UNIVERSITÄT HEIDELBERG
ZUKUNFT SEIT 1386

AIPHES
ADAPTIVE INFORMATIONSAUFBEREITUNG AUS HETEROGENEN QUELLEN

Ranking and Selecting Multi-Hop Knowledge Paths to Better Predict Human Needs

Debjit Paul and Anette Frank
Heidelberg University

NAACL 2019

Research in Sentiment Analysis

Who expressed what kind of attitude towards *what or whom?*

or

What is the underlying emotion?

Research in Sentiment Analysis

Who expressed what kind of attitude towards *what* or *whom*?

or

What is the underlying emotion?

Our interest

Why is an attitude expressed?

or

What is the reason behind the emotion?

Research in Sentiment Analysis

Why is an attitude expressed?

or

What is the reason behind the emotion?

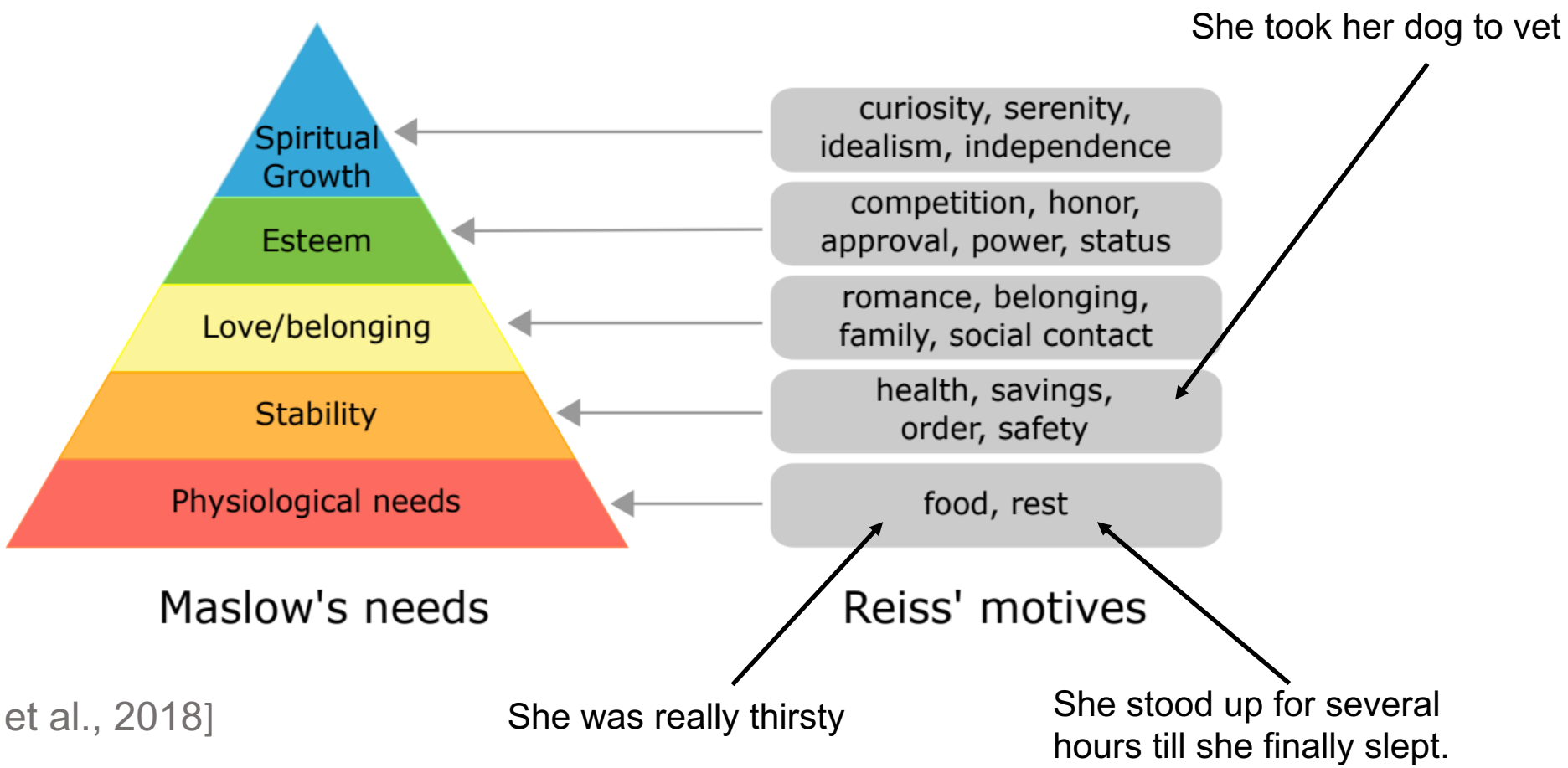
*"An adequate and complete account of utilitarian based sentiment is possible only with reference to the **goals** of the opinion holder" –*

