressions (regex)

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# 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**



# Regular Expressions wildcards: \*+.

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



Stephen C Kleene

# 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]

# 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)**

# 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?”

# 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



# 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?/

## Other text preprocessing (normalization)

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# 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)



# 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

ATIONAL → ATE (e.g., relational → relate)

ING → € if stem contains vowel (e.g., motoring → motor)

SSES → SS (e.g., grasses → grass)

# 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: Text normalization

- Regular expressions match flexible sequences of characters and allow substitution of groups of characters
- Tokenization: splitting texts into sequences of words
  - Subword tokenization finds tokens based on frequencies of sequences of characters in data
- 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

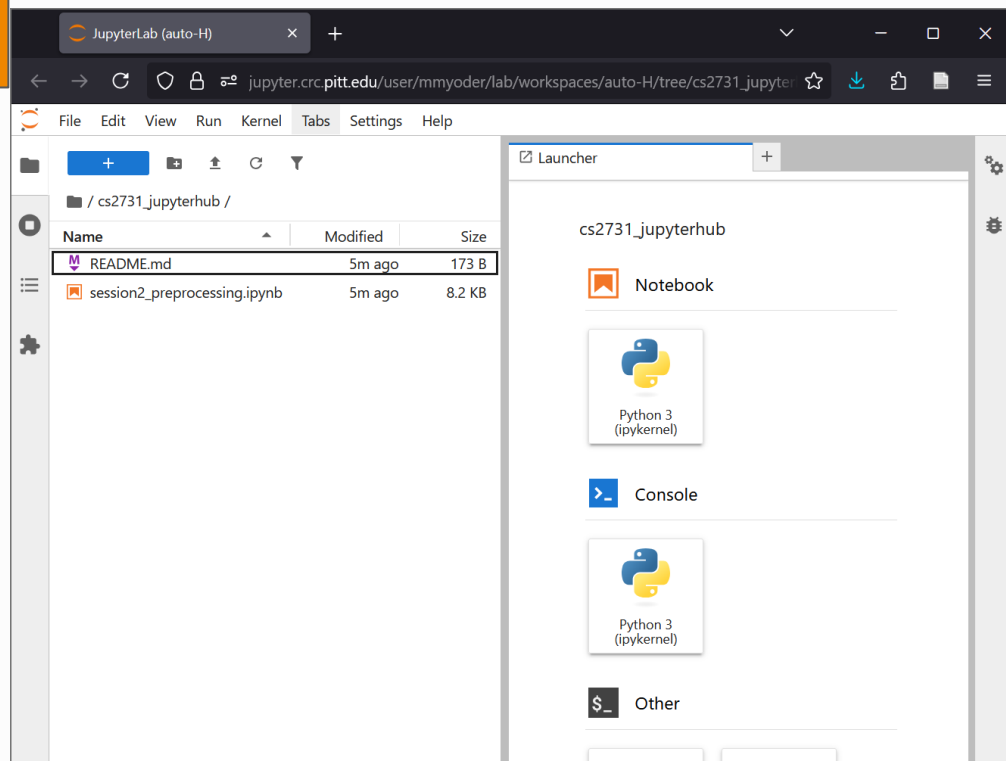
# Coding activity: Preprocessing Airbnb listings

