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Heidelberg Natural Language Processing Group

Argumentative Relation Classification with Background Knowledge

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COMMA 2020

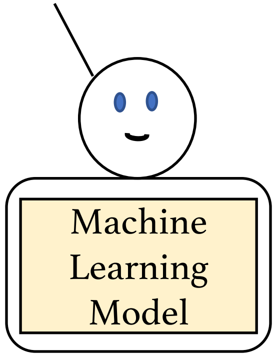
Argumentative Relation Classification

Support or Attack?

Argument1: *Online classes have many advantages.*

Argument2: *Traditional learning still has many benefits to the students.*

Argumentative Relation Classification



Argument1: *Online classes have many advantages.*

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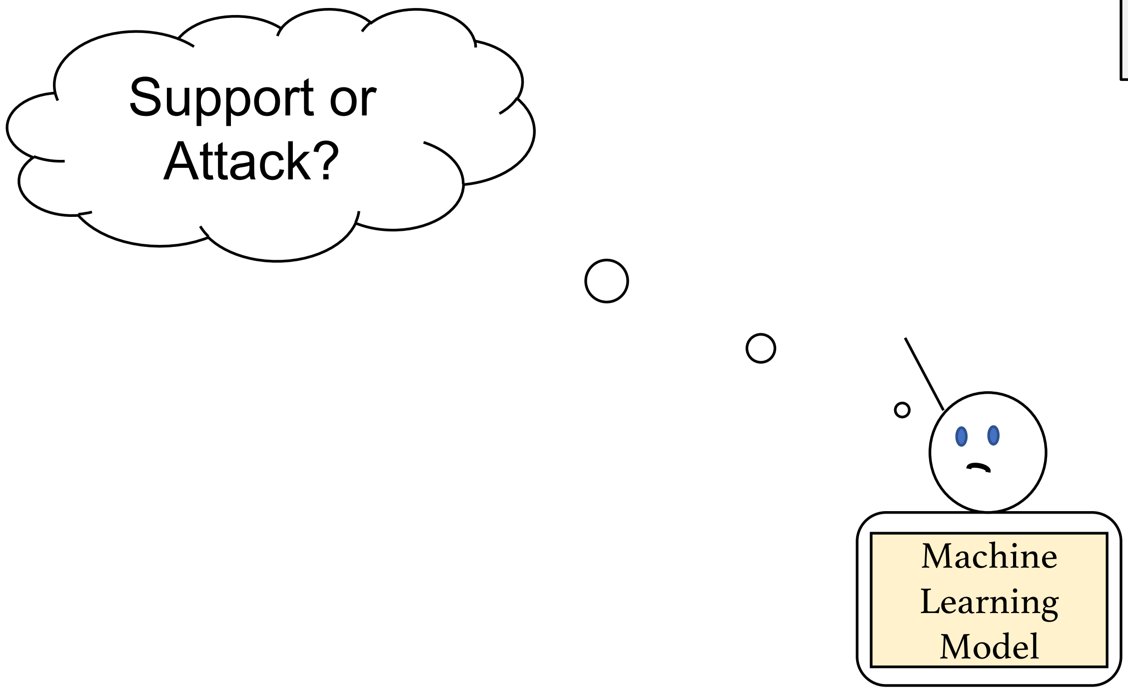
Argumentative Relation Classification

Determining relations between arguments requires ***knowledge*** *beyond the text.*



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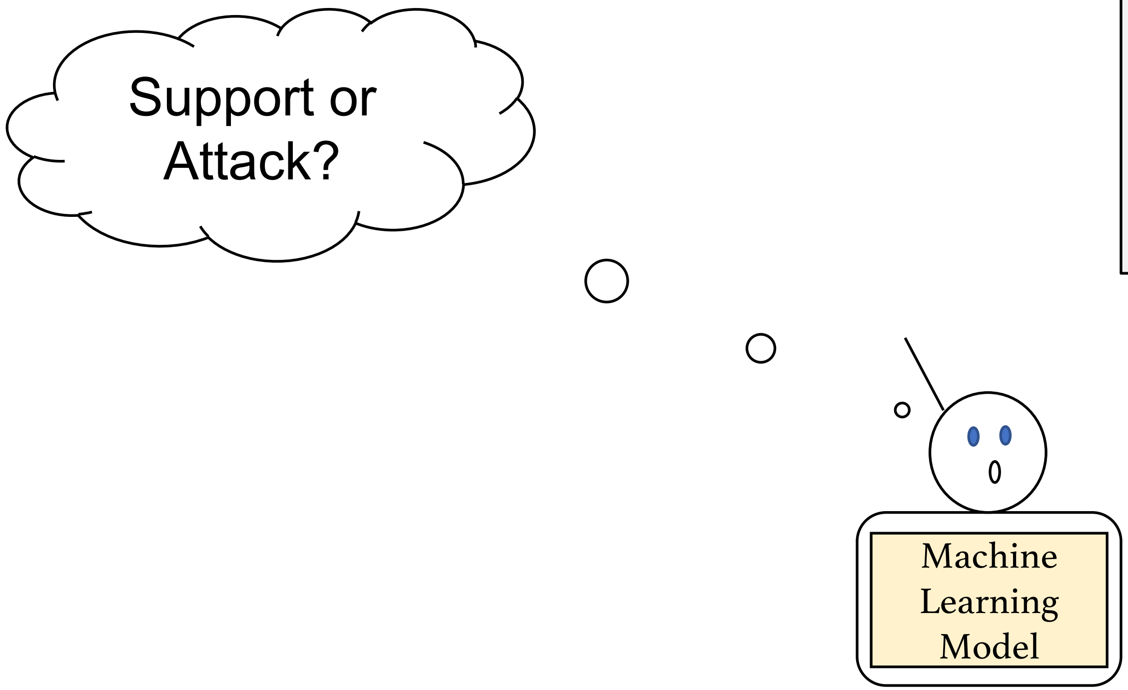
Argumentative Relation Classification



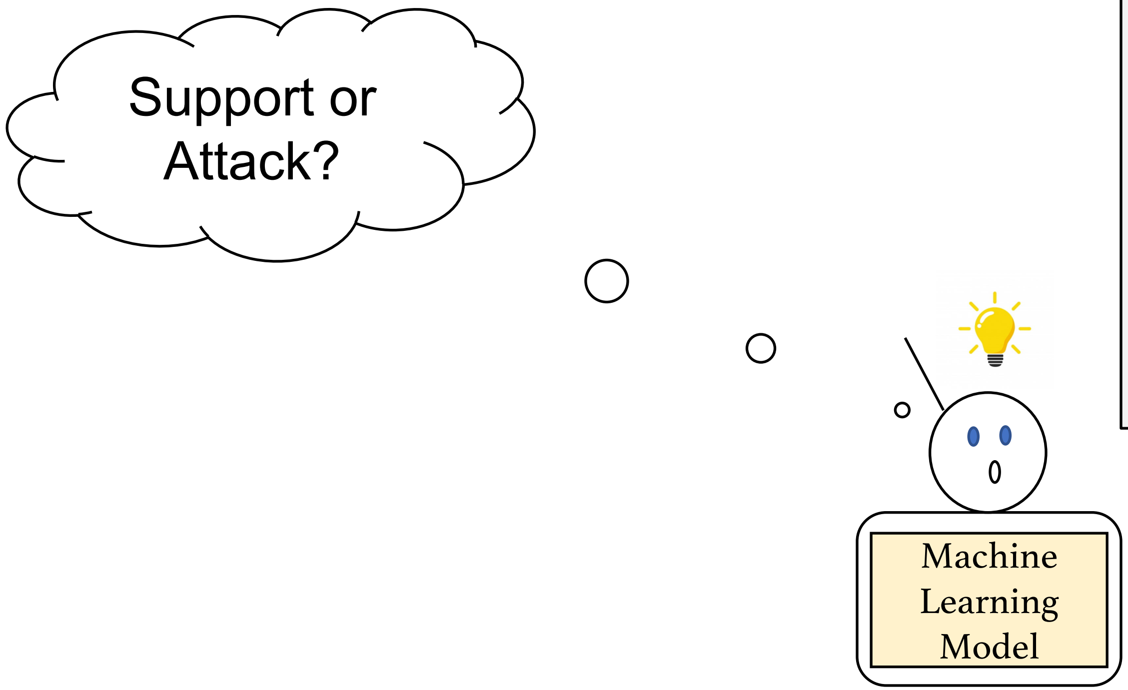
Background Knowledge:

- *What does tradition mean?*
- *What is the relation between tradition and online?*
- *How is online and learning related?*

Argument1: *Online classes have many advantages.*

Argument2: *Traditional learning still has many benefits to the students.*

Argumentative Relation Classification



Background Knowledge:

- ***Implicit Relational Knowledge:***

Online--> AtLocation-->Information-->RelatedTo-->Learning
Online--> Antonym--> Brick and Mortar--> Synonym--> traditional

- ***Definitional Knowledge:***

Tradition: a specific practice of long standing.

