

# Adopting Description Logics to NLP: Towards the Formal Semantics of the Natural Language

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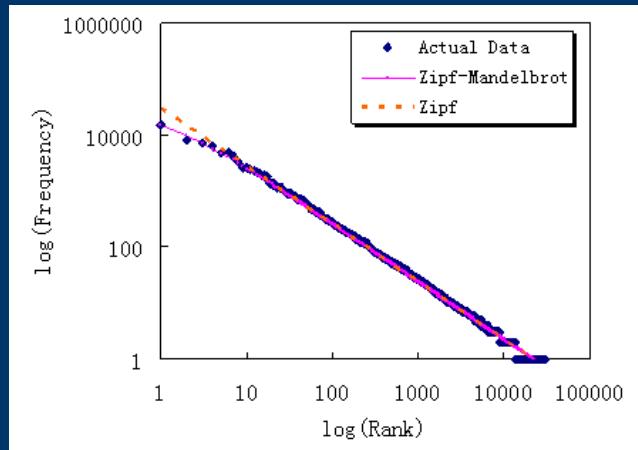
# What is Natural Language Processing(NLP)?

Teaching Natural Language to Computers

- NLP : Teaching computers to understand language
  - Humans can understand natural language easily
  - However, computers are not...
- Major Difficulties in NLP
  - Vague objective : What is the *Semantic* of natural language?
  - Data sparsity : Zipf's Law

# What is Natural Language Processing(NLP)?

Zipf's Law : Sparsity of the Natural Language



The distribution of word frequencies in the novel "Ulysses"

→ Most words are very 'Rare'!!

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# Meaning Representation(MR) of Natural Language

Two Major Paradigms

- Why MR?
  - A computable, standardized representation of natural language
  - "Believed" to carry semantics of natural language
- Two Major Approaches
  - Symbolic Representation Approach
  - Vector Representation Approach

# MR of Natural Language: The Symbolic Approach

## Symbolic Approach

- Symbolic MR
  - Adopting meta-language for Semantic Representation
  - Usually First-Order Logic, Lambda-Calculus Style
  - ex) Aristotle is a human → *Aristotle* ⊑ *human*
- Pros & Cons
  - Pros : Human-readable
  - Cons : Difficulty in sparsity handling / verification

## Cons of Symbolic MR

Why does sparsity matter?

- Consider following three sentences;

1. Aristotle is a male.
2. Aristotle is a man.
3. Man is mortal.



Aristotle

male

man

mortal

## Cons of Symbolic MR

Why does sparsity matter?

Aristotle is a male.

male



Aristotle

*Aristotle ⊆ male*

## Cons of Symbolic MR

Why does sparsity matter?

Aristotle is a male.

male



Aristotle

*Aristotle ⊆ male*

Aristotle is a man.

man



Aristotle

*Aristotle ⊆ man*

## Cons of Symbolic MR

Why does sparsity matter?

Aristotle is a **male**.

male



Aristotle

*Aristotle ⊆ male*

Aristotle is a **man**.

man



Aristotle

*Aristotle ⊆ man*

## Cons of Symbolic MR

Why does sparsity matter?

Aristotle is a **male**.

male



Aristotle

*Aristotle*  $\subseteq$  **male**

Aristotle is a **man**.  
**Man** is **mortal**.

man



Aristotle

*Aristotle*  $\subseteq$  **man**

mortal

**man**  $\subseteq$  **mortal**

## Cons of Symbolic MR

Why does sparsity matter?

mortal

male ~ man



Aristotle

## Cons of Symbolic MR

Why does sparsity matter?

Aristotle is a **male**.

