Advanced NLP
Lecture 1: Introduction + Intrinsic Tasks

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Suggested reading: Speech and Language Processing: an Introduction to Speech Recognition, Computational Linguistics and Natural Language Processing. Daniel Jurafsky & James H Martin

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Target Audience

- **Background in machine learning**
  - That's all we'll do
- **Background in NLP to varying degrees**
  - From students who just did first NLP course to PhD students
- **Want to learn more about current tech & research trends**

Course Agenda

- We aim to bring you up to speed with **latest NLP innovations**
- **NLP is fast moving field**
  - Likely to change as we're giving the course
- We built the syllabus around **long-standing challenges and themes**
- **Ask questions, challenge assumptions**
  - Mid-size, diverse course to prompt discussion
  - Some (many?) questions which we don't know the answer to
  - We'll be happy for feedback

This isn't a seminar

- Lectures are **self-contained**
- But we provide a bibliography for additional reading
- and you'll benefit from reading into what you find interesting
- Lots of room for **creativity**

Today

1. Course Structure
2. Pretraining, Intrinsic, and Extrinsic Tasks
3. Intrinsic NLP Applications
   - Textual Entailment (or NLI)
   - Coreference
   - Entity Linking
4. Discussion
5. Conclusion

In previous chapters you learned . . .

- **Q: How do we define NLP?**
  - Models taking natural language as part of their input or output
  - **Q: Can you give example of tasks?**
- **Automatically understanding language is hard**
  - **Q: Why?**
- **Linguistic background**
  - Lexical (POS), syntactic (dep trees), semantic (SRL)
- **Machine learning is ubiquitous**
- **Word embedding is a powerful technique**
  - As word features (e.g., Word2vec)
  - With finetuning (e.g., ELMo, BERT)

Where we're going

- **Better understanding of our tasks & data**
- **Finetuning and zero-shot**
- **Interpreting model performance**
- **Efficient models**
- **Real-world tasks**

Disclaimer: We're biased towards our research topics

- We don't aim to give an exhaustive overview of NLP
- **Many courses from other researchers**
  - Self-supervised Statistical Models (Daniel Khashabi, JHU)
  - Local Explanations for Deep Learning Models (Ana Marasovic, Utah)
  - Exploration on Language, Knowledge, and Reasoning (Yejin Choi, UW)
  - Computational Ethics in NLP (Emma Strubell, Maarten Sap, CMU)
- **Interesting to contrast & compare**

Course Objectives

- Familiarize with **topics at the forefront** of NLP today
- Exprience phrasing a **research question**
- **Hands-on exprience** with state-of-the-art NLP
- Read relevant **literature**
- Present your work in **scientific writing**

Course Requirements (w/o the gritty details)

- Two relatively small **coding & evaluation excercises**
- **An Open-Ended Research Project**
  - **You formulate your idea**
  - Define goals and intended outcomes
  - Describe your work in a final report
  - Work in groups

Start thinking about your project today

- Today we'll talk about **longstanding NLP tasks**
- **We won't discuss modelling**
- Focus on understanding **importance & challenges**

Pretraining vs. Intrinsic vs. Extrinsic

- **Extrinsic tasks** (aka *downstream*)
  - Tasks which have applicable value for external users
  - Machine translation, information extraction, summarization...
- **Intrinsic tasks** (aka *intermediate*)
  - Inherently required across extrinsic tasks
  - But are not directly useful on their own
  - Often correspond to much-studied linguistic phenomena
  - You've seen: SRL, grammar (dependency trees)
- **Pretraining tasks**
  - Do not fall neatly into any of the above
  - But we have order of magnitudes more data for them
  - and they transfer well to other tasks

Synthetic vs. Real-World Data

- **Synthetic data** is constructed specifically for training the model
  - E.g., asking humans to write text according to guidelines
- **Real-world data** is written independently from model development
  - E.g., news outlets, books, or financial reports
- **Orthogonal to the type of task**
- We'll come back to this later in the course