Argument1: *Online classes have many advantages.*

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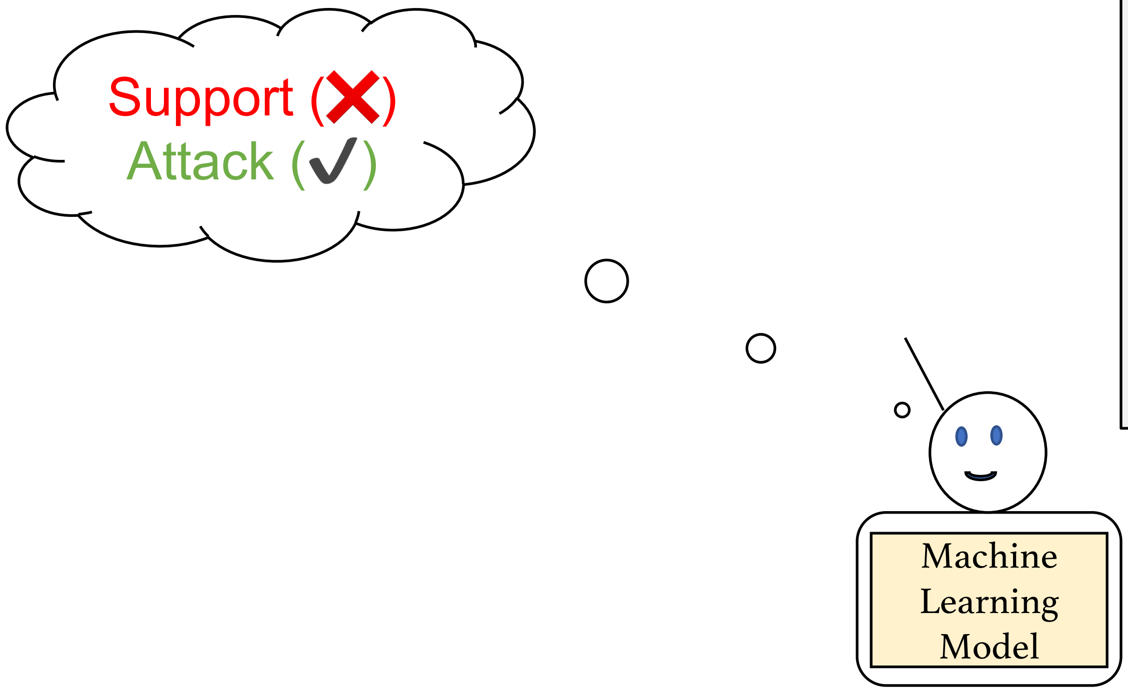
Argumentative Relation Classification



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Argument1: *Online classes have many advantages.*

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Background Knowledge

- Common knowledge sources used are WordNet, ConceptNet, FrameNet, etc.

- Identifying and extracting contextually relevant information from such a large knowledge base is a non-trivial task.

Related Work

- Frame- and Entity-Based Knowledge for Commonsense Argumentative Reasoning.

  ✓ Enriching models with event and fact knowledge.
  ✓ Knowledge sources used are: FrameNet and WikiData.
  ✓ As an additional knowledge: Append pre-trained frame and entity embeddings with word vectors on the token-level.

Botschen et al., 2015

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  ✔ Enriching models with event and fact knowledge.
  ✔ Knowledge sources used are: FrameNet and WikiData.
  ✔ As an additional knowledge: Append pre-trained frame and entity embeddings with word vectors on the token-level.

💡 In this work, we go **beyond** token-level knowledge and use relational knowledge.

Botschen et al., 2015

Related Work

- Exploiting Background Knowledge for Argumentative Relation Classification.
  - ✔ Extract knowledge paths from ConceptNet and DBpedia connecting argumentative units (AUs).
  - ✔ Due to large number of paths:
    - ✔ Derive shallow quantitative features from knowledge paths (based on the relation types).

Kobbe et al., 2019

Related Work

- Exploiting Background Knowledge for Argumentative Relation Classification.

  ✓ Extract knowledge paths from ConceptNet and DBpedia connecting argumentative units (AUs).
  ✓ Due to large number of paths:
    ✓ Derive shallow quantitative features from knowledge paths (based on the relation types).

💡 In contrast to Kobbe et al., 2019 , we emphasize on selecting relevant knowledge.

Kobbe et al., 2019

Commonsense Knowledge Extraction

Arg1: Landlords may want to earn as much as possible.

Arg2: Rent prices should be limited by a cap when there's a change of tenant.

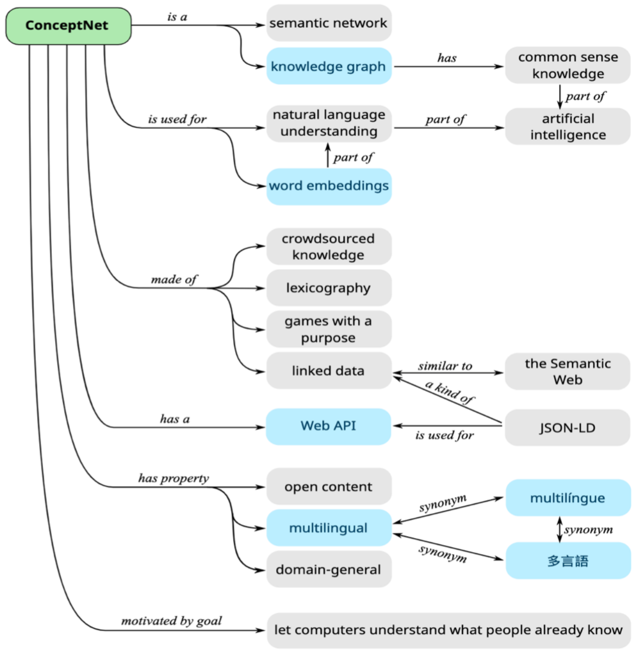
arg1

arg2

Commonsense Knowledge Extraction

Arg1: **Landlords** may want to **earn** as **much** as possible.

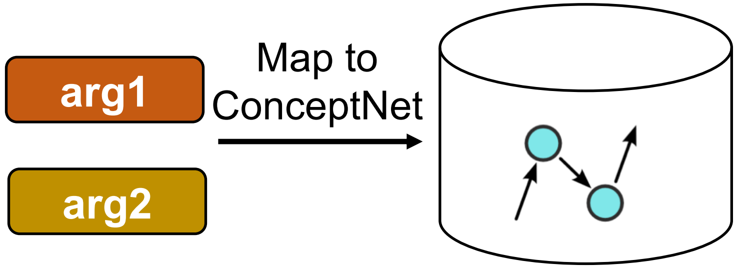
Arg2: **Rent prices** should be **limited** by a **cap** when there's a change of **tenant**.



ConceptNet 5.6.0: [Speer and Havasi, 2012]

ConceptNet is a knowledge graph of semantic relation between concepts.

Each edge represents one of 37 types of semantic relationship. For e.g., UsedFor, FormOf, CapableOf, etc.



ConceptNet

Commonsense Knowledge Extraction

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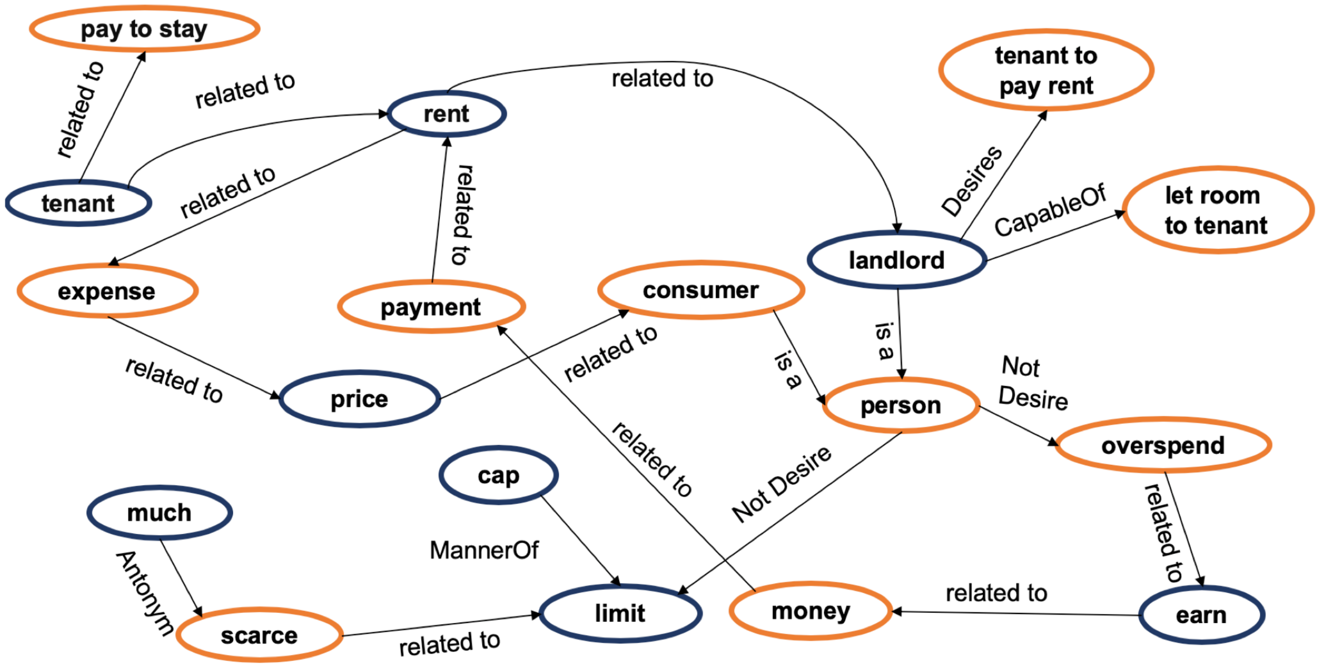

