# Lecture 7: Text as data

## LING-351 Language Technology and LLMs

Instructor: Hakyung Sung

September 16, 2025

*Acknowledgment: These course slides are based on materials by Lelia Glass @ Georgia Tech (Course: Language & Computers)

# Table of contents

# Review

# CALL

- CALL stands for Computer-Assisted Language Learning

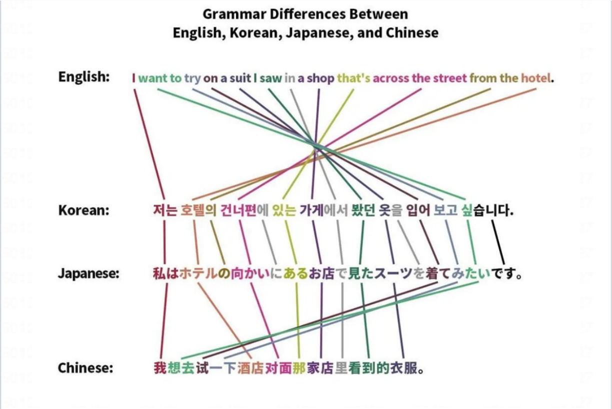
# Language Learning

L1 vs. L2: - what is the similarity? - what is the difference?

# Language transfer

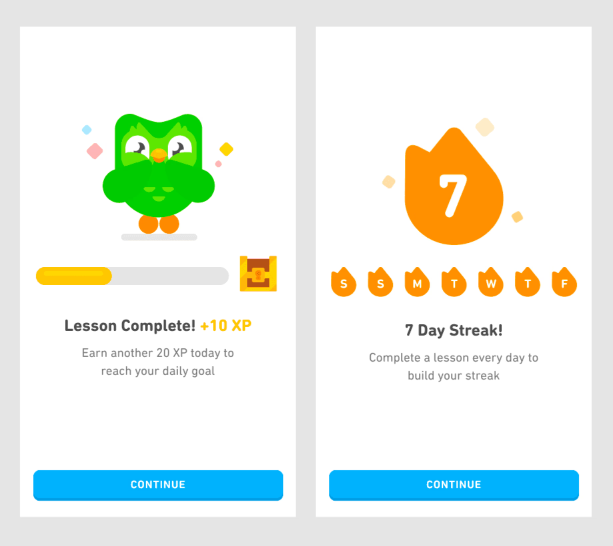
L1 vs. L2: - positive transfer - negative transfer - typology

# Language typology




*https://wals.info/*

# Motivation: Gamification and reinforcement




Sourced from 2024 Duolingo language report : *https://nudgenow.com/blogs/duolingo-gamification-strategy*

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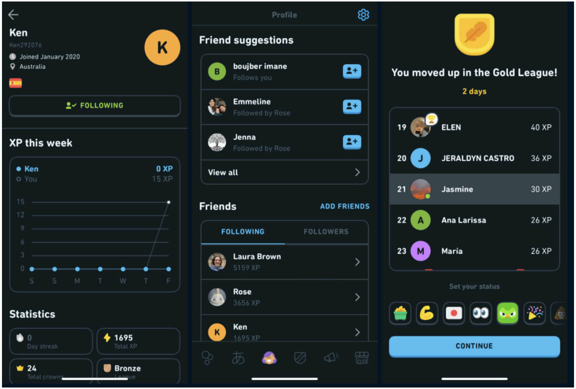
  - Competence: sense of progress (points, levels, streaks)

# Social comparison

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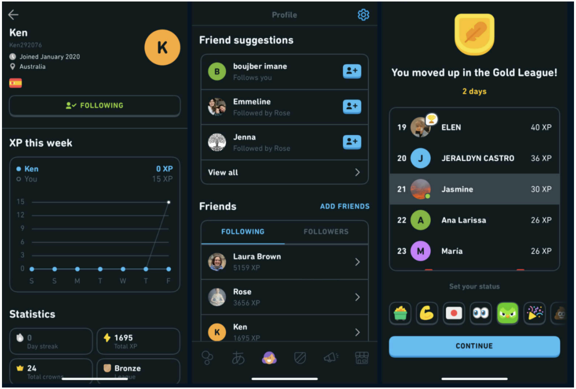