Task vs. Format

- **Task:** The human skill required by the model
  - E.g., translation, commonsense, information extraction
- **Format:** How it's encoded or collected
  - E.g., sequence labeling, seq2seq, span selection
- **Q: Is QA a task or a format?** [1]
  - We'll see how it's used to collect data for different tasks

Recognizing Textual Entailment (Or NLI)

The task of deciding whether the meaning of one text (the **Hypothesis***) is entailed, or can be inferred, from another text (the* **Premise***)*[2]

- Typically consisting of **three labels**
  - **Premise:** "Yoko Ono unveiled a bronze statue for her late husband, John Lennon."
- **Entailment**
  "Yoko Ono is John Lennon's widow"
- **Contradiction**
  "John Lennon is Yoko Ono's widow"
- **Neutral**
  "John Lennon and Yoko Ono married in 1969"

Why is NLI Important?

- Traditionally considered a **facet of many NLP tasks**
- Consider QA model answering the question
  Who is John Lennon's widow?
- Would require understanding it is **entailed** from hypothesis above

Why is NLI challenging?

- Requires a combination of **world knowledge and common sense**
  - **Q: How did we infer the contradiction above?**
- Language if often **ambiguous and evades logic operators**
  - Reconsider:
    "Yoko Ono unveiled a bronze statue for her late husband, John Lennon."
- **Q: Maybe John was late to the event so Yoko unveiled for him?**
  - Thus changing many of the labels we gave before
- NLI (and NLP in general) goes for the **most reasonable reading**
  - Compare with:
    "Yoko Ono ordered a sandwich for her late husband, John Lennon."

NLI Datasets

- **Recognizing Textual Entailment** (RTE) [3]
  - Yearly challenges
  - 1600 annotated pairs in each
  - Directly coupled with a downstream application
- **Stanford Natural Language Inference** (SNLI) [4]
  - 500K training pairs, 10K for test
  - Annotators write hypotheses on image caption premises
- **Multi-Genre NLI** (MNLI) [5]
  - 433K pairs from multiple generes (chat, literature, ...)
  - Collected similarly to SNLI
- **We'll discuss SNLI & MNLI in future lectures**

Grounding

- The next tasks we'll discuss today revolve around **Grounding**
- Mapping from **text** (or form) to a world (**ontology, or meaning**)
  - Form: *"Quick call John!"*
  - Grounding: Identify the correct John, find his number, call, etc.
- In fierce debate around LLMs
  - **Q: How is grounding and meaning defined?**
  - **Q: Are LLMs exposed only to form?**
  - **Q: If so, can they still learn meaning?** [6]

Coreference: Task Definition

An important component of language processing is knowing who is being talked about in a text.[7] [Chap. 26]

Victoria Chen, CFO of Megabucks Banking, saw *her* pay jump to $2.3 million, as *the 38-year-old* became the company's president. It is widely known that *she* came to Megabucks from rival Lotsabucks.

- **mentions** (or *coreferring expression*)
  Refer to the same entity in an extra-textual world
- **evoking mention** (or *antecedent*)
  The first mention in which the entity is identified
- *anaphoras*
  Other mentions which accesses an entity evoked elsewhere
- Other variants include **event coreference**

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- **Output:** Coreference chains (or *clusters*)
  {Victoria Chen, her, the 38-year-old, She}
  {Megabucks Banking, the company, Megabucks}
  {her pay}
  {Lotsabucks}
- The last two are termed **singletons**
- **Note that coreference doesn't link to an ontology** (only form)
  - But assumes an ontology exists?

Coreference Tasks

- **Mention detection**:
  Identifying spans of texts referring to external entities
- **Finding coreference links**:
  Forming coreference clusters from mentions

Why is coreference challenging?