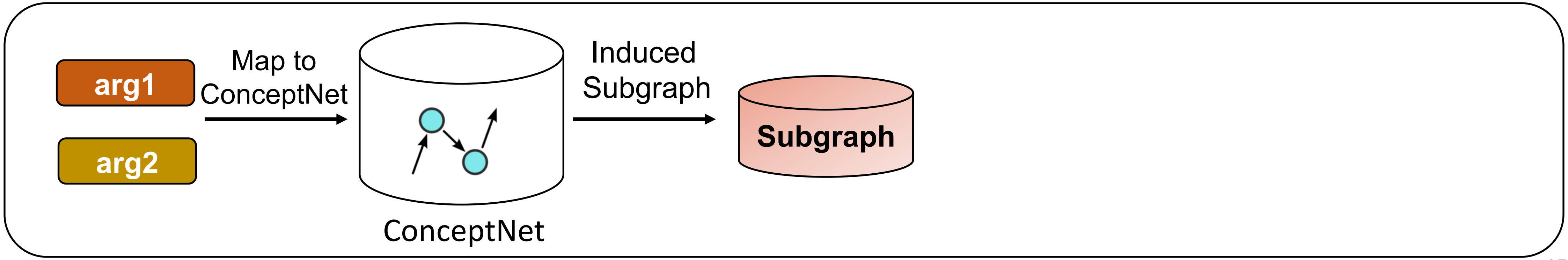

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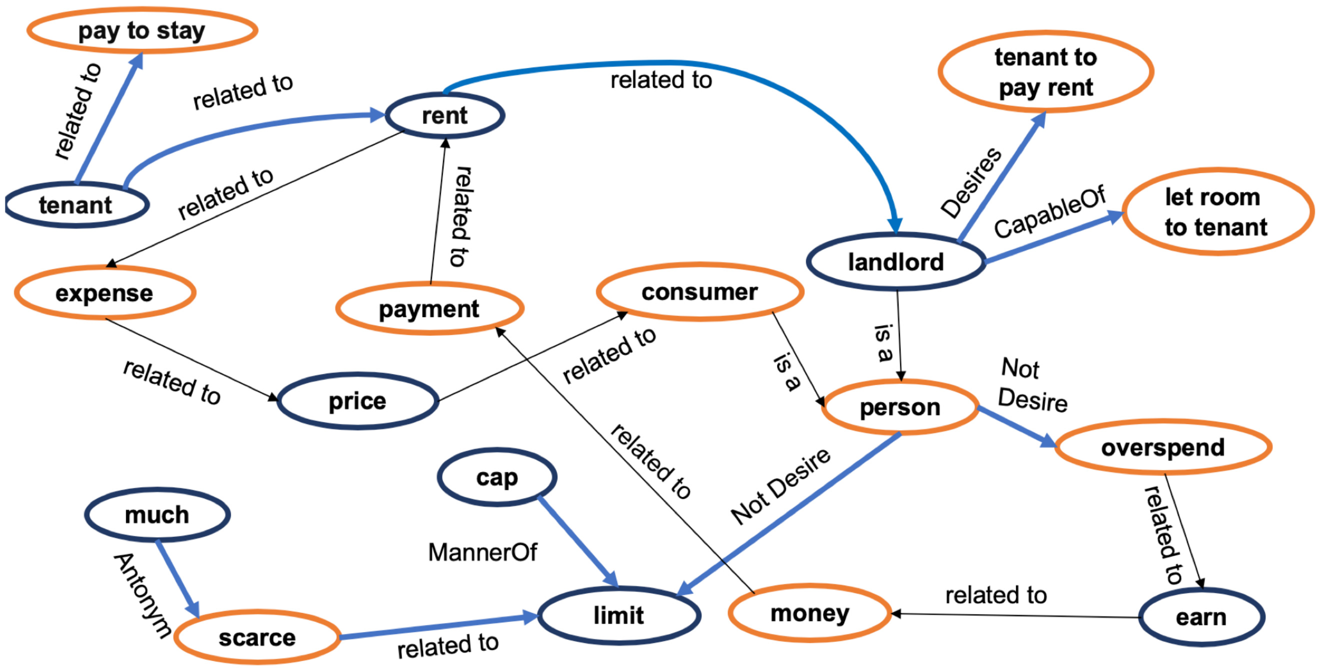
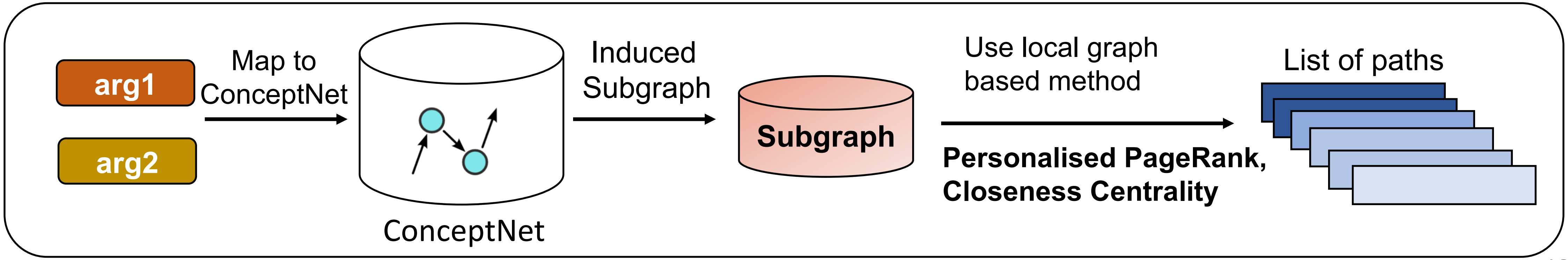
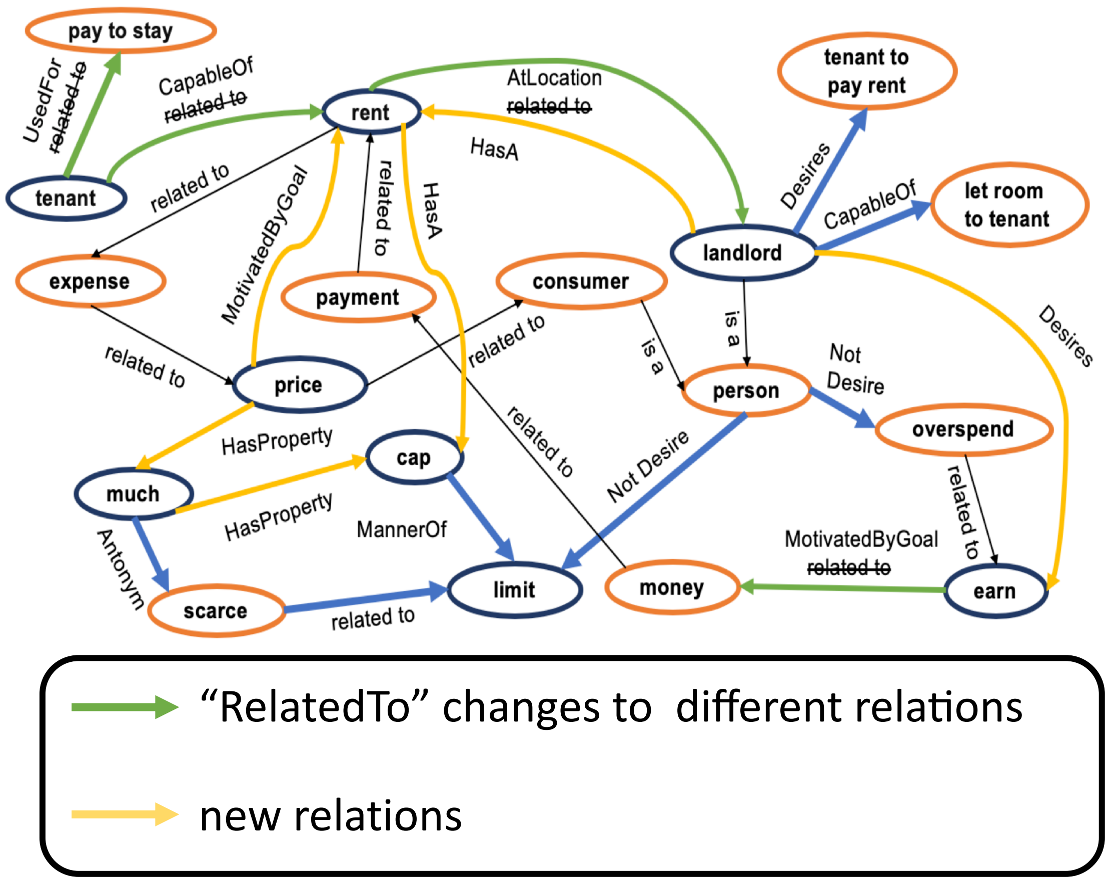