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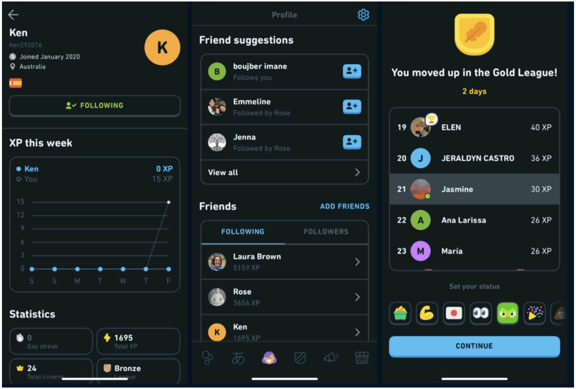


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- Leaderboards and friend lists create social competition
- Similar to SNS: recognition and belonging motivate persistence
- Learners compare progress and are encouraged to “keep up”

# Attitude, motivation, and growth mindset

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- Other factors:
    - Intrinsic/extrinsic motivation
    - Positive attitudes toward the target language and culture
    - Willingness to take risks and make mistakes

# Coming back to CALL

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At the intersection of language learning and educational technology, the field of Computer-Assisted Language Learning (CALL) develops tools to support and enhance second language acquisition.

# What do we mean by CALL?

- **Broad sense**: Refers to the many ways computers intersect with education and society in language learning.
- Examples: multimedia textbooks, online dictionaries, digital writing tools, consuming media, and connecting socially with L2 speakers.

# What do we mean by CALL?

- **Narrow sense**: Describes instructional tools that deliver sequenced exercises, provide feedback on responses, and are often used in *language assessment contexts*.

# Example: *Fill-in-the-blank*

The detective lives _____ Baker Street.

- Free-text input?
  - One correct answer: *on*?
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    - How are these distractors chosen?
    - What feedback should be given for a wrong choice?
- Sequencing:
    - How to ensure the question is not too hard or too easy?

# Motivating intelligent CALL

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- Recently, ITS are also used in domains like:
  - Math
  - Computer science (teaching coding skills)
- These domains are often **more constrained**, which may make:
  - Feedback and hints easier to automate
  - Learner modeling more reliable

## CALL design considerations

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- How fun or useful is it for learners?
- Trade-offs:
  - Multiple choice: easy to grade, but limited expression
  - Free-text: richer data, but harder to parse and evaluate

*https://www.tandfonline.com/action/showAxaArticles?journalCode=ncal20*

# Lesson plan

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- ~~Review: CALL~~

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Key idea: Language technology is not only for answering linguistic questions—it can also address a wide range of issues using text data.

# Intro

# Language technology always built on linguistic theory?

So far, our tour of language technology has incorporated a great deal of linguistic representations and theories:

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- Different encodings (e.g., alphabetic, syllabic, logographic)

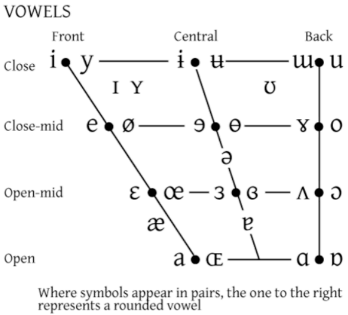


Figure 1.2: International Phonetic Alphabet of vowels (https://commons.wikimedia.org/wiki/File:Ipa-chart-vowels.png)

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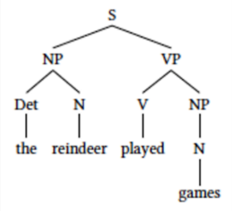
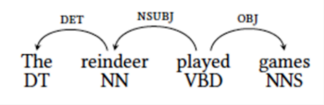
- Theories of grammar for writers' aids



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You might be getting the impression that language technology always builds on constructs from linguistics.

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But there's also much to be gained from letting language data speak for itself—**independent of any particular theory.**

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This vast amount of text reflects patterns in:

- society, education, law, economics, health science, etc.