**Man** is **mortal**.

male



Aristotle

*Aristotle*  $\subseteq$  **male**

man

**mortal**

# MR of Natural Language: The Deep-Learning Approach

## Deep Learning Approach

- Vector as MR
  - Extract abstract features automatically from text data
- Vector of Features
  - Example: Big Five Personality Trait Test
  - Express personality as 5-dimension vectors

Openness to experience	.....	79 out of 100
Agreeableness	.....	75 out of 100
Conscientiousness	.....	42 out of 100
Negative emotionality	.....	50 out of 100
Extraversion	.....	58 out of 100

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## MR of Natural Language: The Deep-Learning Approach

Very Quick Introduction to word2vec

- How do we represent a word as a vector?
  - *"You shall know a word by the company it keeps"* - J.R.Firth
- Word2vec Scheme
  - Express word as a vector
  - Train the vector to contain semantics of each word

# MR of Natural Language: The Deep-Learning Approach

Very Quick Introduction to word2vec

input/feature #1

input/feature #2

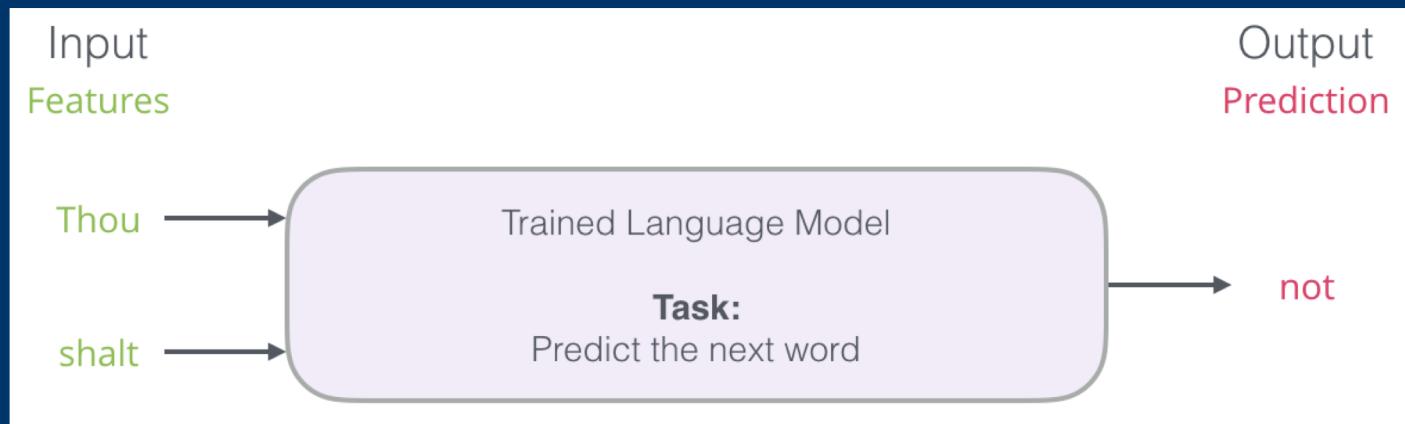
output/label

Thou    shalt



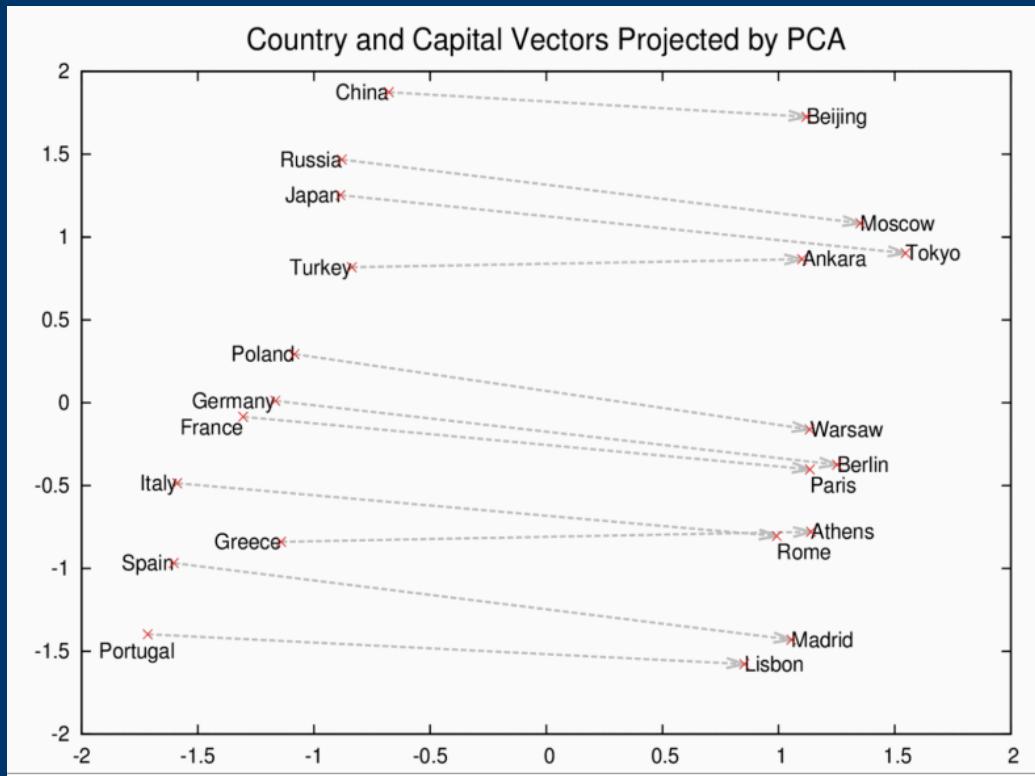
# MR of Natural Language: The Deep-Learning Approach

Very Quick Introduction to word2vec



# MR of Natural Language: The Deep-Learning Approach

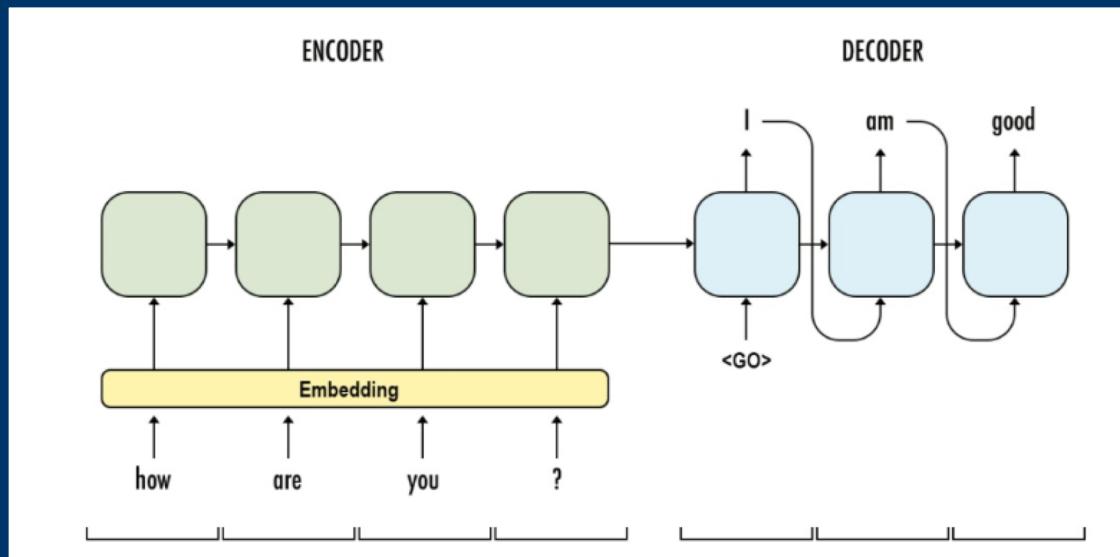
Very Quick Introduction to word2vec



# MR of Natural Language: The Deep-Learning Approach

## Deep Learning Approach

- Word → Vector. How about sentences?
  - Words → sequence of vectors → sentence vector!