Knowledge Graph Completion

Arg1: **Landlords** may want to **earn** as **much** as possible.

Arg2: **Rent prices** should be **limited** by a **cap** when there's a change of **tenant**.



– Knowledge graphs are incomplete.
– Apply relational classifier to predict ConceptNet relation types for given pairs of concepts.

Becker M et al., 2019

Lexical Knowledge

Arg1: **Landlords** may want to **earn** as **much** as possible.

Arg2: **Rent prices** should be **limited** by a **cap** when there's a change of **tenant**.

- We hypothesize that definitional knowledge about the entities in context should help the model.
- We use WordNet to extract definitional knowledge.

"WordNet"

Landlord: a landowner who leases to others.

Tenant: someone who pays rent to use land or a building or a car that is owned by someone else.

Model

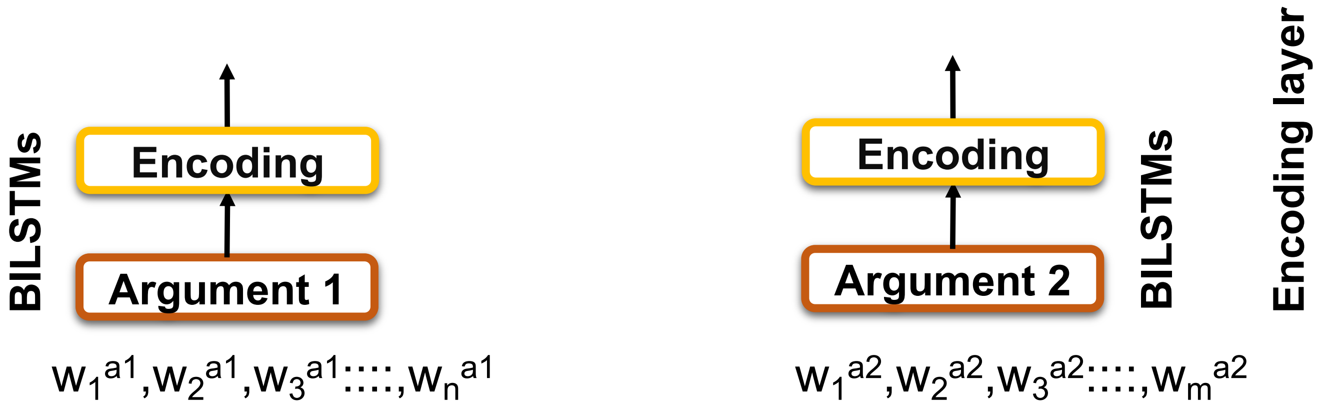
Argument 1

$w_1^{a1},w_2^{a1},w_3^{a1}::::,w_n^{a1}$

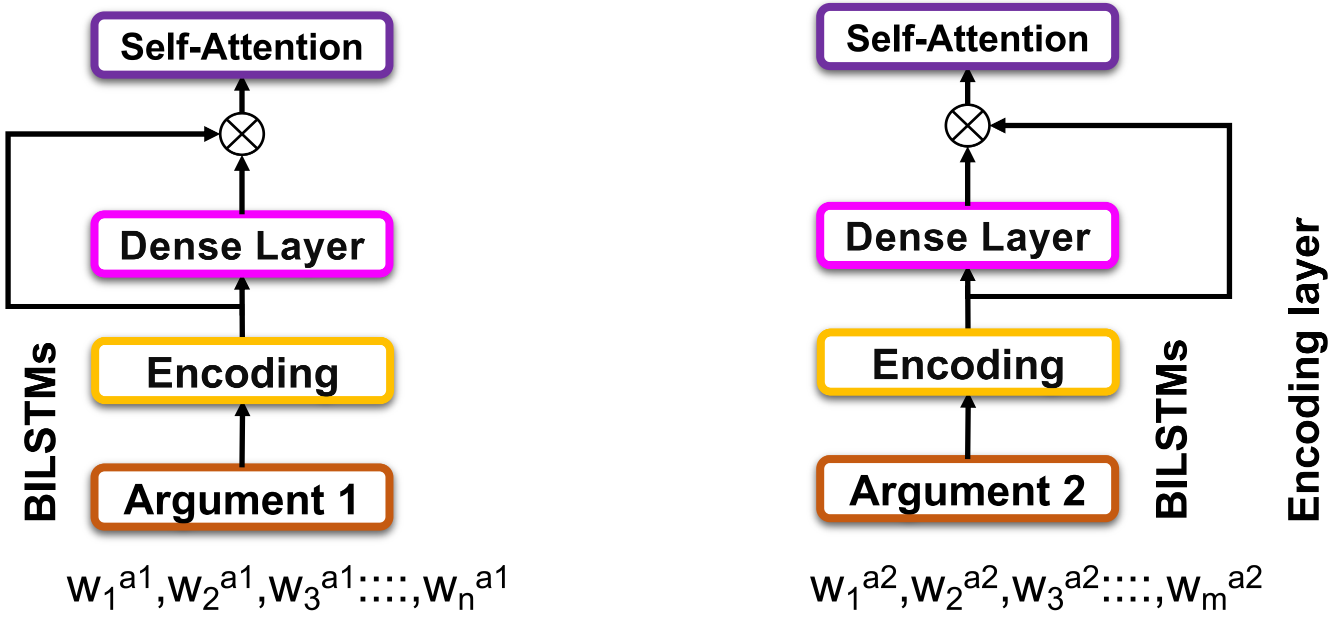
Argument 2

$w_1^{a2},w_2^{a2},w_3^{a2}::::,w_m^{a2}$

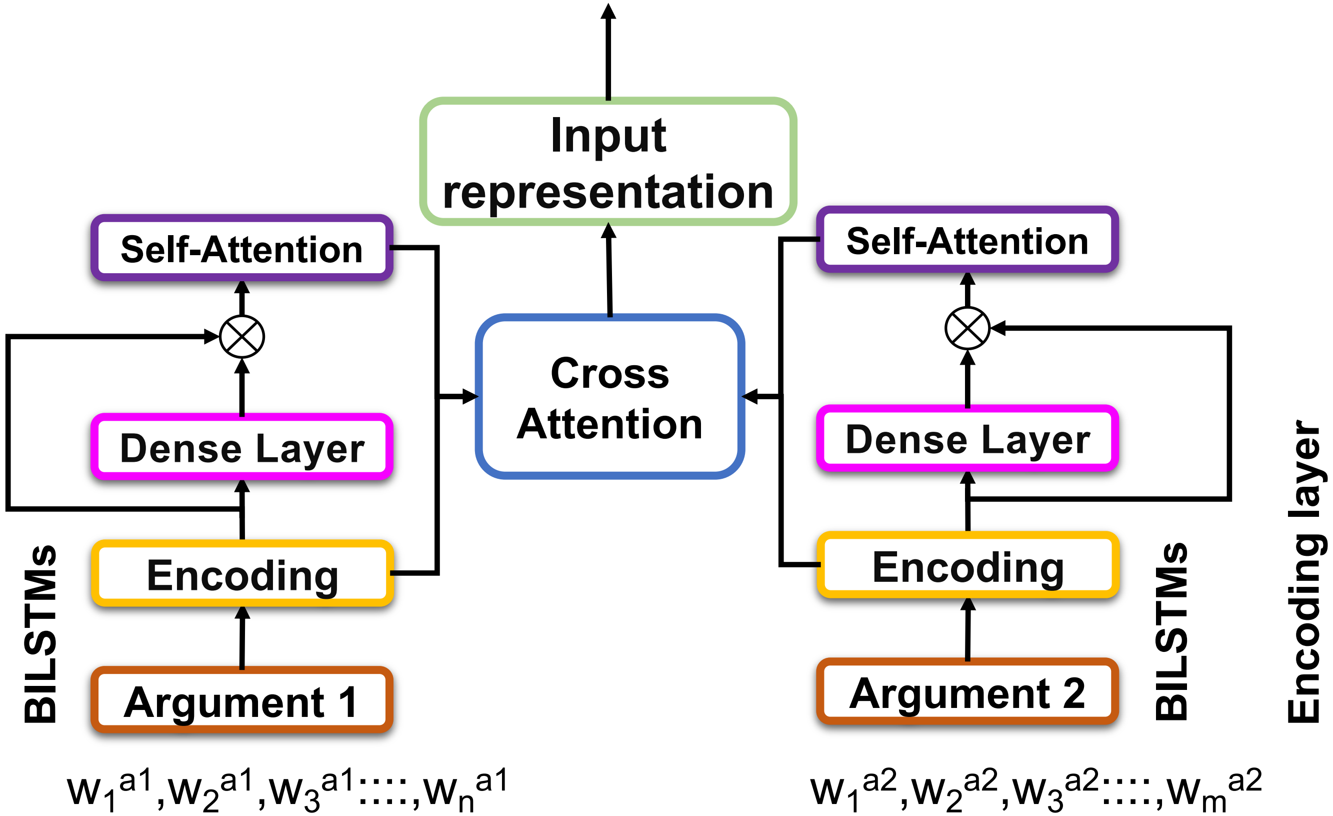
Model


BILSTMs
Encoding
Argument 1
$w_1^{a1}, w_2^{a1}, w_3^{a1} ::::, w_n^{a1}$
Encoding
Argument 2
BILSTMs
$w_1^{a2}, w_2^{a2}, w_3^{a2} ::::, w_m^{a2}$
Encoding layer

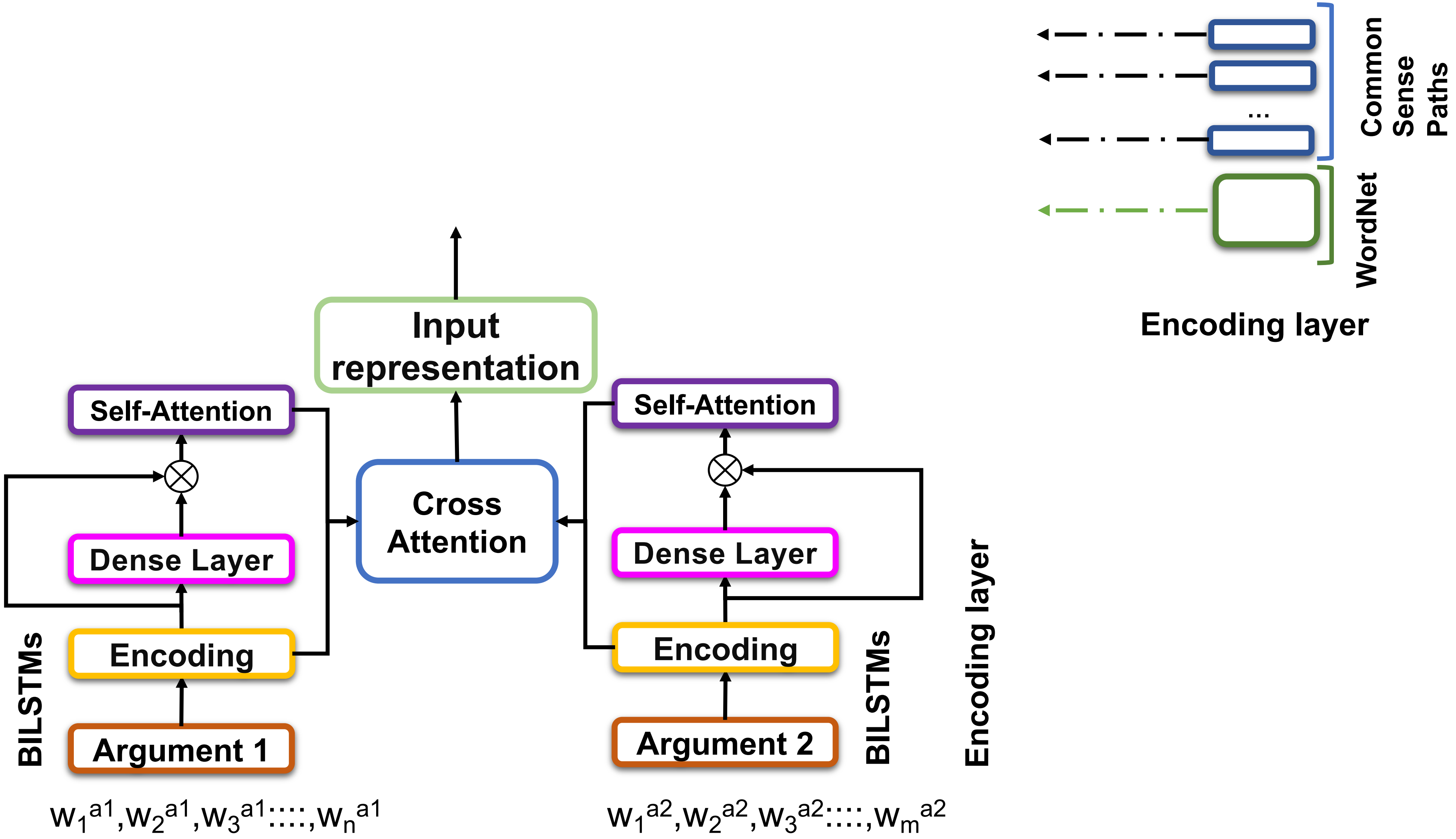
Model


Self-Attention
Dense Layer
Encoding
Argument 1
BILSTMs
$w_1^{a1}, w_2^{a1}, w_3^{a1} \dots, w_n^{a1}$
Self-Attention
Dense Layer
Encoding
Argument 2
BILSTMs
Encoding layer
$w_1^{a2}, w_2^{a2}, w_3^{a2} \dots, w_m^{a2}$