# What is Text as Data?

**Text as data** is a cross-disciplinary endeavor to:

- Extract information from large-scale corpora

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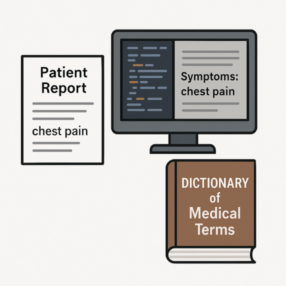
*This marks a pivot from:*

- Top-down, **knowledge-driven** applications
- Bottom-up, **data-driven** language technology

# Example 1

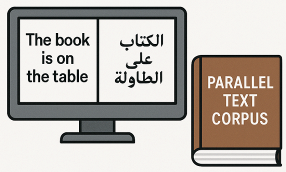
I'm trying to build a system that uses a hand-crafted dictionary of medical terms and explicit grammar rules to extract symptoms from patient reports.




Q. Knowledge-driven or data-driven? Why?

# Example 2

I'm trying to build a translation tool trained on millions of parallel sentences between English and Arabic, and produces translations by predicting word sequences statistically.

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# Example 3

The research team recently built a chatbot which follows *if–then* rules written by linguists and domain experts, where every possible user input is matched against a predefined template.

Q. Knowledge-driven or data-driven? Why?

# Example 4

We now use an algorithm that detects fake news by training on large corpora of labeled real vs. fake news articles, learning which word patterns correlate with each label.

Q. Knowledge-driven or data-driven? Why?

# Example 5

A researcher builds a sentiment analyzer by creating a list of positive/negative words and assigning scores manually.

Q. Knowledge-driven or data-driven?

# Example 6

A system identifies people's names in text using a neural named entity recognition (NER) model trained on millions of labeled sentences.

Q. Knowledge-driven or data-driven?

# Example 7

In a low-resource language project, linguists encode morphology and syntax rules by hand because there isn't enough digital text to train a model.

Q. Knowledge-driven or data-driven?

## Key considerations when using Text

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- **Statistics** — What inference methods are applied?

# Questions with answers in text

# Touring text-as-data Questions

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- Mining digital archives for silenced voices

# Examples from the textbook

Followings are example studies from the textbook.

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- Library acquisition records

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- Decline of women authors during mid-1800s to mid-1900s
- Women authors depict men and women equally; men tend to depict more male characters

# 2. Computational social science

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Computational Social Science (CSS) = Use of corpora to study social science questions.

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- Media analysis: Topic coverage across news outlets
- Network analysis: Spread of ideas on social media
- Community behavior: Conformity and uniqueness in forums
- Online harm: Trolling, misinformation, fake news

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A snippet of the findings:

- Wikipedia editors become **less polite** after gaining power

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- *Democrats*: reversed pattern, and more likely to mention gun laws

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- **Cheap menus:** more words, traditional authenticity (e.g., Grandma's recipe)
- **Expensive menus:** fewer words, natural authenticity (e.g., wild-caught salmon)
- Quality on cheap menus is described; on expensive menus, it's implied

**Author profiling** = Inferring characteristics of a writer from their text.

- Gender, age, personality, political ideology

# 3. Author profiling and identification

Author profiling = Inferring characteristics of a writer from their text.

- Gender, age, personality, political ideology
- Mental health, native language

**Goal:** Use language to identify or describe authors in criminal cases

**Technique:** Analyze phrasing, spelling, vocabulary, etc.

Even when the author is known, we can quantify their style:

- Frequent n-grams (e.g., bigrams like “of course”)

# 3-2. Stylometry and literary voice

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Even when the author is known, we can quantify their style:

- Frequent n-grams (e.g., bigrams like “of course”)
- Common word classes: verbs, adjectives, nouns
- Lexical diversity (diverse words? limited words?)