# Pros of vector-based MR

The Chinese Room Nowadays....

TEXT PROMPT	an armchair in the shape of an avocado, an armchair imitating an avocado.				
AI-GENERATED IMAGES					

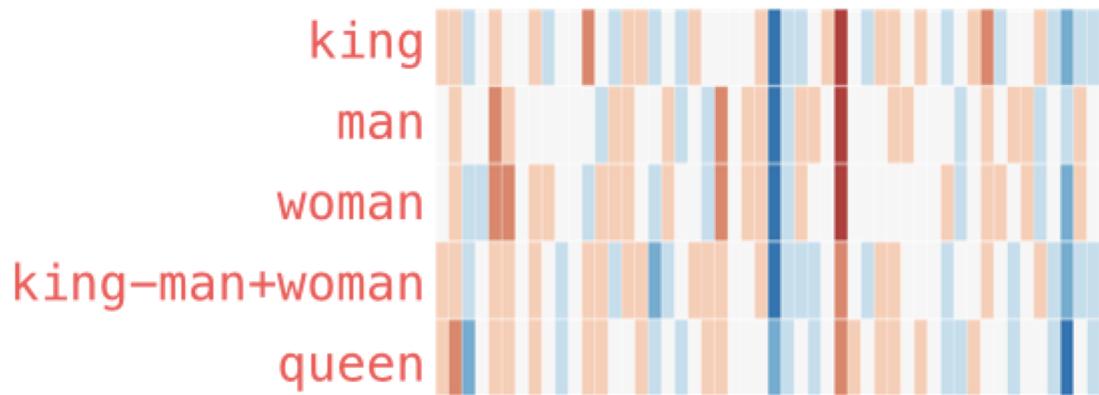
In the preceding visual, we explored DALL-E's ability to generate fantastical objects by combining two unrelated ideas. Here, we explore its ability to take inspiration from an unrelated idea while respecting the form of the thing being designed, ideally producing an object that appears to be practically functional. We found that prompting DALL-E with the phrases "in the shape of," "in the form of," and "in the style of" gives it the ability to do this.

When generating some of these objects, such as "an armchair in the shape of an avocado", DALL-E appears to relate the shape of a half avocado to the back of the chair, and the pit of the avocado to the cushion. We find that DALL-E is susceptible to the same kinds of mistakes mentioned in the previous visual.

## Cons of vector-based MR

So "what" Actually Happens in the Room?

$$\text{king} - \text{man} + \text{woman} \approx \text{queen}$$



## Why Symbolic + Distributional?

Benefits of Augmenting Distributional Semantics

Distributional Semantic Augmented Formal Semantic

- **Similarity between Semantics**
- Probabilistic Deduction : Deduction to Classification
  - ex)  $P(Aristotle \subseteq male \rightarrow Aristotle \subseteq man)$   
 $= P(mankind \subseteq human)$
  - *mankind*  $\subseteq$  *human* : classification problem
    - Solvable by embedding
    - Interpretable reasoning

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Symbolic MR of this Paper: sent2dl

Sentence → Description Logic

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## Symbolic MR of this Paper: sent2dl

Quick Introduction to DL

Description Logic Formula :

$$S \sqsubseteq \forall V.O \equiv S \subseteq \{x \mid \exists y, V(x, y) \wedge y \in O\}$$

- $S, O$  : Set
- $V$  : Relationship (a binary predicate)