Model

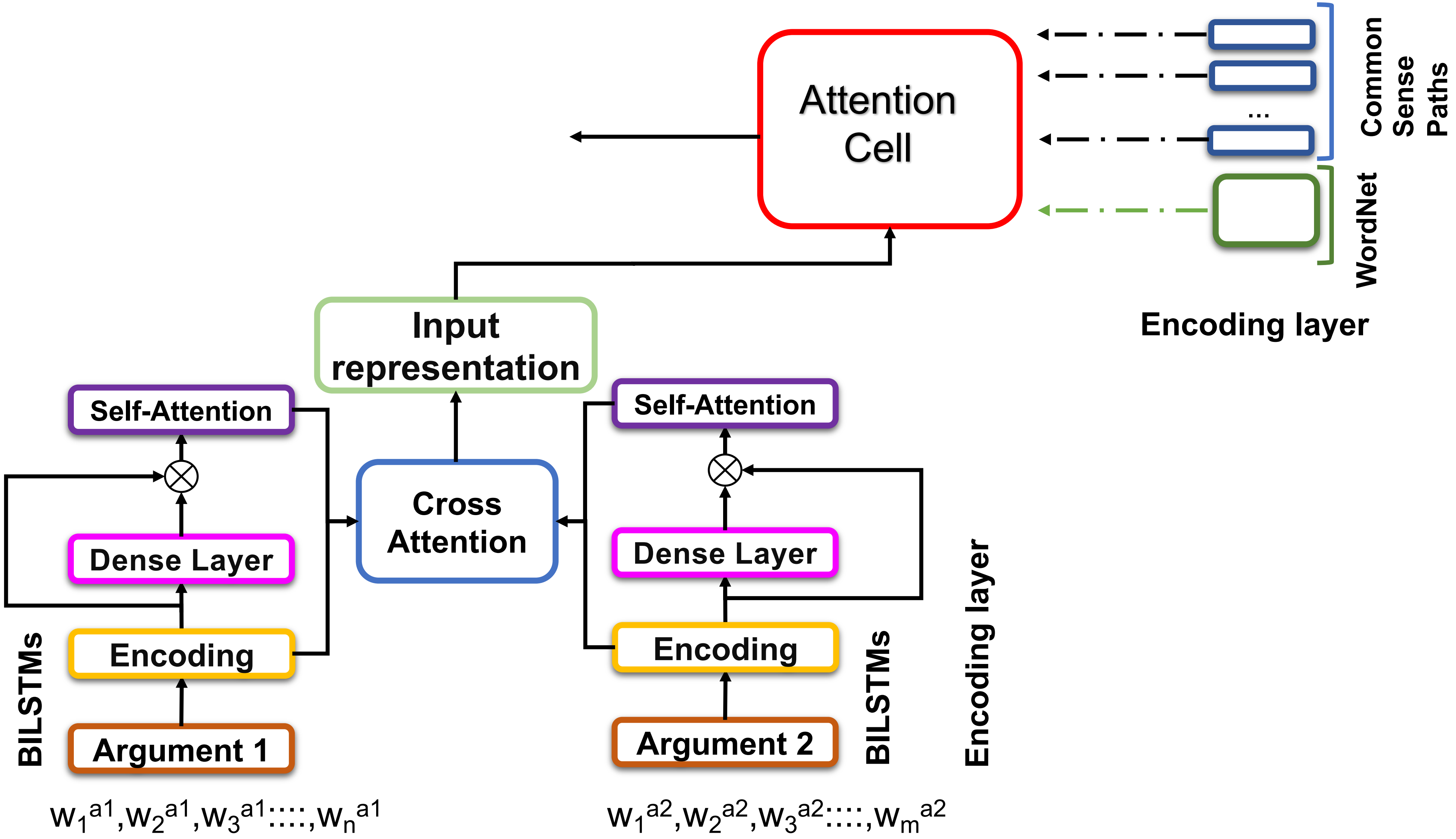

Input representation
Cross Attention
Self-Attention
Dense Layer
Encoding
Argument 1
BILSTMs
Self-Attention
Dense Layer
Encoding
Argument 2
BILSTMs
Encoding layer
$w_1^{a1}, w_2^{a1}, w_3^{a1} ::::, w_n^{a1}$
$w_1^{a2}, w_2^{a2}, w_3^{a2} ::::, w_m^{a2}$

Model

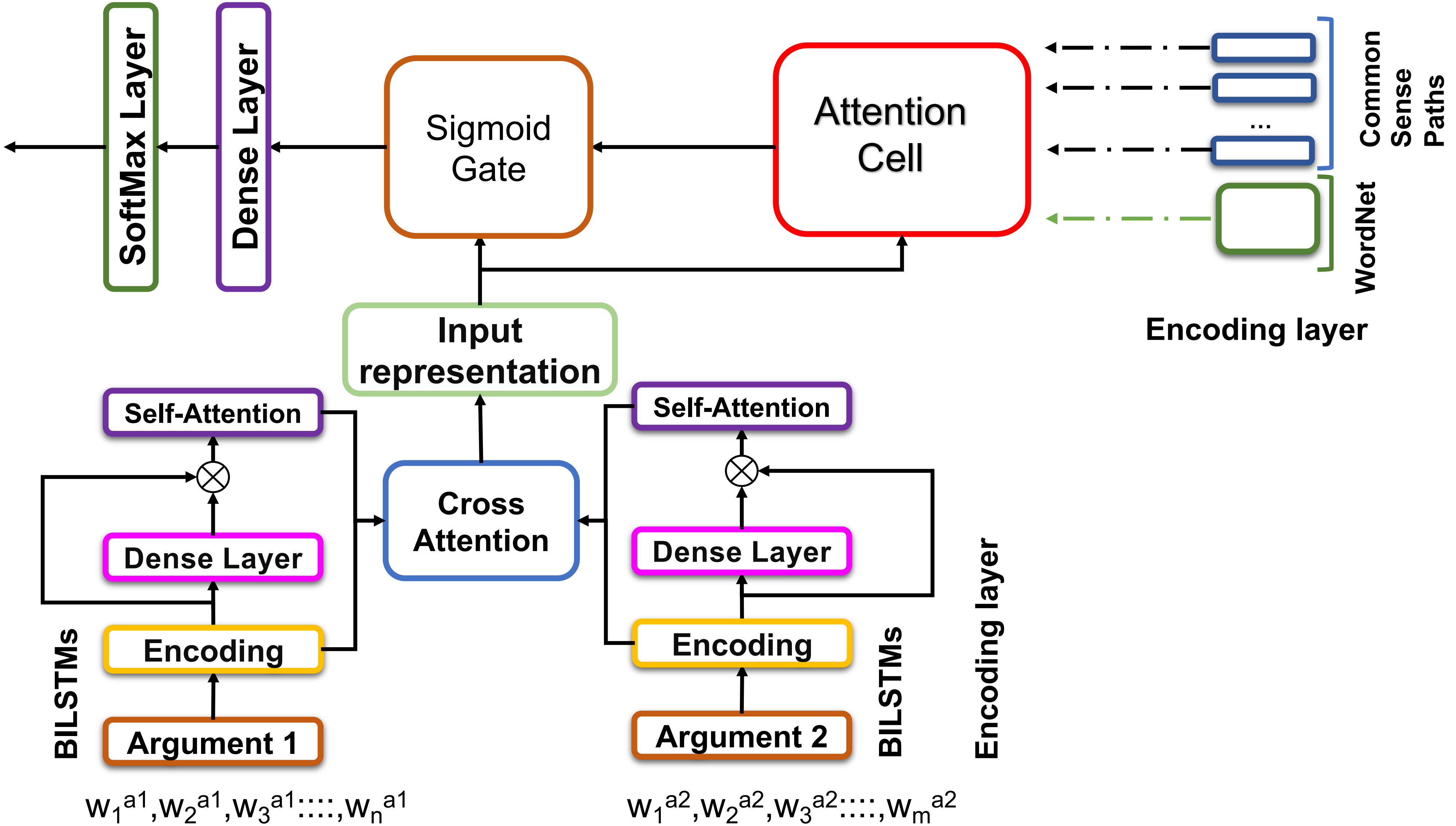


Common Sense Paths
...
WordNet
Encoding layer
Input representation
Self-Attention
Cross Attention
Self-Attention
Dense Layer
Dense Layer
Encoding
Encoding
BILSTMs
BILSTMs
Argument 1
Argument 2
Encoding layer
$w_1^{a1}, w_2^{a1}, w_3^{a1}::::, w_n^{a1}$
$w_1^{a2}, w_2^{a2}, w_3^{a2}::::, w_m^{a2}$

Model


Attention Cell
Common Sense Paths
...
WordNet
Encoding layer
Input representation
Self-Attention
Self-Attention
Cross Attention
Dense Layer
Dense Layer
Encoding
Encoding
BILSTMs
BILSTMs
Encoding layer
Argument 1
Argument 2
$w_1^{a1}, w_2^{a1}, w_3^{a1} ::::, w_n^{a1}$
$w_1^{a2}, w_2^{a2}, w_3^{a2} ::::, w_m^{a2}$

Model


SoftMax Layer
Dense Layer
Sigmoid Gate
Attention Cell
Common Sense Paths
...
WordNet
Encoding layer
Input representation
Self-Attention
Dense Layer
Encoding
Argument 1
BILSTMs
Cross Attention
Self-Attention
Dense Layer
Encoding
Argument 2
BILSTMs
Encoding layer
$w_1^{a1}, w_2^{a1}, w_3^{a1} \ldots, w_n^{a1}$
$w_1^{a2}, w_2^{a2}, w_3^{a2} \ldots, w_m^{a2}$