# 3-2. Stylometry and literary voice

Even when the author is known, we can quantify their style:

- Frequent n-grams (e.g., bigrams like “of course”)
- Common word classes: verbs, adjectives, nouns
- Lexical diversity (diverse words? limited words?)
- Average sentence length and starter words

**Corpus linguistics** = Studying *language itself* through large collections of real-world text (corpora)

- Annotated corpora (e.g., POS tags, syntax trees)
- Used to test linguistic theories and train computational models
- Enables empirical observation on how different language users actually produced their languages

## Example: L2-English Speakers' Production (Sung & Kyle, 2025)

Goal: Investigate whether more proficient L2-English speakers produce

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*This might sound obvious, but it has been challenging to measure in large datasets—previous studies have often remained descriptive rather than computational.*

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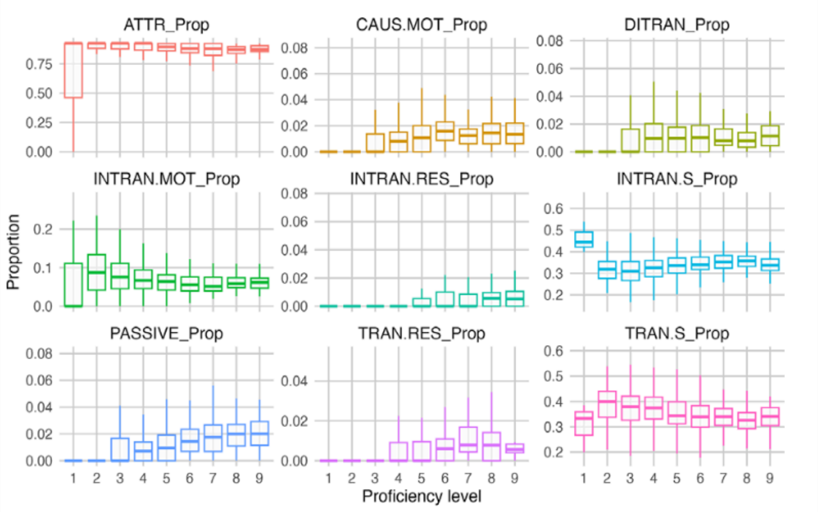
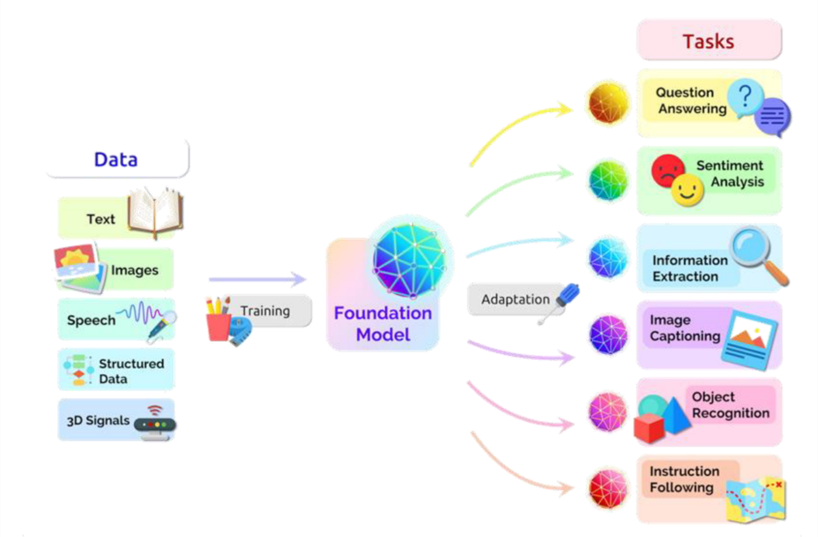