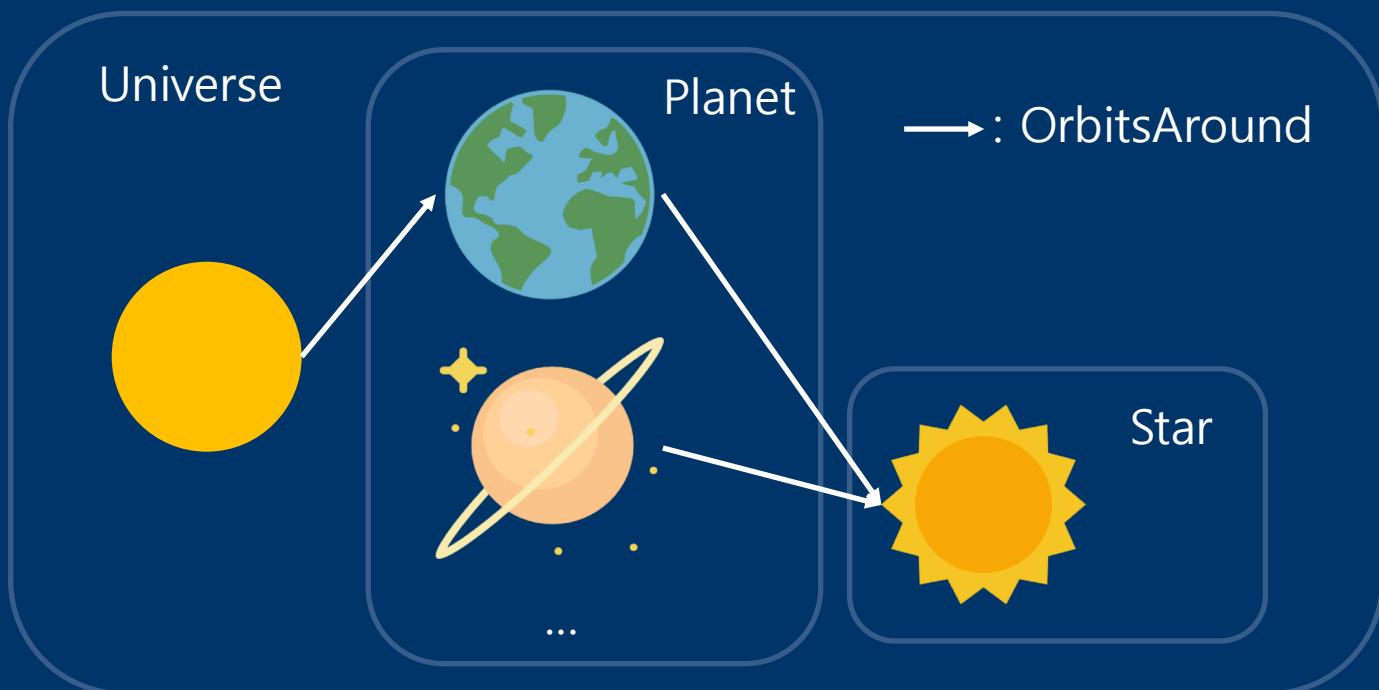
Ex)

