

Advanced Language Processing Winter School 2021

17–22 January 2021, Grenoble, France



Schedule

- Seven Zoom Q&A sessions with pre-recorded lectures by [the speakers](#).
- Three [student poster sessions](#).
- Two Slack lab sessions.
- A Zoom social session, playing [Codenames](#) by [Vladimír Chvátíl](#) (FI alumnus).

Outline

1. [Kyunghyun Cho](#): Language Modeling (Lecture [[1](#), [2](#), [3](#)], [Lab](#), [Q&A](#))
2. [Claire Gardent](#): Natural Language Generation ([Lecture](#), [Q&A](#))
3. [Laurent Besacier](#): Self-Supervised Learning from Speech ([Lecture](#), [Q&A](#))
4. [Yejin Choi](#): Neuro-Symbolic Common-Sense Knowledge (Lec. [[1](#), [2](#)], [Q&A](#))
5. [Grzegorz Chrupała](#): Visually-Grounded Models of Speech ([Lecture](#), [Q&A](#))
6. [Tim Baldwin](#): NLP for User-Generated Content ([Lecture](#), [Q&A](#))
7. [Isabelle Augenstein](#): Explainability for NLP ([Lecture](#), [Lab](#), [Q&A](#))
8. [Poster sessions](#)

Cho: Language Modeling and Machine Translation

- Cho is one of the authors of the Attention mechanism. ([Bahdanau et al, 2016](#))
- Lecture introduces N-gram language models and motivates neural models:
 - N-gram language models suffer from data sparsity (traditional solutions: smoothing, backoff).
 - N-gram language models can't capture long-term dependencies (no traditional solutions).
- For language modeling, lecture develops CBOW and RNNs (LSTM, GRU).
- For machine translation, lecture develops LSTM+Attention and Transformers.
- Lab shows how CBOW, recurrent models, LSTM+Attention, and Transformers can be implemented and used for language modeling & machine translation.

Choi: Neuro-Symbolic Common-Sense Reasoning

- In the lecture, Choi frames common-sense reasoning as language generation:
 - [Kahnemann \(2003\)](#) argues intuitive reasoning is part of System 1, evoked by language.
 - [Hofstadter and Sander \(2013\)](#): “categories [...] outnumber words, require [...] text descriptions.”
- Several works by Choi et al. are introduced:
 - Unsupervised inference-time algorithms:
 - i. Reasoning through neural backpropagation ([Qin et al., 2020](#))
 - ii. Reasoning through search with logical constraints ([Lu et al., 2020](#))
 - iii. Reasoning through distributional neural imagination ([West et al., 2020](#))
 - Supervised knowledge modeling algorithms:
 - i. Neural and symbolic common-sense knowledge ([Hwang et al., 2020](#))
 - ii. Visually grounded common-sense knowledge ([Park et al., 2020](#))
 - iii. Social, ethical, and moral norms ([Forbes et al., 2020](#))
- Common-sense challenges by Choi et al. are introduced:
 - Physical/Social IQA, Visual/Abductive Cms. Reasoning, [HellaSwag](#), [WinoGrande](#), CosmosQA

Chrupała: Visually-Grounded Models of Speech

- In the lecture, Chrupała motivates visually-grounded modeling of speech:
 - Additional modality helps solve the lack of annotated data for most spoken languages.
- Existing datasets for visually-grounded modeling of speech are introduced:
 - [MIT Flickr Audio Caption Corpus](#) – 8K Flickr images with ~48 hours of spoken captions
 - [Places Audio Captions](#) – 100K images w/ spoken descriptions in English/Hindi (w/o captions)
 - [Synthetically Spoken COCO](#), [SPEECH COCO](#) – 300K images w/ synthesized spoken captions
- Existing works on visually-grounded modeling of speech are introduced:
 - Cross-Channel Early Linguistic Learning ([Roy and Pentland, 2002](#))
 - Deep Multimodal Semantic Embeddings for Speech and Images ([Harwath and Glass, 2015](#))
 - Unsupervised Learning of Spoken Language with Visual Context ([Harwath et al., 2016](#))
 - Representations of Language in a Model of Visually Grounded Speech ([Chrupała et al., 2017](#))
 - Language Learning Using Speech to Image Retrieval ([Merks et al., 2019](#))
- Analyses of visually grounded model representations are discussed:
 - Bottom layers encode phonemes (form), top layers encode meaning. ([Chrupała et al., 2020](#))

Augenstein: Explainability for Natural Lang. Proc.

- In the lecture, Augenstein motivates and defines explainability:
 - **Decision Understanding** – How does the model arrive at predictions for specific instances?
 - **Model Understanding** – What features and parameters has a model learnt?
- Several works of Augenstein et al. about explainability are introduced:
 - Decision Understanding:
 - i. Generating Fact Checking Explanations ([Atanasova et al., 2020](#))
 - ii. A Diagnostic Study of Expl. Techniques for Text Classification ([Atanasova et al., 2020](#))
 - Model Understanding:
 - i. Generating Label-Cohesive and Well-Formed Advers. Claims ([Atanasova et al., 2020](#))
 - ii. TX-Ray: Quantifying & Explaining Model-Knowledge Transfer in (Un-)Supervised Natural Language Processing ([Rethmeier et al., 2020](#))
- Post-hoc **explainability methods** and **evaluation measures** are introduced:
 - Gradient-based, Perturbation-based, Simplification-based (see also [the interpretability book](#))
 - Agreement with Human, Confidence Indication, Faithfulness, Rationale/Dataset Consistency