- Often requires long-range dependencies
- How are *external entities* defined?
- Often ambiguous
  - The trophy didn't fit in the suitcase because **it** was too **big**
  - The trophy didn't fit in the suitcase because **it** was too **small**
- This format is known as the **Winograd Schema** [8]

Evaluating coreference is hard

- **Requires comparing & aligning two groups of clusters**
- **Many types of errors**
  - Missing entities, missing mentions, different spans
- Compare gold:
  {Victoria Chen; her; *the* 38-year-old; She}
  {<u>Megabucks Banking</u>; *the* company; Megabucks}
- ... with predicted:
  {Victoria Chen, *CFO of Megabucks Banking*; her; 38-year-old; She}
  {company; Megabucks}

Coreference Evaluation Metrics

- **Many metrics measuring different aspects of coreference**
  - Most popular are MUC, B^3, CEAF
  - Common practice is to report their average
- **MUC: Definition**
  - Let R - reference clusters, H - predicted hypothesis
  - MUC precision: $\frac{\#\text{common links}}{\#\text{links in } H}$
  - MUC recall: $\frac{\#\text{common links}}{\#\text{links in } R}$
  - A *link* is any (unordered) pair of mentions in the same cluster
- **Q: What does MUC miss?**
  - No reward for slight errors in spans
  - Doesn't reward (or punish) singletons

Coreference Datasets

- **Ontonotes** [9]
  - About 1M words in English and 1M words in Chinese
  - Newswire, web data and conversational speech
- **Quoref** [10]
  - Annotates coreference through QA
  - 24K questions over Wikipedia

Byzantines were avid players of tavli (Byzantine Greek: τάβλη), a game known in English as backgammon, which is still popular in former Byzantine realms, and still known by the name tavli in Greece. Byzantine nobles were devoted to horsemanship, particularly ***tzykanion***, now known as *polo*. The game came from Sassanid Persia in the early period and a Tzykanisterion (stadium for playing *the game*) was built by Theodosius II (r. 408–450) inside the Great Palace of Constantinople. Emperor Basil I (r. 867–886) excelled at **it**; Emperor Alexander (r. 912–913) died from exhaustion while playing, Emperor Alexios I Komnenos (r. 1081–1118) was injured while playing with Tatikios, and John I of Trebizond (r. 1235–1238) died from a fatal injury during a game. Aside from Constantinople and Trebizond, other Byzantine cities also featured tzykanisteria, most notably Sparta, Ephesus, and Athens, an indication of a thriving urban aristocracy.

Q1. What is the Byzantine name of the game that Emperor Basil I excelled at? **it → tzykanion**
Q2. What are the names of the sport that is played in a Tzykanisterion? *the game → tzykanion; polo*
Q3. What cities had tzykanisteria? cities → Constantinople; Trebizond; Sparta; Ephesus; Athens

Coreference: Annotation

- Traditionally requires **highly-experienced annotators**
  - Dozens of pages of annotation guidelines
- QA annotation (e.g., Quoref) **eases annotation difficulty**
  - At the cost of exhaustiveness, inter-annotator agreement

Coreference Variants

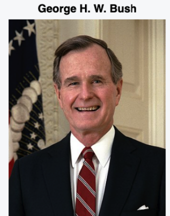
- **Multi-document coreference**
  - Annotates entity mentions across different documents
  - E.g., news reports of the same events
- **Event coreference**
  - Annotates mentions of events rather than entities
  - E.g., *The Great War*; *World War I*; *WWI*

Entity Linking: Task Definition

Entity linking is the task of associating a mention in text with the representation of some real-world entity in an ontology.[11, 7] [Chap. 14.3]

George Bush reveals how he repeatedly turned to **his father** for advice as he contemplated following him into war against Saddam Hussein.

- Requires a representation of an extra-textual world (often Wikipedia)
  - Assigns a Wikipedia page to each entity mention
  - This is sometimes called **Wikification** [12]



Why is entity linking challenging?