$$\{Moon\} \sqsubseteq \forall OrbitsAround. (\neg Star)$$

$$Planet \sqsubseteq \forall OrbitsAround. Star$$

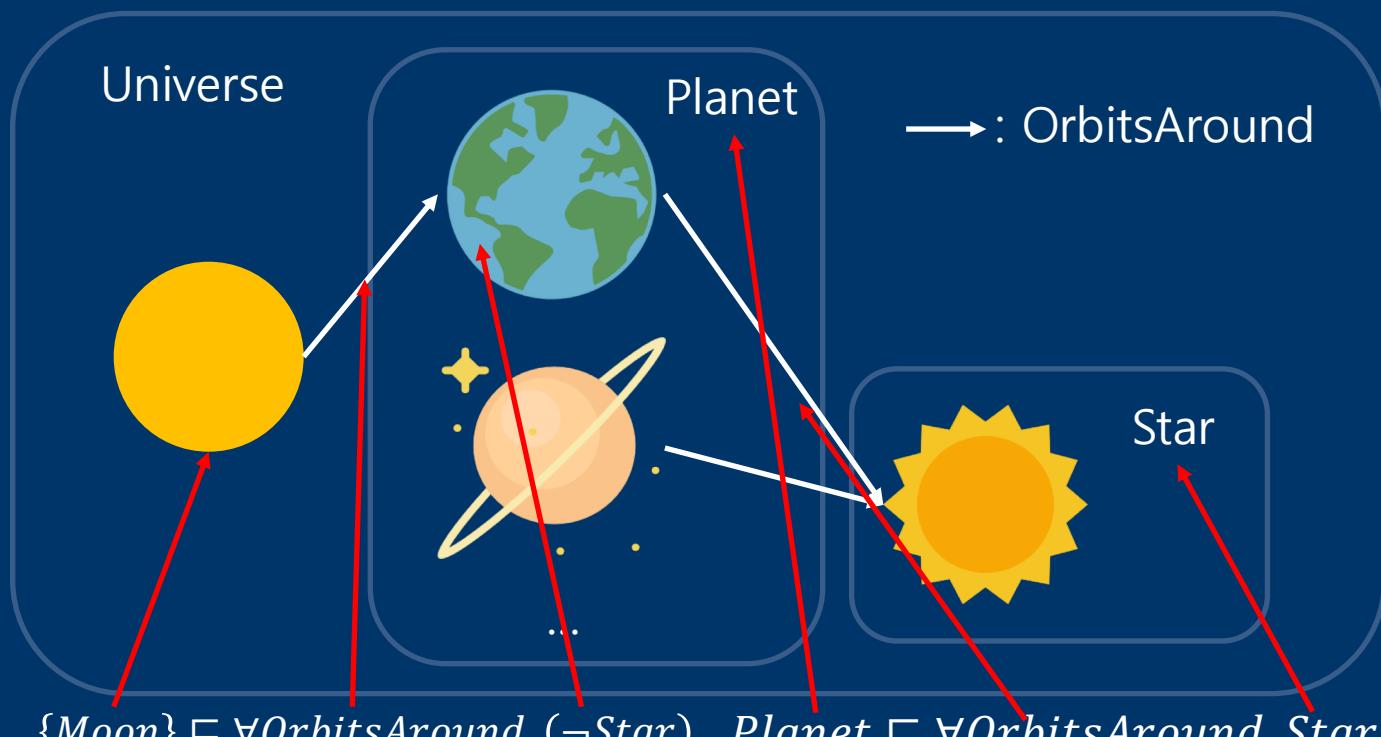
## Symbolic MR of this Paper: sent2dl

Sentence → Description Logic



## Symbolic MR of this Paper: sent2dl

Quick Introduction to DL : Solar System Example



## Symbolic MR of this Paper: sent2dl

Sentence → Description Logic

### Recursive / Iterative Composition

- Make parse tree of a given sentence
- Preprocessing : 안긴 문장 분할, 주어 앞 부사구 삭제 등
- Re-parse processed sentence segments
- Recursively get formula corresponding to each constituent
- Compose subtree-formulae according to the rules

Recursively transform SOV-sentence to DL Formula

$$\begin{aligned} \textit{sent2dl}(SOV - sentence) \\ = \textit{sent2dl}(S) \sqsubseteq \forall \textit{sent2dl}(V). \textit{sent2dl}(O) \end{aligned}$$

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## Symbolic MR of this Paper: sent2dl

Sentence → Description Logic Example

ex) 예시 문장 변환

kt는 수원에서 열린 NC와의 시즌 14차전 경기에서 10-0으로 대승을 일궈냈다.

- 문장 Preprocessing

- kt는 경기에서 10-0으로 대승을 일궈냈다.
- NC와의 시즌 14차전 경기가 수원에서 열렸다.

## Symbolic MR of this Paper: sent2dl

Sentence → Description Logic Example

ex) 예시 문장 변환

kt는 수원에서 열린 NC와의 시즌 14차전 경기에서 10-0으로 대승을 일궈냈다.