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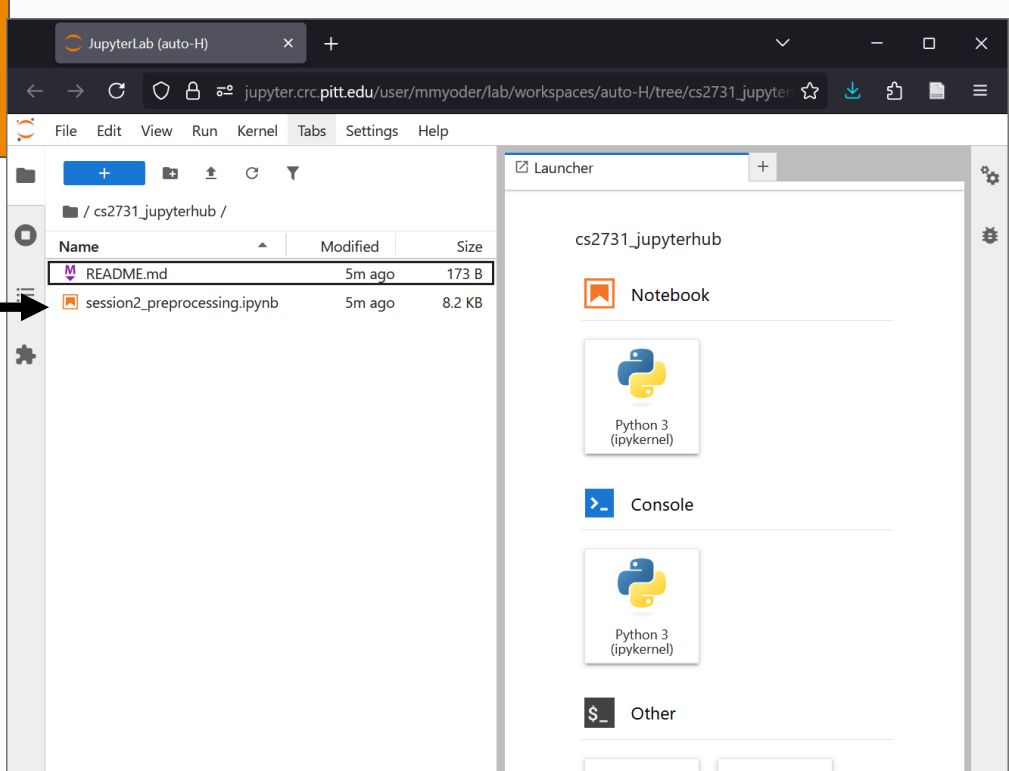
# Load in-class notebooks

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 `/ihome/myoder/mmyoder/cs2731_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



