Indirect Supervision from Natural Language Inference
Indirectly Supervised Natural Language Processing (Part I)

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Textual Entailment (Dagan et al., 2006)

Textual entailment, a unified inference framework for NLP
- zero-shot text classification (Yin et al., 2019)
- summarization (Falke et al., 2019)
- QA & Coreference (Yin et al., 2020)
- relation extraction (Xia et al., 2021)
- entity typing (Li et al., 2022)
- ...

Premise entail ? Hypothesis
Textual Entailment (Dagan et al., 2006)

Textual entailment, a unified inference framework for NLP
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- …

“Textual Entailment” was referred to as “Natural Language Inference (NLI)” (Bowman et al., 2015)
Example task: Text Classification

health

anger

news

sad

...
Example task: Text Classification

Humans implicitly build a hypothesis then infer its truth value.

Is the person writing this angry?

My car was smashed last night.
Example task: Text Classification

My car was smashed last night.

The person is angry.

The person is not angry.

The classification problem is inference (text \(\rightarrow\) hypothesis)
The road to Grandpa’s house was long and winding. [...] Finally, Jimmy arrived at Grandpa’s house and knocked. Grandpa answered the door with a smile and welcomed Jimmy inside. They sat leisurely by the fire and talked about the insects. They watched the lightning bugs light up as night came.

Where do Jimmy and his Grandpa sit?
A) On insects
B) Outside
C) By the fire
D) On the path
The road to Grandpa’s house was long and winding. [...] Finally, Jimmy arrived at Grandpa’s house and knocked. Grandpa answered the door with a smile and welcomed Jimmy inside. They sat leisurely by the fire and talked about the insects. They watched the lightning bugs light up as night came.

Where do Jimmy and his Grandpa sit?

A) On insects
B) Outside
C) By the fire
D) On the path

Because “by the fire” and “sat” co-occur in the same sentence? NO!
The road to Grandpa’s house was long and winding. [...] Finally, Jimmy arrived at Grandpa’s house and knocked. **Grandpa answered the door with a smile and welcomed Jimmy inside.** They sat leisurely **by the fire and talked about the insects.** They watched the lightning bugs light up as night came.

Where do Jimmy and his Grandpa sit?

A) On insects
B) Outside
C) **By the fire**
D) On the path

“Jimmy and his Grandpa sit by the fire”
The road to Grandpa’s house was long and winding. [...] Finally, Jimmy arrived at Grandpa’s house and knocked. Grandpa answered the door with a smile and welcomed Jimmy inside. They sat leisurely by the fire and talked about the insects. They watched the lightning bugs light up as night came.

Where do Jimmy and his Grandpa sit?
A) On insects
B) Outside
C) By the fire
D) On the path

**Example task: Question Answering (QA)**

**QA is inference (text → hypothesis)**
Example task: Coreference Resolution

The **troph**y would not fit in the brown **suit**case because it was too big.
Example task: Coreference Resolution

The trophy would not fit in the brown suitcase because it was too big.

➔ The trophy would not fit in the brown suitcase because trophy was too big. (True)

➔ The trophy would not fit in the brown suitcase because suitcase was too big. (False)

Coreference resolution is inference (text → hypothesis)
Why and when to convert NLP to NLI?

**Task:** conference resolution

**Dataset:** GAP (Webster et al., 2018)

*Universal Natural Language Processing with Limited Annotations: Try Few-shot Textual Entailment as a Start* (Yin et al., EMNLP’2020)
Why and when to convert NLP to NLI?

**Task:** conference resolution  
**Dataset:** GAP (Webster et al., 2018)

When an NLP task has rich annotations: classical classifiers $\approx$ NLI
Why and when to convert NLP to NLI?

**Task**: conference resolution

**Dataset**: GAP (Webster et al., 2018)

In reality, what we truly care about is "limited annotation"

- Both standard classifiers and NLI exhibit poor performance.
- NLI performs even worse because NLI is generally a more challenging task when the availability of labeled examples is severely limited.

*Universal Natural Language Processing with Limited Annotations: Try Few-shot Textual Entailment as a Start* (Yin et al., EMNLP’2020)
Why and when to convert NLP to NLI?

- The main strength of NLI is **NOT** its pairwise modeling architecture.
- Our central interest lies in its potential to **utilize NLI datasets to supervise different target tasks**, i.e., “Indirect Supervision”

**Task**: conference resolution  
**Dataset**: GAP (Webster et al., 2018)

*Universal Natural Language Processing with Limited Annotations: Try Few-shot Textual Entailment as a Start* (Yin et al., EMNLP’2020)
NLI-based indirect supervision: outline

- Implementation & Applications
- Benefits
- Challenges & Solutions
NLI-based indirect supervision: outline

- Implementation & Applications
- Benefits
- Challenges & Solutions
The plague in Mongolia, occurring last week, has caused more than a thousand isolation

"topic" aspect

health, finance, politics, sports, etc.

"emotion" aspect

anger, joy, sadness, fear etc.