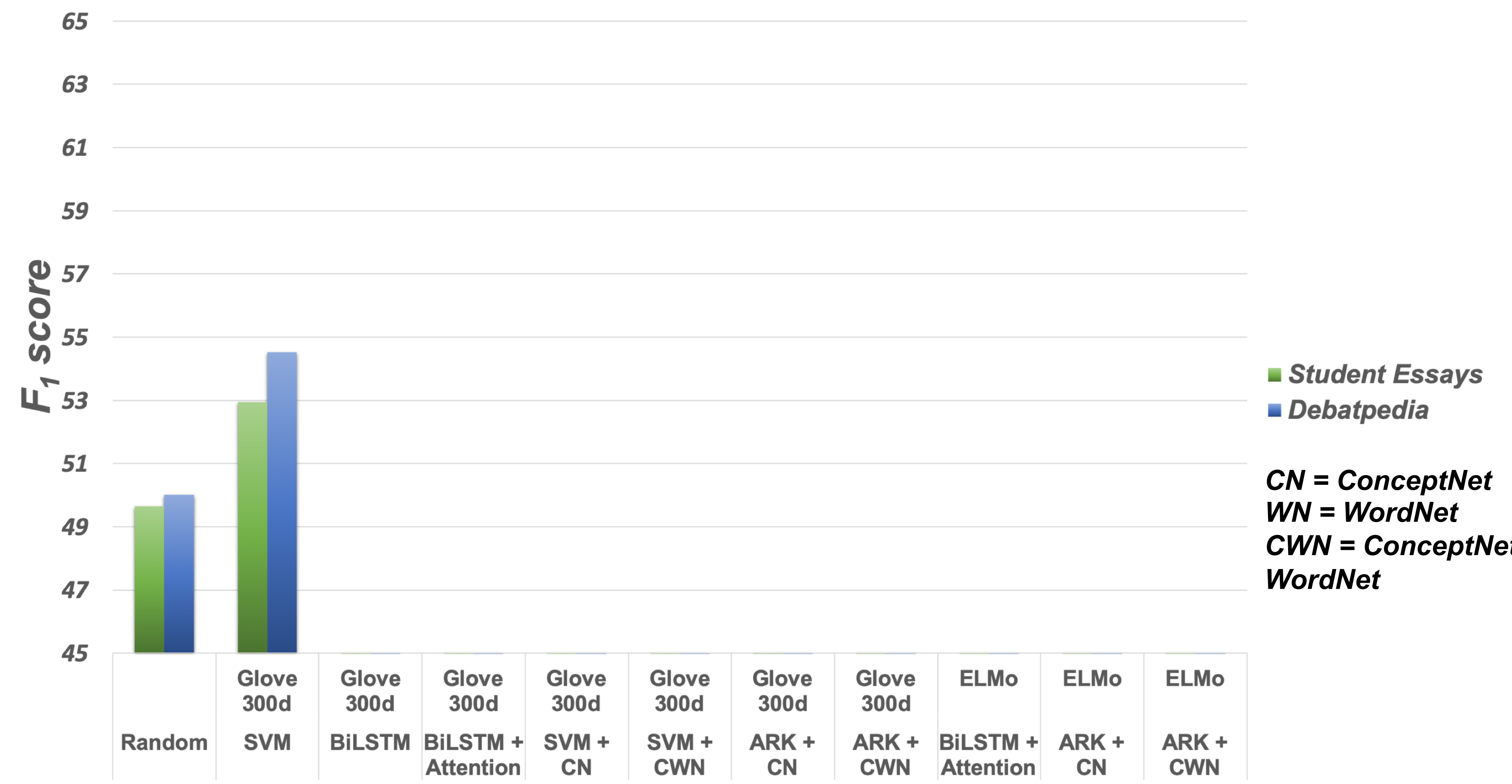
Task Setup

– Dataset: Student Essay, Debatepedia

– Task: Argumentation Relation Classification

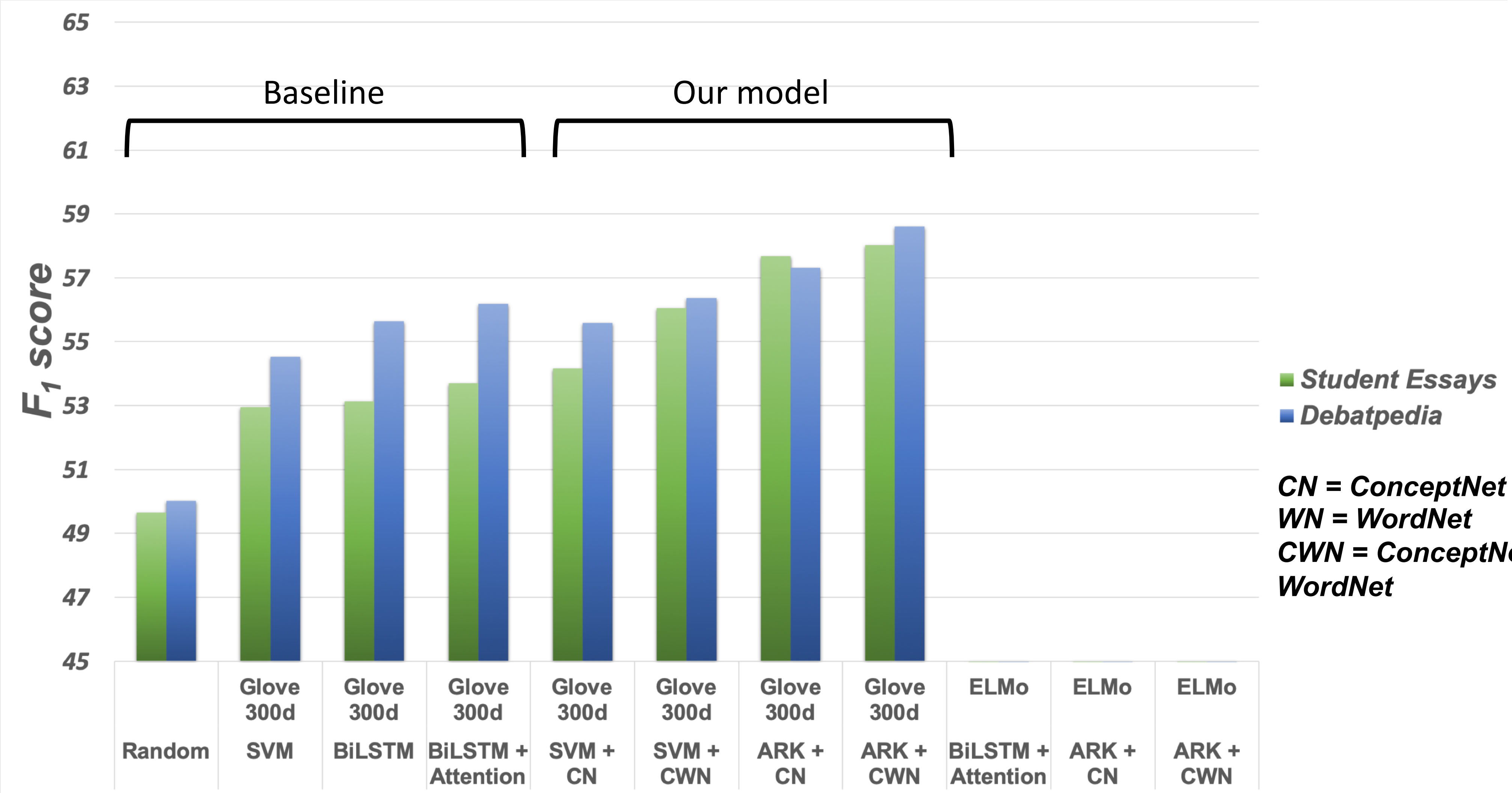
– Knowledge Sources:
  – Commonsense Knowledge: ConceptNet 5.6.0
  – Lexical Knowledge: WordNet

Baseline Results



CN = ConceptNet
WN = WordNet
CWN = ConceptNet + WordNet

Baseline Results



CN = ConceptNet
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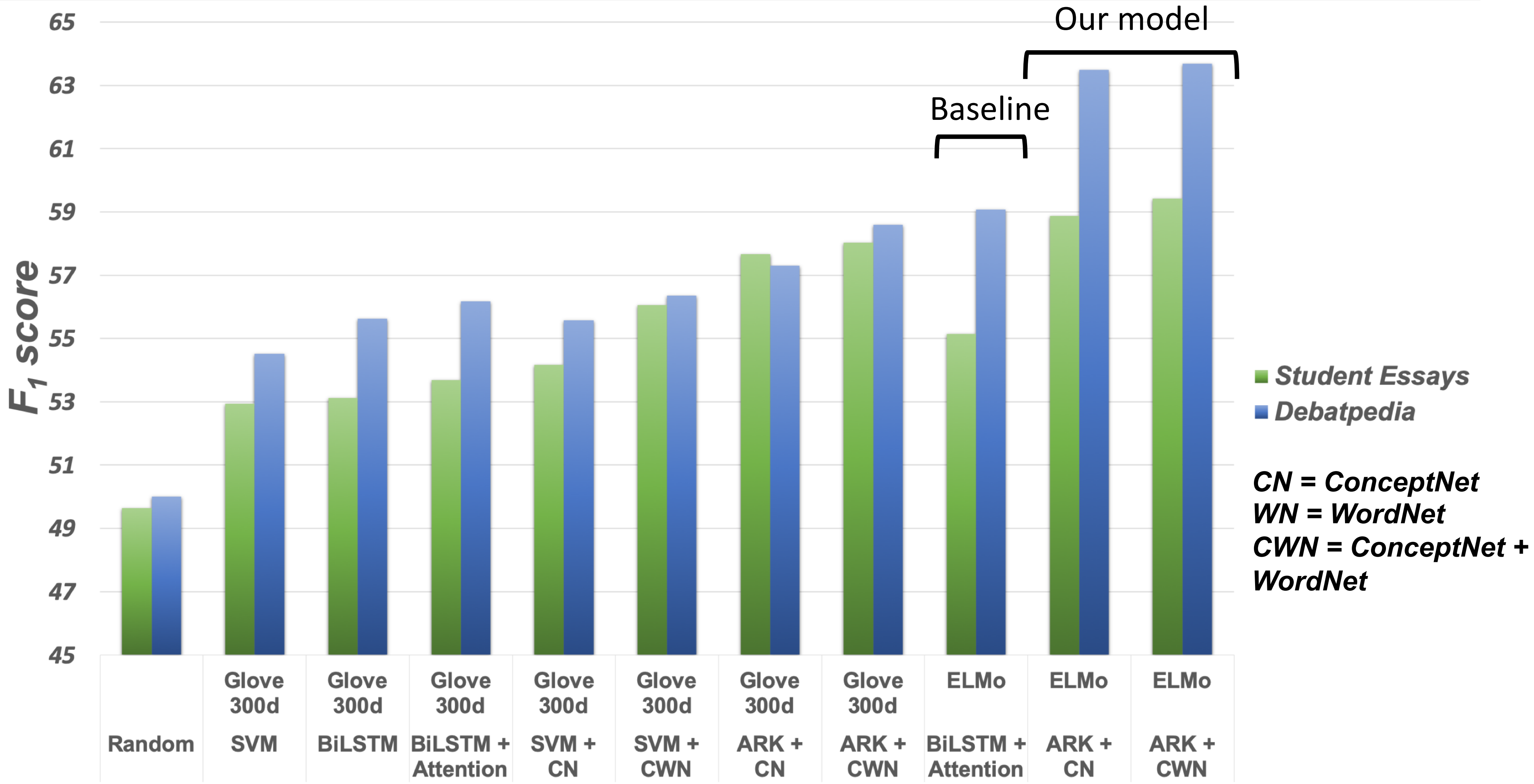
Results