- A mention span may be ambiguous with respect to the ontology
  - Consider the George Bush example
- Requires world knowledge corresponding to the reference ontology

Other Ontologies

- **Medical**
    - E.g., SNOMED [13], NCBI
    - Ontology of e.g., drugs, symptoms, adverse reactions
- **Knowledge graphs**
    - E.g., Freebase [14], Wikidata [15], YAGO [16]
    - Represent entities in the world as well as events and relations

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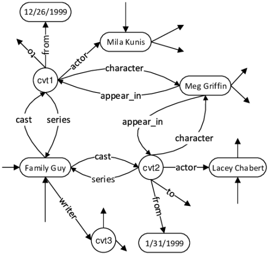

Entity Linking: Datasets & Annotation

- **Entity linking as Question Answering** [17]
- **AIDA CoNLL-YAGO** [18]
  - News texts mapped to YAGO & DBPedia
- **CADEC** [19]
  - Blog posts mapped to a medical ontology (SNOMED)

Grounding: Connecting Coreference and Entity Linking

- **Coreference + entity linking** assigns an entity per cluster
- **Facilitates agents interacting in the world**

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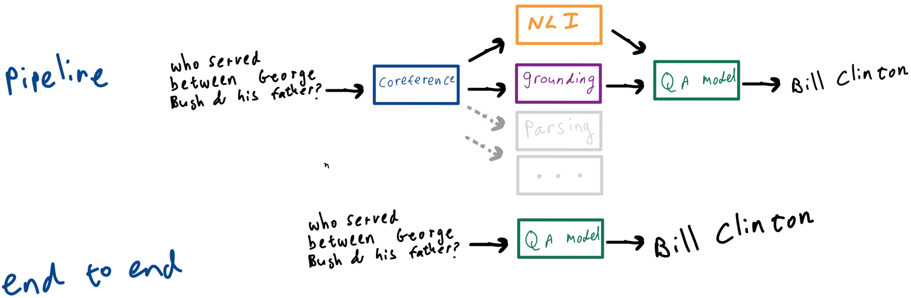
- {Victoria Song, her, the 38-year-old, She}

Pipeline vs. End-to-End Approaches

- **E2E models do not require intermediate task labels**
- **NLP has shifted almost entirely to E2E approaches**
  - Trained on input and outputs w/o intermediate labels



How does E2E learning intrinsic tasks?

- They observe intrinsic phenomena from **downstream examples**
  - E.g., coreference in enough relevant parallel data
- The data is rich enough $\Rightarrow$ they'll learn the required intrinsic tasks
- This is often tested with **probing**
  - More on this later in the course

- **Q: Do large language models observe only form?**
  - An open research question

- **For example, in entity linking, they may observe**
  - George Bush Senior *link-to-wiki-page*

  - **Effectively training LLM with entity linking labels**

So we don't need intrinsic tasks?

- The set of intrinsic tasks is **arbitrary and incomplete**
- **Q: Can we enumerate all subtasks required for e.g. MT?**
- E2E models improve **without additional supervision**

Then why should we still study intrinsic tasks?

- **Integrating intrinsic signal into models can alleviate biases**
  - E2E models often sidestep intrinsic tasks with shortcuts
  - E.g., gender bias in coreference resolution [20]
  - More on this later
- **Using intrinsic tasks to evaluate E2E model performance**
  - To understand their boundaries and bottlenecks
- **E2E learning of complex phenomena may not be data efficient**

  $\Rightarrow$ Not applicable for low-resource domains and languages

  $\Rightarrow$ Wasteful in terms of compute

Conclusion

- **Extrinsic tasks are readily useful for end users**
  - E.g., Machine translation, summarization, information extraction
- **Intrinsic tasks are needed for many extrinsic tasks**
  - Aren't useful on their own
- We discussed **grounding**
  - Maps text (form) and extra-textual entities (ontology)
  - E.g., database entries such as Wikipedia
- **QA is an intuitive annotation paradigm**
  - Project idea: extend to other tasks
- Originally motivated by a **pipeline approach**
- Recently for **interpretability & mitigating biases**

Next Week

Extrinsic tasks!

Which you can also think about for inspiration for your project!

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