# GNMT
# vs
# Ontology-based DNN Machine Translation

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# Introduction & Motivation

## *Ontology and Neural Networks in Machine Translation*

- Main goal: Explore how ontologies can enhance neural machine translation (NMT).
- Primary sources
  - *Wu et al., 2016* – Google's NMT system
  - *Tian et al., 2021* – Ontology-based DNN translation framework
- Importance
  - MT still struggles with semantics, context, and domain adaptation
  - Ontologies encode structured semantic knowledge → potential synergy with NMT

# First paper
## *Google NMT (Wu et al., 2016)*

- Architecture: 8-layer encoder–decoder with attention (residual connections in deeper layers); trained end-to-end on parallel corpora.
- Highlights
  - Wordpiece modeling (handles rare words)
  - Layer-normalized LSTMs
  - Multilingual zero-shot translation
- Impact
  - Major BLEU improvements on WMT benchmarks (En→Fr, En→De); established neural MT dominance
- Limitations
  - Data-driven → lacks explicit semantic grounding or world knowledge

**Example 3: Sentence with a variation of a known word**

Sentence: ***"The quickness of the brown fox surprised the lazy dog"***

Tokenization: ['the', 'qu', '<h>ick', '<h>ness', 'of', 'the', 'brown', 'fox', '[UNK]', 'the', 'lazy', 'dog']

Table 10: Mean of side-by-side scores on production data

| | PBMT | GNMT | Human | Relative Improvement |
|---|---|---|---|---|
| English → Spanish | 4.885 | 5.428 | 5.504 | 87% |
| English → French | 4.932 | 5.295 | 5.496 | 64% |
| English → Chinese | 4.035 | 4.594 | 4.987 | 58% |
| Spanish → English | 4.872 | 5.187 | 5.372 | 63% |
| French → English | 5.046 | 5.343 | 5.404 | 83% |
| Chinese → English | 3.694 | 4.263 | 4.636 | 60% |

# Second paper

## *Ontology-Based DNN MT (Tian et al., 2021)*

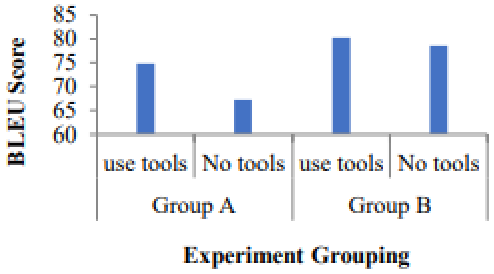
- Idea: Integrate ontology (domain knowledge model) into DNN translation.
- Highlights
  - Knowledge management + translation + user interface subsystems
  - Use of ontology as a domain knowledge source
    - case library / case pattern library component that matches input sentences to stored patterns (example patterns) as part of the translation pipeline
    - a hybrid of rule/pattern matching + neural components
  - Uses GRU/LSTM + attention within translation subsystem
  - Complex overall structure
    - (part-of-speech tagging, lexical analyzer, pattern matching) + prototype
- Evaluation (English-Chinese experiments)
  - Performance of human translators when using/not using the tool
  - Junior translators: translation time −34 %, BLEU +7.59
  - Senior translators: time −11 %, BLEU +1.67
- Conclusion
  - Ontology support mainly helps less-experienced translators

| Translator Number | Translation time | BLEU score |
|---|---|---|
| A-1 | 1:02:30 | 88.40 |
| A-2 | 0:50:30 | 77.90 |
| A-3 | 0:30:09 | 67.70 |
| A-4 | 0:54:32 | 76.90 |
| A-5 | 0:52:40 | 71.40 |