[Li and Hovy, 2017]

*"The polarities of **affective events** often stem from whether experiencers' **human needs** are satisfied or violated" –*

[Ding and Riloff, 2018]

Research in Sentiment Analysis



[Rashkin et al., 2018]

Human Needs in Narrative Stories

Meg

Mom

Meg was invited to a fancy dinner party.

But she could not afford any fancy clothing to wear.

Her mom encouraged her to go anyways.

Meg decided to take her mom's advice.

She attended the party and had a great time in her old dress!

esteem; approval

sadness, disgust, anticipation

esteem; approval

trust, fear

love; family

joy, trust, anticipation

esteem; approval, belonging, contact

joy; surprise

love; family

joy

love; family

joy, trust, anticipation

[Rashkin et al., 2018]

Human Needs in Narrative Stories

Meg

esteem; approval

sadness, disgust, anticipation

esteem; approval

trust, fear

love; family

joy, trust, anticipation

esteem; approval, belonging, contact

joy; surprise

Meg was invited to a fancy dinner party.

But she could not afford any fancy clothing to wear.

Her mom encouraged her to go anyways.

Meg decided to take her mom's advice.

She attended the party and had a great time in her old dress!

Mom

love; family

joy

love; family

joy, trust, anticipation

[Rashkin et al., 2018]

Hypotheses

- Leveraging **commonsense knowledge** to better predict human needs
- We need **relevant commonsense knowledge**
- Therefore, we apply ranking methods to select **knowledge paths**

Overview

- Commonsense Knowledge for Human Needs Prediction
- Selecting and Ranking Multi-Hop Knowledge Paths
- Gated Attention Model for Knowledge Integration
- Experiments, Results & Analysis

Commonsense Knowledge

Narrative Story

Meg was invited to a fancy dinner party.

Previous Sentence

But she could not **afford** any **fancy clothing** to **wear**.