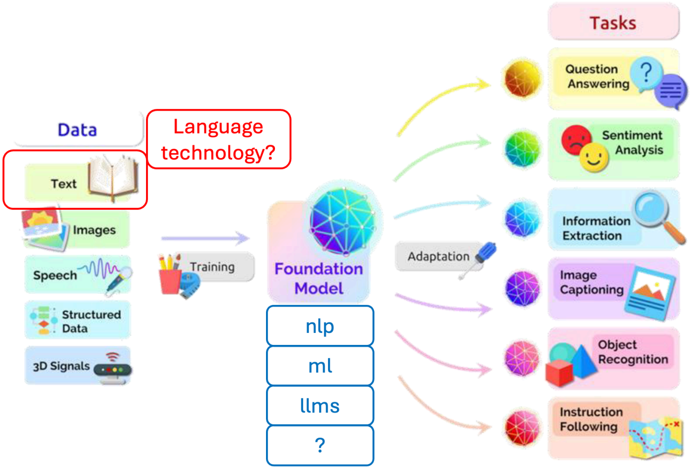
# Good data for training

# Logistics of the data-driven approach



# Logistics of the data-driven approach

In particular domain: *humanities, social sciences, business, linguistics*...



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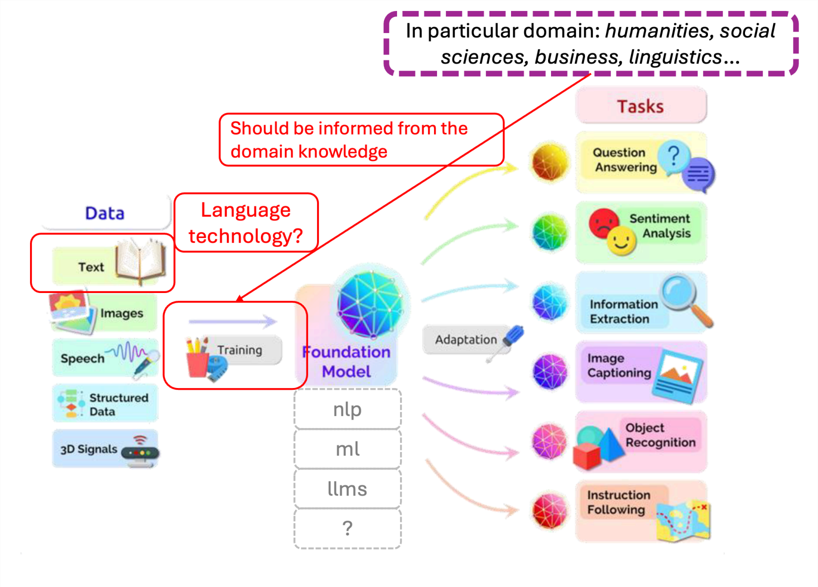

# Recall: Example 1

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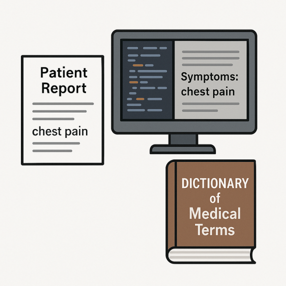
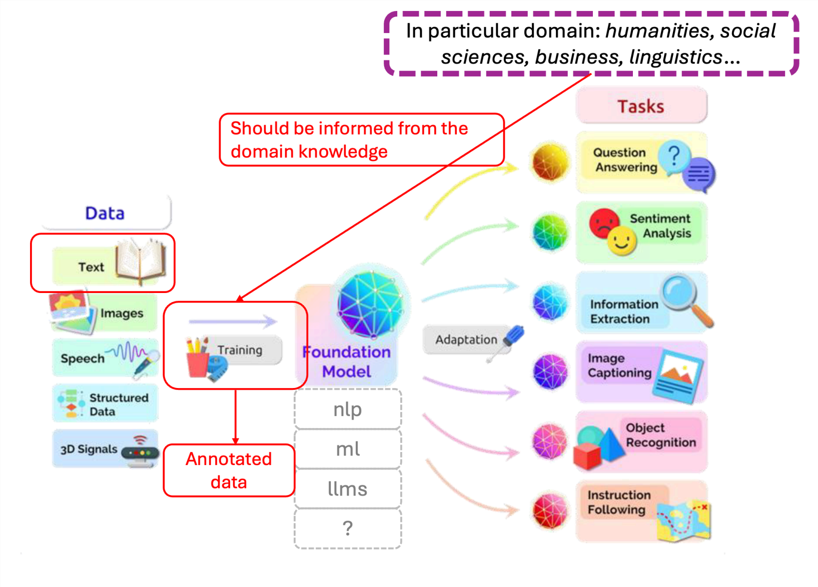
I’ve used a system that uses a hand-crafted dictionary of medical terms and explicit grammar rules to extract symptoms from patient reports.