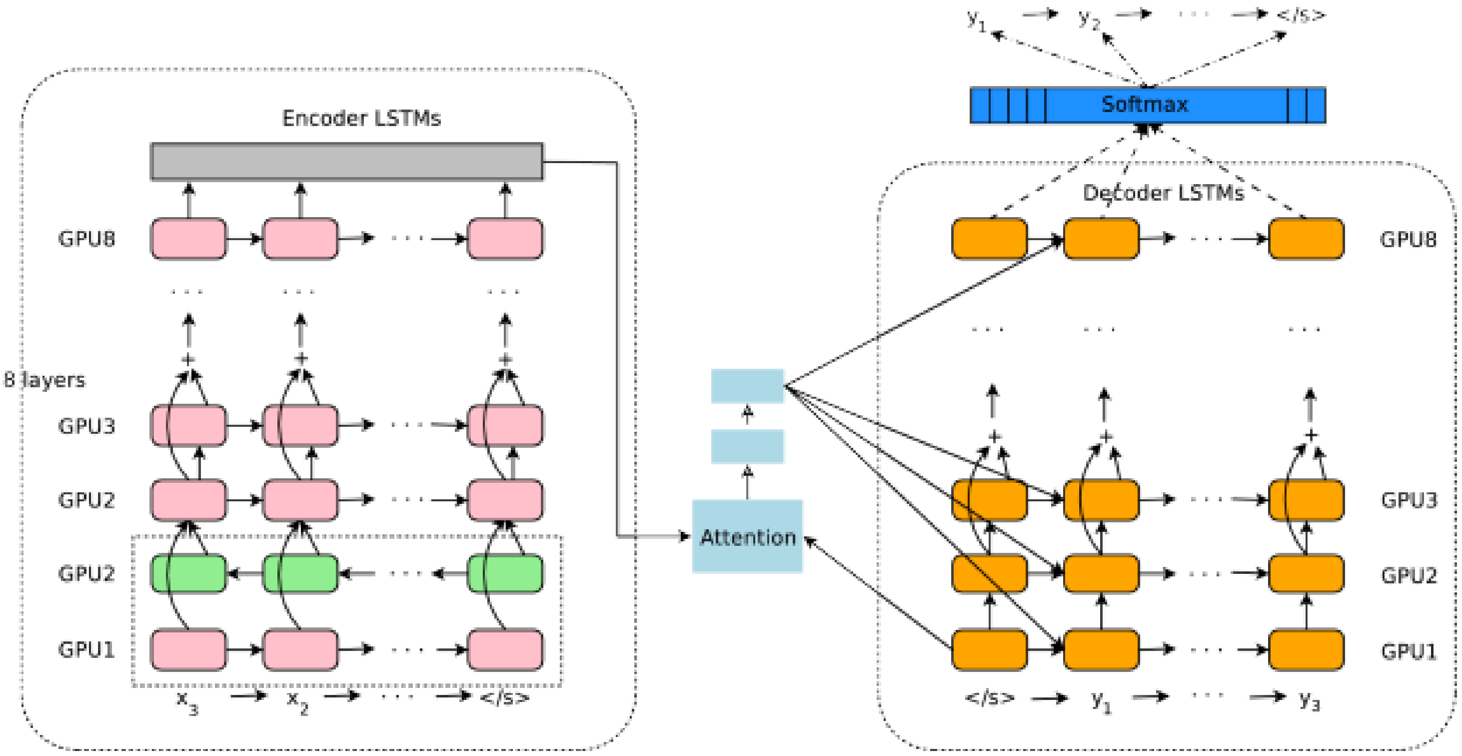
Table 2: Experimental results of tools used by junior translators.

| Translator Number | Translation time | BLEU score |
|---|---|---|
| A-11 | 0:59:15 | 50.05 |
| A-12 | 1:20:10 | 74.00 |
| A-13 | 0:49:05 | 69.20 |
| A-14 | 1:05:53 | 70.90 |
| A-15 | 1:30:26 | 72.90 |

Table 3: Experimental results of junior translators not using tools.



# System design (GNMT)



# System design (Ontology-based NMT)

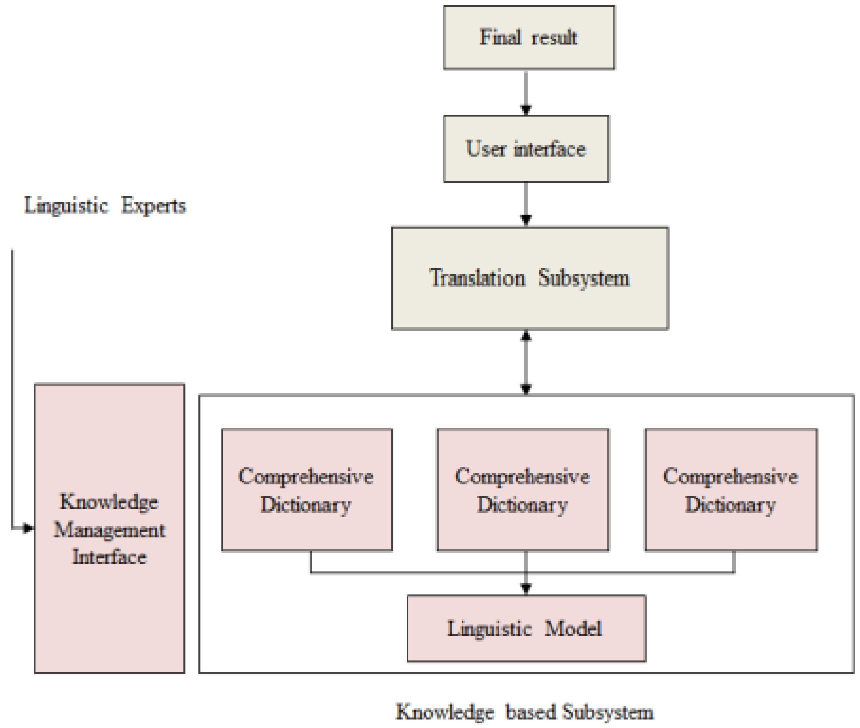



Figure 3: The overall structure of the system.