Sentence

Her mom **encouraged** her to **go** anyways

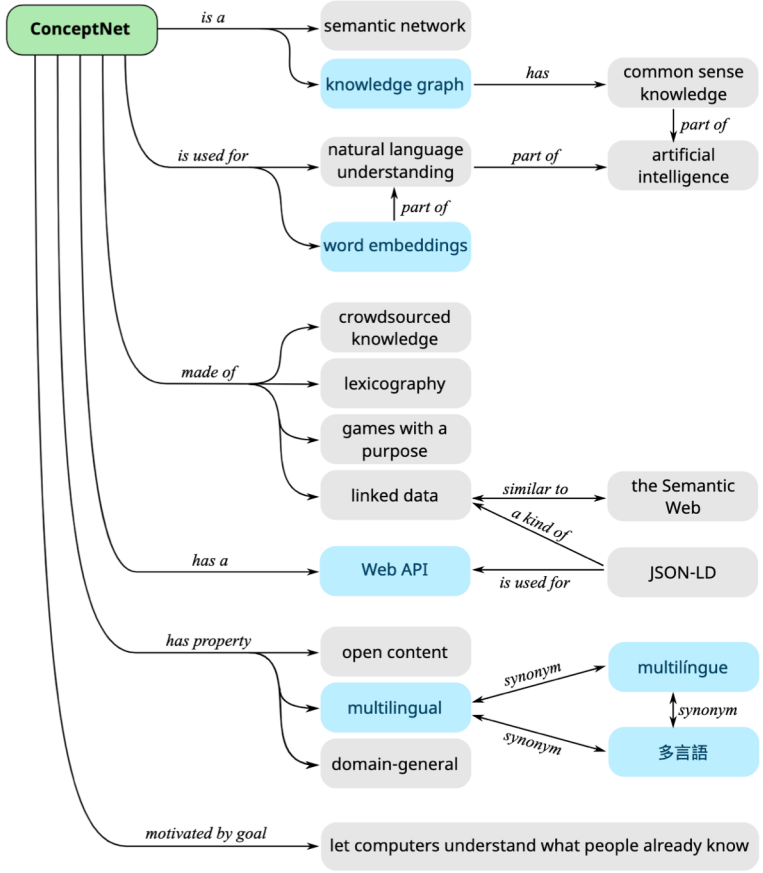
Character: **'Meg'**, Emotion: **'trust'**

Human needs: **'approval, esteem'**

Concepts that appear in the text (C) :

wear | encourage | afford | cloth | fancy | go | fancy clothing

ConceptNet 5.6.0: [Speer and Havasi, 2012]



Commonsense Knowledge

Narrative Story

Meg was invited to a fancy dinner party.

Previous Sentence

But she could not **afford** any **fancy clothing** to **wear**.

Sentence

Her mom **encouraged** her to **go** anyways

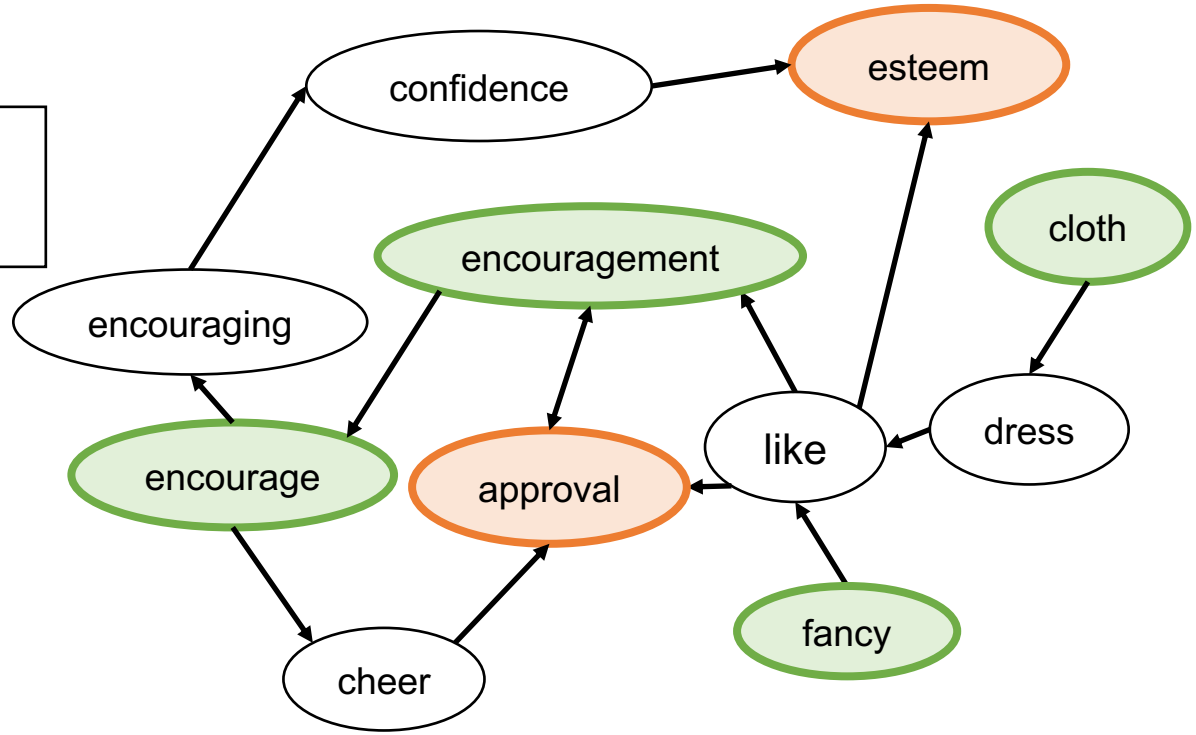
Character: **'Meg'**, Emotion: **'trust'**