Our model
Baseline
65
63
61
59
57
55
53
51
49
47
45
F_1 score
Random
Glove 300d SVM
Glove 300d BiLSTM
Glove 300d BiLSTM + Attention
Glove 300d SVM + CN
Glove 300d SVM + CWN
Glove 300d ARK + CN
Glove 300d ARK + CWN
ELMo BiLSTM + Attention
ELMo ARK + CN
ELMo ARK + CWN
Student Essays
Debatpedia
CN = ConceptNet
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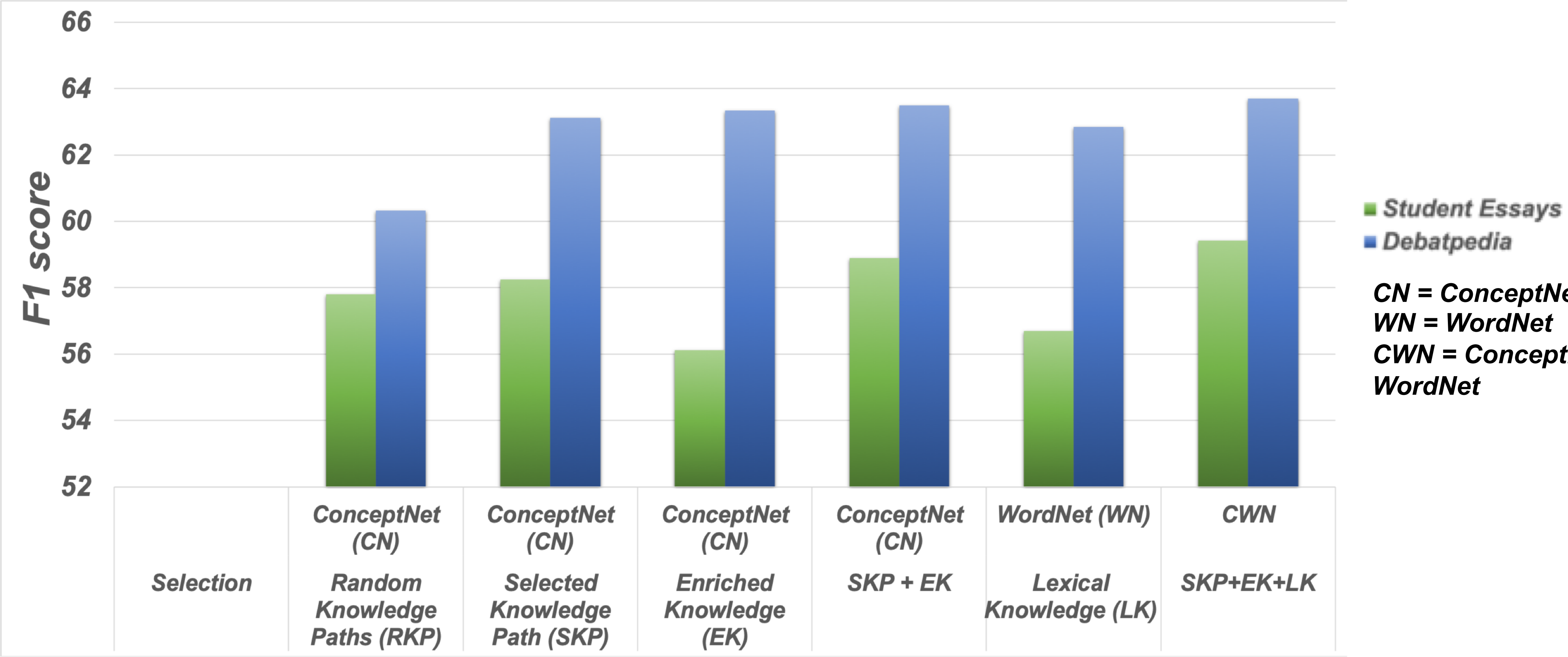
Ablation Study



CN = ConceptNet
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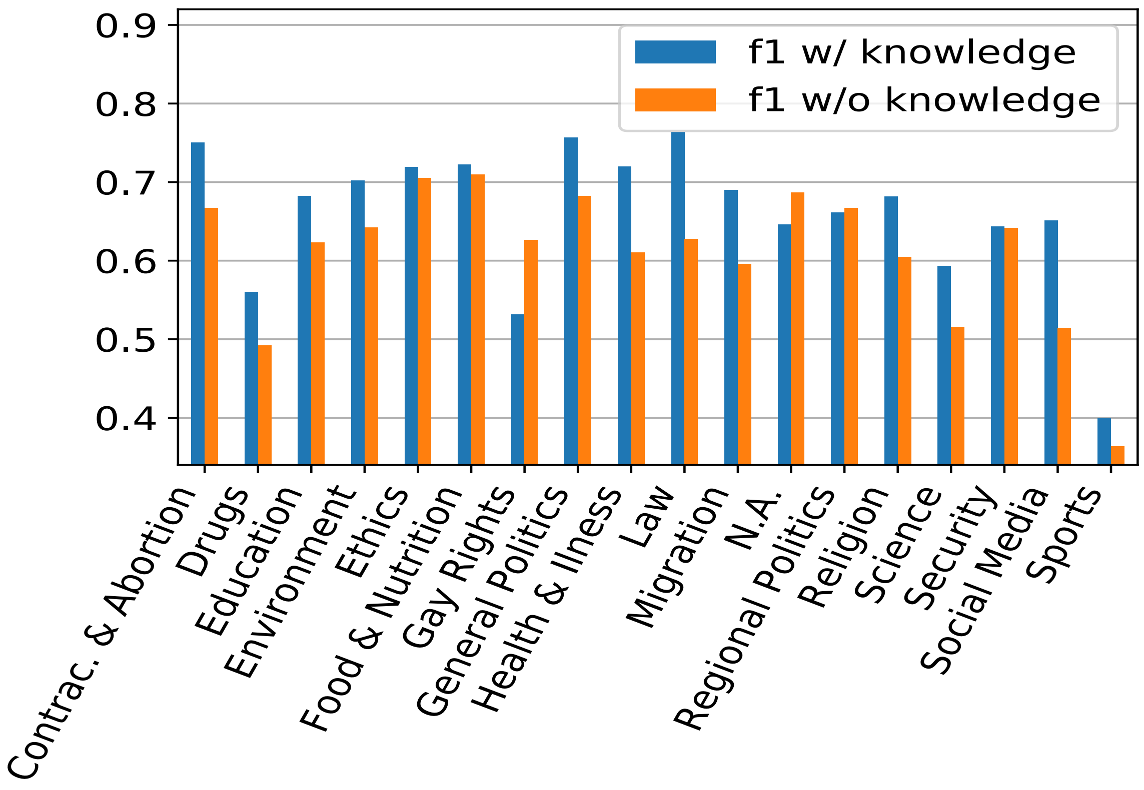
Analysis

- We manually divided the data into 15 topics.
- Analysed the performance of ARK vs Bi-LSTM + Attention.
- Knowledge improves the performance across many topics.
- Topics like Gay Rights, Regional Politics injecting knowledge didn’t help.



Conclusion

- In this work,
  - We present our **graph-based method** that extracts relevant commonsense knowledge.
  - We show **selectively integrating** it into the model improves over a strong neural and a linear ARC system on two datasets.
  - We show that extending the knowledge ***'on the fly'*** can further improve results.

Debatepedia data link: https://madata.bib.uni-mannheim.de/324/

Reference

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Thank you for listening!

Questions?

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