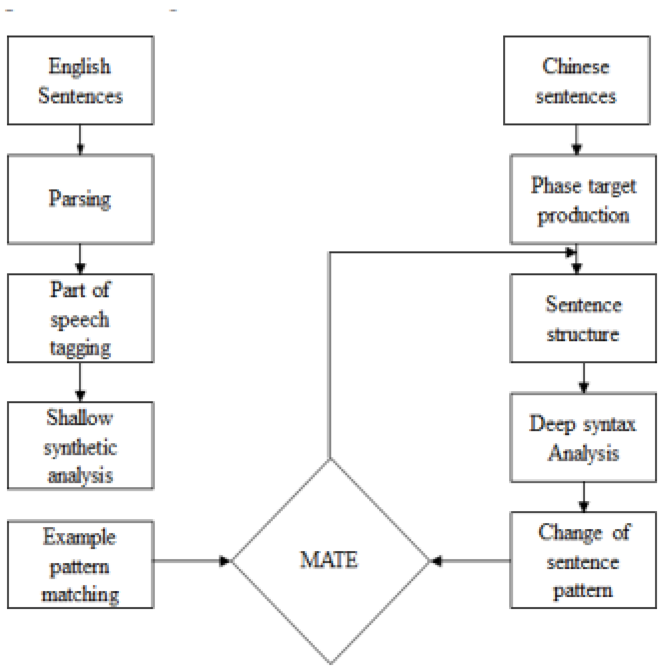



Figure 4: System translation process structure.

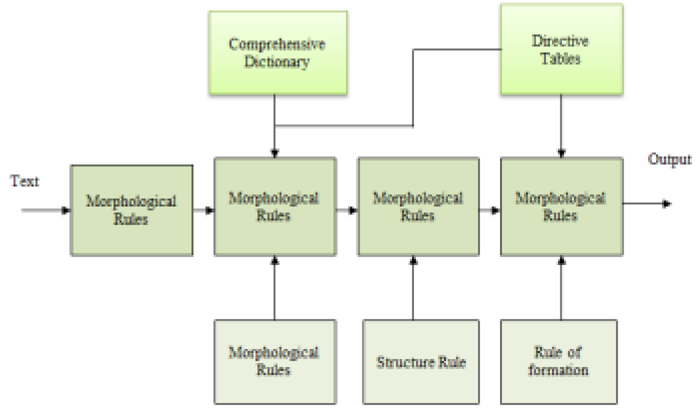



Figure 5: The structural model of the lexical analyzer.

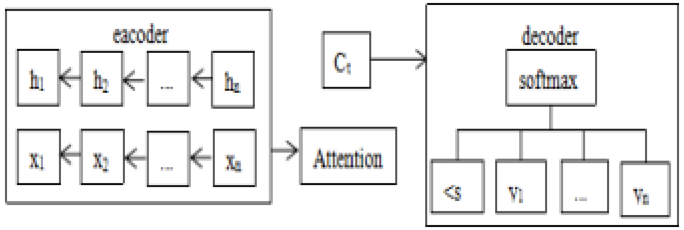



Figure 2: The structure of neural network machine translation.

# Comparison & Discussion

| | GNMT | Ontology-based DNN MT |
|---|---|---|
| Focus | Large-scale neural translation | Ontology-guided semantic translation |
| Knowledge used | Implicit, learned from data | Explicit ontology concepts |
| Architecture | Encoder-decoder with attention | Hybrid DNN + rule/ontology |
| Evaluation | BLEU on WMT datasets | BLEU/time with human translators |
| Key strength | Fluency, scalability | Semantic accuracy, knowledge integration |

Ontologies could address GNMT's semantic limitations by providing interpretable domain knowledge

# Project proposal

- Objective: Study ontology-enhanced NMT → prototype small-scale example
- Planned tasks:
  - Build a *mini ontology* for a narrow domain
    - Ontology: ΑΜΑΛΘΕΙΑ , FoodOn
    - Corpus: Open Parallel Corpus (OPUS)
  - Implement a simple encoder–decoder model integrating ontology constraints or pre-processing
  - Evaluate translation quality vs baseline (BLEU/time)
- Challenges:
  - Ontology alignment & representation integration with neural embeddings
  - Dataset availability & semantic consistency

# Thank you!