Human needs: **'approval, esteem'**

Concepts that appear in the text (C) :

wear | encourage | afford | cloth | fancy | go | fancy clothing

ConceptNet 5.6.0: [Speer and Havasi, 2012]



Sample subgraph

Commonsense Knowledge

Narrative Story

Meg was invited to a fancy dinner party.

Previous Sentence

But she could not **afford** any **fancy clothing** to **wear**.

Sentence

Her mom **encouraged** her to **go** anyways

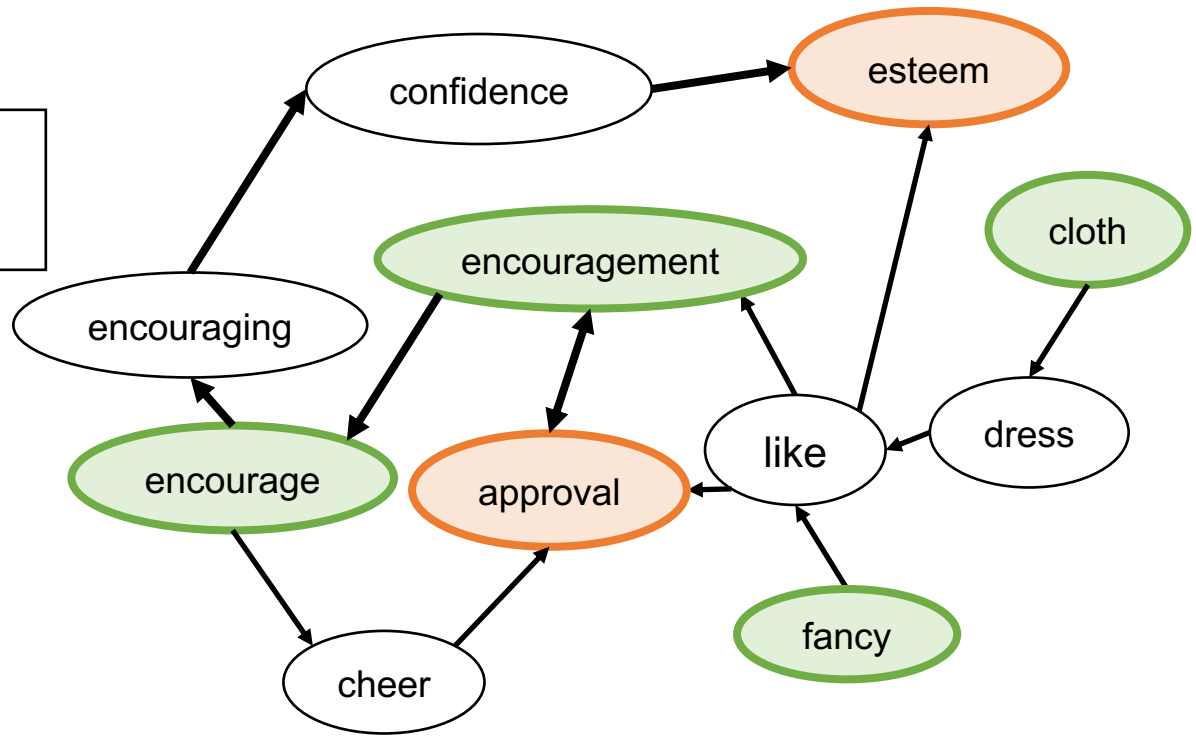
Character: **'Meg'**, Emotion: **'trust'**