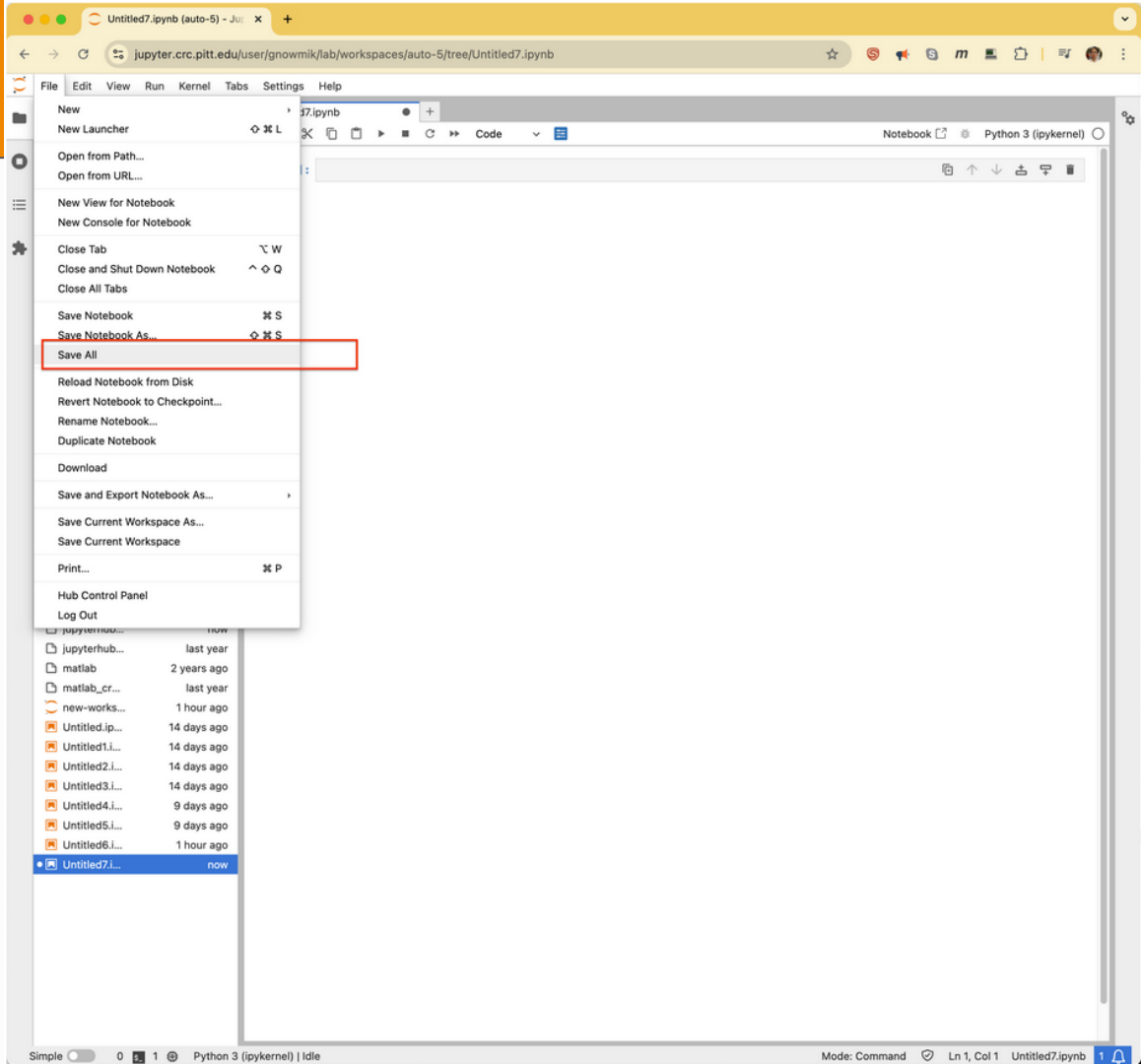
# Jupyter Notebook basics

- 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

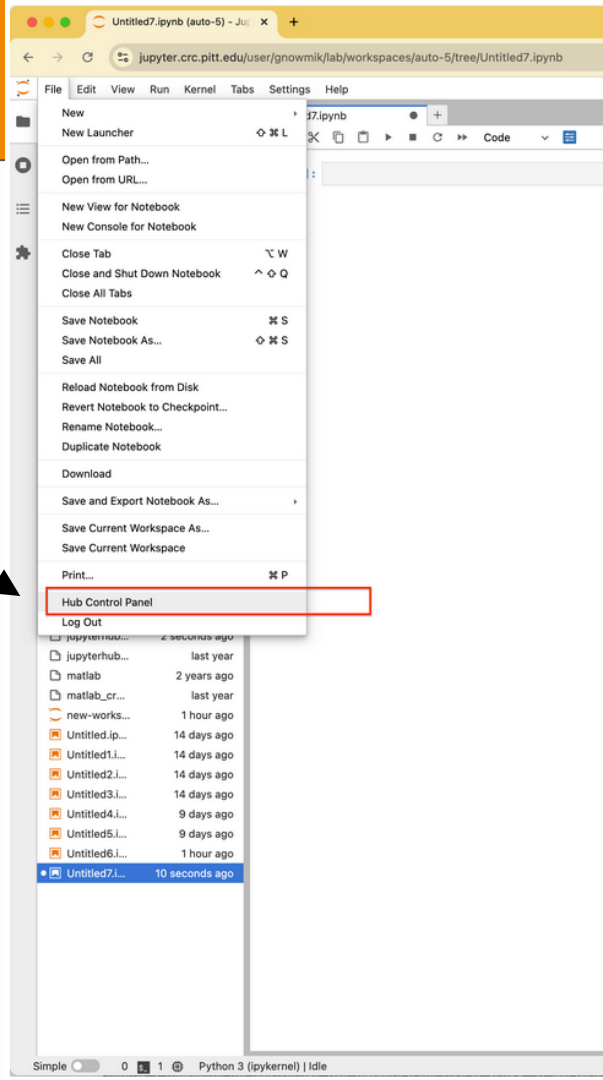
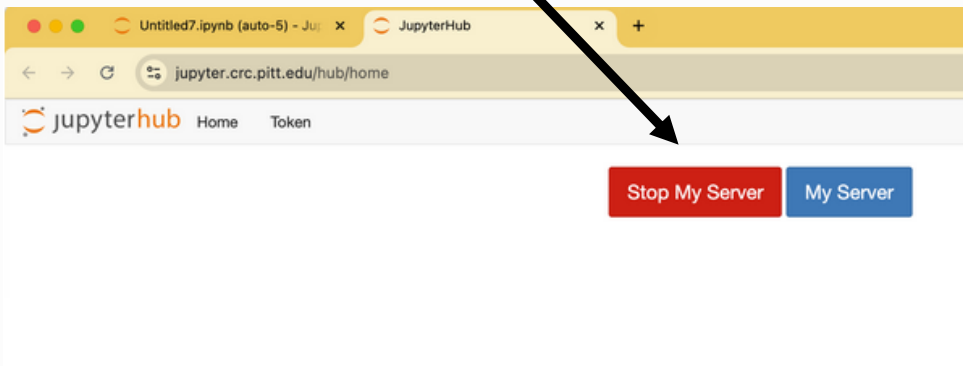
# Saving your work



# 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