- 문장 Re-parse

- (VP
    - (NP-SBJ kt는)
    - (NP-AJT 경기에서)
    - (NP-AJT 10-0으로)
    - (NP-OBJ 대승을)
    - (VP 일궈냈다.)

## Symbolic MR of this Paper: sent2dl

Sentence → Description Logic Example

ex) 예시 문장 변환

kt는 수원에서 열린 NC와의 시즌 14차전 경기에서 10-0으로 대승을 일궈냈다.

- 문장 형태에 맞는 rule 적용

ex)  $(VP (NP-SBJ) (NP-AJT^*) (NP-OBJ) (VP))$  의 경우,  
 $f(NP - SBJ) \sqsubseteq \forall f(NP - AJT) \circ f(VP). f(NP - OBJ)$   
의 규칙 적용.

- 재귀적으로 depth가 2인 트리가 될 때까지 적용, 그 후에는 base-rule 적용

ex)  $(NP (kt NNP) (는 JX)) \rightarrow \{kt\}$

- 그 후 병합 (Principle of Compositionality)

## Augmenting Distributional Semantics to Logical Formulae

Giving Similarity Between Logic Formulae

Given two DL Formulae

$$S_1 \sqsubseteq \forall V_1. O_1$$

$$S_2 \sqsubseteq \forall V_2. O_2$$

Distance between formulae is defined as

$$\text{sim}(S_1, S_2) + \text{sim}(V_1, V_2) + \text{sim}(O_1, O_2)$$

where

$$\text{sim}(a, b) = w2v(a, b), \quad a, b \in \text{Vocab}$$

$$= \min_{\{\pi(a), \pi(b)\}} \left[ \sum_{i \in \pi(a), j \in \pi(b)} w2v(i, j) \right], \quad a, b \text{ is Set}$$

## Experimental Verification

On unsupervised sentence clustering

Dataset : Baseball match recap data

Benchmark

- Benchmark 1 : Multitask-Learning
  - Sentence Representation Learning Task via Quick Thought
  - Seq2Seq based Neural Machine Translation Task
- Benchmark 2: Sentence-Bert
  - Sentence-transformer의 multilingual 옵션 적용

Metric : AMI , NMI

## Experimental Verification

	Multitask Learning	Sentence-Bert	Ours
AMI	0.12 / 0.47	0.12	0.65
NMI	0.11 / 0.48	0.10	0.65

## Experimental Verification

### Example Results

Benchmark(Multitask-Learning)	ours(sent2dl)
<ul style="list-style-type: none"><li>- 두산은 4월 15일 고척 스카이돔에서 열린 키움과의 원정 경기에서 3-2로 승리했다.</li><li>- LG는 19일 고척에서 열린 키움과의 원정 경기에서 8-3으로 이겼다.</li><li>- NC는 시즌 순위 10위를 유지했다.</li><li>- 한화는 5월 30일 대전 한화생명 이글스 파크에서 열린 NC와 7차전 홈 경기에서 10-4로 이겼다,</li></ul>	<ul style="list-style-type: none"><li>- 키움 임병욱이 1안타 1타점으로 팀 승리에 기여했다.</li><li>- 7번 지명타자로 출전한 김동엽이 2타수 1득점의 활약했다.</li><li>- 데뷔전을 치룬 이도윤은 1타수 무안타에 그쳤다.</li><li>- 데뷔전을 치룬 이도윤은 1타수 무안타로 물러났다.</li><li>- 박기혁은 4타수 1안타 1타점으로 팀 승리에 기여했다.</li></ul>

## Conclusion

- Things done
  - Tried to Merge vector-based MR and symbolic MR
    - Made Description-Logic based MR
    - Only SYNTAX, no interpretation/formal semantic
  - Indirectly verified via unsupervised clustering task
- Further TODOs
  - Assign formal semantics to proposed language



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