"situation" aspect

shelter, water, medical assistance, etc.

more possible labels

news, serious etc.
How do conventional classifiers work

input text
How do conventional classifiers work

health → 0
finance → 1
politics → 2
sports → 3
... → ...
education → N-1

input text
How do conventional classifiers work

input text
How do conventional classifiers work

real labels are converted into indices; label semantics are missing
Issues of conventional classifiers

1) needs a large number of labeled examples to learn existing types
Issues of conventional classifiers

1) needs a large number of labeled examples to learn existing types
2) cannot generalize to new types
The conventional approach is inapplicable to low-annotation text classification—we need indirect supervision.
NLI for zero-shot text classification

Zero-shot text classification

Natural language inference

My car was smashed last night.

(0) health
(1) anger
(2) accident
(3) crime
...

(Yin et al., 2019; Xia et al., 2021, Xu et al., 2022, etc)
This text expresses anger.

**Zero-shot text classification**

- **Premise**: My car was smashed last night.
- **Hypothesis**: This text expresses anger.

**Categories**:

0: (health)
1: (anger)
2: (accident)
3: (crime)
...

*(Yin et al., 2019; Xia et al., 2021, Xu et al., 2022, etc)*
Zero-shot text classification

Premise

My car was smashed last night.

Hypothesis

This text expresses anger.

This text is about accident.

(Yin et al., 2019; Xia et al., 2021, Xu et al., 2022, etc)
Zero-shot text classification

Premise

My car was smashed last night.

Hypothesis

This text expresses **anger**.

This text is about **accident**.

We can keep the original label strings, or use other related words — **label verbalizer** (Schick and Schütze, 2020)
NLI datasets:
- MNLI (Williams et al., 2018)
- ANLI (Nie et al., 2020)
- SNLI (Bowman et al., 2015)
- DocNLI (Yin et al., 2021)
- SciTail (Khot et al., 2018)
- RTE (Dagan et al. 2005)
- …

PLMs:
- BERT, RoBERTa, T5, etc.

Training pairs
- are from the NLI datasets;
- are not specific to any target labels

(Yin et al., 2019; Xia et al., 2021, Xu et al., 2022, etc)
NLI system — finetuning (optional)

PLMs:
- pretrained NLI model

Training pairs
- are from the target task (if available);
  - topic classification (Yin et al., 2019)
  - multi-choice QA and coreference (Yin et al., 2020)
  - intent identification (Xia et al., 2021)
  - stance detection (Xu et al., 2022)
  - ultra-fine entity typing (Li et al., 2022)
  - event argument extraction (Sainz et al., 2022)
  - (biomedical) relation extraction (Sainz et al., 2021; Xu et al., 2023)
- are in the NLI format
Ultra-fine entity typing (Li et al., TACL 2022)
NLI can handle zero-shot & few-shot
Performance

Ultra-fine entity typing (Li et al., TACL 2022). NLI can handle zero-shot & few-shot.

Zero-shot text classification (Yin et al., EMNLP 2019). One NLI system can handle various zero-shot tasks.
NLI-based indirect supervision: outline

- Implementation & Applications
- Benefits
- Challenges & Solutions
Indirect supervision from NLI: benefits

- Reduce task-specific annotation requirements and address few-shot and zero-shot scenarios in a unified approach.

(Li et al., TACL 2022)
Indirect supervision from NLI: benefits

- Reduce task-specific annotation requirements and address few-shot and zero-shot scenarios in a unified approach.

- Facilitate cross-task transferability, encompassing not only NLI to target tasks but also task A to task B.

<table>
<thead>
<tr>
<th>original task</th>
<th>domain</th>
<th>premise length</th>
<th>hypothesis length</th>
</tr>
</thead>
<tbody>
<tr>
<td>ANLI</td>
<td>NLI</td>
<td>various wiki, news, etc.)</td>
<td>multi-sentence (20~94 words)</td>
</tr>
<tr>
<td>SQuAD</td>
<td>QA</td>
<td>wiki</td>
<td>paragraph (27~237 words)</td>
</tr>
<tr>
<td>DUC (2001)</td>
<td>summarization</td>
<td>news</td>
<td>doc. (124~879 words)</td>
</tr>
<tr>
<td>CNN/Daily Mail</td>
<td>summarization</td>
<td>news</td>
<td>doc. (247~652 words)</td>
</tr>
<tr>
<td>Curation</td>
<td>summarization</td>
<td>news</td>
<td>doc. (229~842 words)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>FEVER</th>
<th>MCTest</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>binary</td>
<td>v160</td>
</tr>
<tr>
<td>random</td>
<td>50.00</td>
<td>25.00</td>
</tr>
<tr>
<td>MNLI</td>
<td>86.64</td>
<td>75.41</td>
</tr>
<tr>
<td>ANLI</td>
<td>87.51</td>
<td>82.50</td>
</tr>
<tr>
<td>DocNLI +finetune</td>
<td>89.44</td>
<td>90.83</td>
</tr>
</tbody>
</table>

Prior state-of-the-art – 80.00 75.50

DocNLI (Yin et al., 2021) converted QA, summarization tasks as NLI-style source tasks. DocNLI generalizes to distinct target tasks.
Indirect supervision from NLI: benefits

- Reduce task-specific annotation requirements and address few-shot and zero-shot scenarios in a unified approach.
- Facilitate cross-task transferability, encompassing not only NLI to target tasks but also task A to task B.
- Enhance the feasibility and potential of employing smaller PLMs.