But, now, I know how to train LLMs to automatically extract medical terms from the patient reports! What do I need first?



# Logistics of the data-driven approach: Annotation



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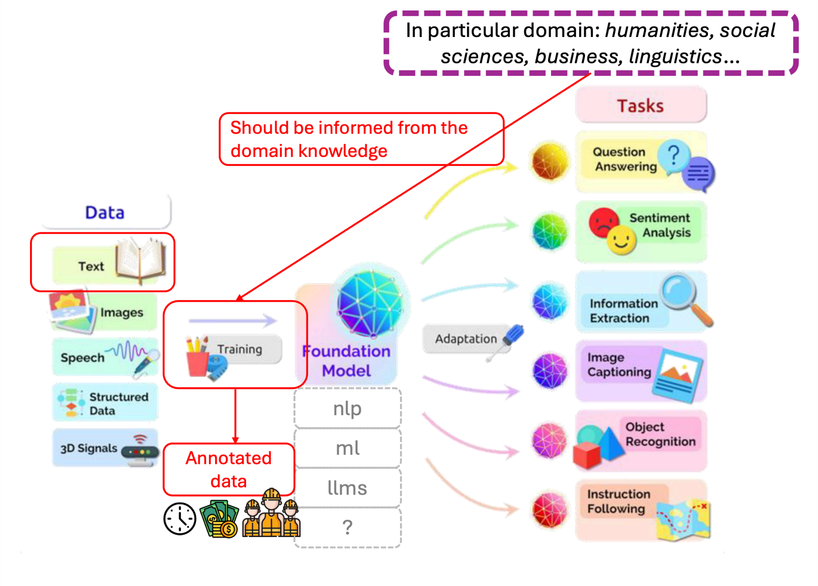

# Annotation sources (in practice)

- **Expert annotation**: an expert of the target domain (e.g., a doctor-medical research)
- **Crowdsourced annotation:** via Mechanical Turk, Prolific
- **Automated tools:** taggers/parsers trained on some annotated data

# Wrap-up

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- Good data for the data-driven approach

Key idea: Language technology is not only for answering linguistic questions—it can also address a wide range of issues using text data. To do this effectively, we first need to understand how the field approaches text as data.

# Brainstorm your research interests

| | | | | |
|---|---|---|---|---|
| 4 | 9/16 | Text as data | [LC] Ch. 4.1-4.3 | |
| | 9/18 | Python tutorial 3 | | |
| 5 | 9/23 | Word vectors | [LC] Ch. 4.4 | |
| | 9/25 | Python tutorial 4 | | Exercise 3 |
| 6 | 9/30 | Text classification | [LC] Ch. 5 | |
| | 10/2 | Python tutorial 5 | | Student presentation topics submission |

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| | | | | |
|---|---|---|---|---|
| 10 | 10/28 | Paper presentation (Papers 1, 2) | | |
| | 10/30 | Paper presentation (3, 4) | | |
| 11 | 11/4 | Paper presentation (5, 6) | | |
| | 11/6 | Paper presentation (7, 8) | | |
| 12 | 11/11 | Paper presentation (9) | | |
| | 11/13 | Paper presentation (10, 11) | | Assignment 1 |
| 13 | 11/18 | Paper presentation (12, 13) | | |
| | 11/20 | Paper presentation (14, 15) | | |
| 14 | 11/25 | Paper presentation (16, 17) | | |
| | 11/27 | **Thanksgiving break (No class)** | | |
| 15 | 12/2 | Paper presentation (18) | | |
| | 12/4 | Final wrap-up | | Assignment 2 |

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1. Review the sample papers on the course website (*https://hksung.github.io/Fall25_LING351/materials/*)

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3. You may also choose articles beyond this list (e.g., CALL), but please check with me first
4. I will form groups of 2–3 people based on your selections