“OpenStance: Real-world Zero-shot Stance Detection” (Xu et al., CoNLL’22)

- Zero-shot
- RoBERTa (355M) + weak&NLI > GPT-3 (175B)
Indirect supervision from NLI: benefits

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- Facilitate cross-task transferability, encompassing not only NLI to target tasks but also task A to task B.
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“ZARA: Improving Few-Shot Self-Rationalization for Small Language Models” (Chen et al., 2023)

- Few-shot
- NLI helps automatic data generation
- T5 (base)+NLI (2M) ≈ InstructGPT (175B)
- T5 (large)+NLI (7M) > InstructGPT (175B)
- T5 (3B)+NLI (2.7B) > InstructGPT (175B)
NLI-based indirect supervision: outline

- Implementation & Applications
- Benefits
- Challenges & Solutions

NLI
Challenge #1: domain discrepancy

Domains of the target problems (T) often differ from that of NLI datasets (S)

Traditional solution: pretrain on S + fine-tune on T (i.e., STILTS (Phang et al., 2018))
Challenge #1: domain discrepancy

Domains of the target problems (T) often differ from that of NLI datasets (S)

*Traditional solution:* pretrain on S + finetune on T (i.e., STILTS (Phang et al., 2018))

Solution I:

- T is few-shot → imitate few-shot learning on S (*meta-learning*)
- Novel strategy: predictions on T (or S) depend on the signals of both T and S
- A solution from the *algorithm* perspective

*Universal Natural Language Processing with Limited Annotations: Try Few-shot Textual Entailment as a Start* (Yin et al., EMNLP 2020)
Challenge #1: domain discrepancy

Domains of the target problems (T) often differ from that of NLI datasets (S)

Traditional solution: pretrain on S + finetune on T (i.e., STILTS (Phang et al., 2018))

Solution II:

- Human annotations: correctness ✅, diversity ❌
- PLMs: creative writing
- Use GPT-3 to generate new examples for reasoning patterns that are challenging
- A solution from the data perspective

WANLI: Worker and AI Collaboration for Natural Language Inference Dataset Creation (Liu et al., Findings of EMNLP 2022)
Each input needs to infer a large number of output-specific hypotheses

- Ultra-fine entity typing (Choi et al. 2018): 10K labels take the NLI model (Li et al., 2022) **35 seconds for each test instance** and about **19.4 hours to infer the entire test set.**
Challenge #2: inefficiency in testing

Each input needs to infer a large number of output-specific hypotheses

- Ultra-fine entity typing (Choi et al. 2018): 10K labels take the NLI model (Li et al., 2022) 35 seconds for each test instance and about 19.4 hours to infer the entire test set.

Solution:

- Pairwise inference → group-wise inference
- Assumption: hypotheses exhibit a binary polarity irrespective of their competitors.

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Learning to Select from Multiple Options (Du et al., AAAI’23)
Recall, Expand and Multi-Candidate Cross-Encode: Fast and Accurate Ultra-Fine Entity Typing (Jiang et al., Arxiv, 2022)
Challenge #2: inefficiency in testing

Each input needs to infer a large number of output-specific hypotheses

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Solution:

- Pairwise inference → group-wise inference

- 15 seconds → 0.02 seconds (per example)

Learning to Select from Multiple Options (Du et al., AAAI’23)
Recall, Expand and Multi-Candidate Cross-Encode: Fast and Accurate Ultra-Fine Entity Typing (Jiang et al., Arxiv, 2022)
Challenge #3: cannot discover new labels

- We often pre-define the label set for classification tasks.
- At times, we may want the model to generate some new labels for the input to “surprise” us.
Challenge #3: cannot discover new labels

- We often pre-define the label set for classification tasks
- At times, we may want the model to generate some new labels for the input to “surprise” us

Will be addressed by the next section of our tutorial
Recap of indirect supervision from NLI

Implementation & Applications
- NLI
- Topic classification
- Coref. resolution
- QA
- Entity typing
- Relation Extraction
- Event argument extraction

Benefits
- Scarce-annotation NLP
- Cross-task transferability
- Maximize the potential of small PLMs

Challenges & Solutions
- Domain discrepancy (solutions by algorithm and data threads)
- Inefficiency in testing (parallel-NLI)
- cannot discover new labels (next chapter…)

Sentences:
- Implementation & Applications
- Benefits
- Challenges & Solutions
Recap of indirect supervision from NLI

Implementation & Applications

- Topic classification
- Entity typing
- Relation extraction
- Coref. resolution
- Event argument extraction
- QA

Benefits

- Scarce-annotation NLP
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Challenges & Solutions

- Domain discrepancy (solutions by algorithm and data threads)
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- Cannot discover new labels (next chapter...)

Thank You