Human needs: **'approval, esteem'**

Concepts that appear in the text (C) :

wear | encourage | afford | cloth | fancy | go | fancy clothing

ConceptNet 5.6.0: [Speer and Havasi, 2012]



Multi Hop Paths

Subgraph Construction

Concepts that appear in the text (C) :

wear | encourage | afford | cloth | fancy | go | fancy clothing

Human needs (h) :

status | approval | … …. … …. …. …. … … | esteem

Initialize V' = (*wear*, *encourage*, .., .., *fancy clothing*, *status*, *approval*, .., .., .., *esteem*)

Shortest Paths

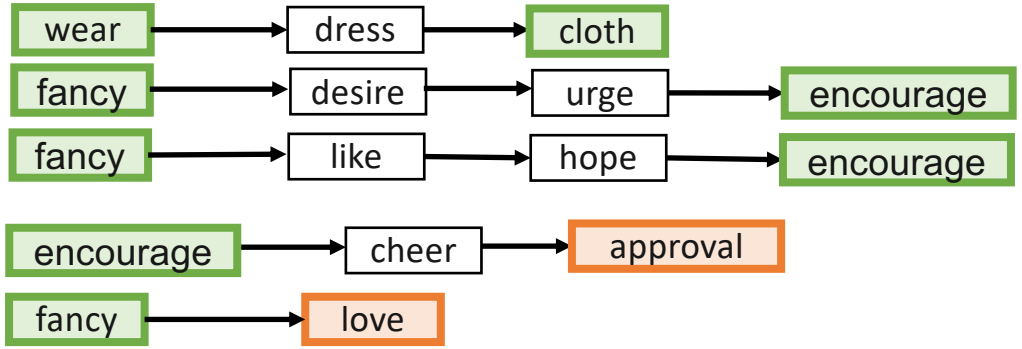
Concepts that appear in the text (C) :

wear | encourage | afford | cloth | fancy | go | fancy clothing

Human needs (h) :

status | approval | … …. … …. …. …. … … | esteem

Example:

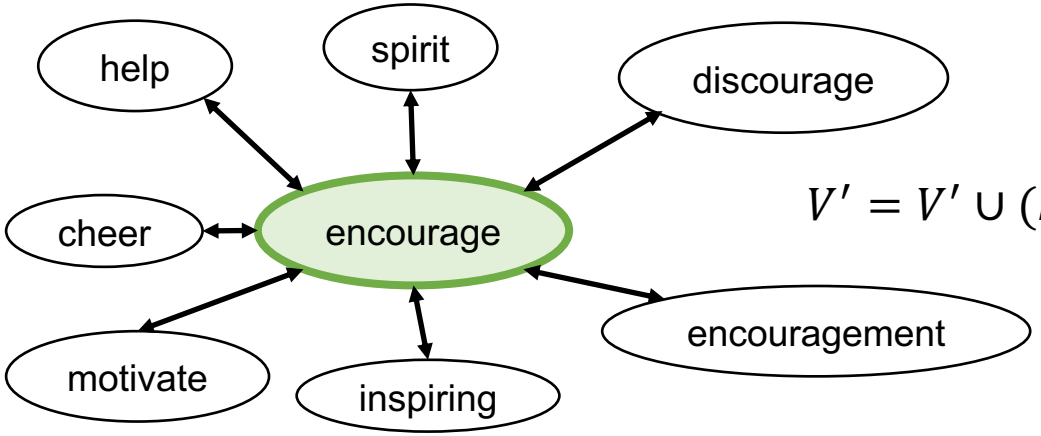


$$V' = V' \cup (dress, desire, urge, hope, admire, cheer)$$

Neighbours

To better represent the meaning of the concepts found in sentence and human needs

Example:

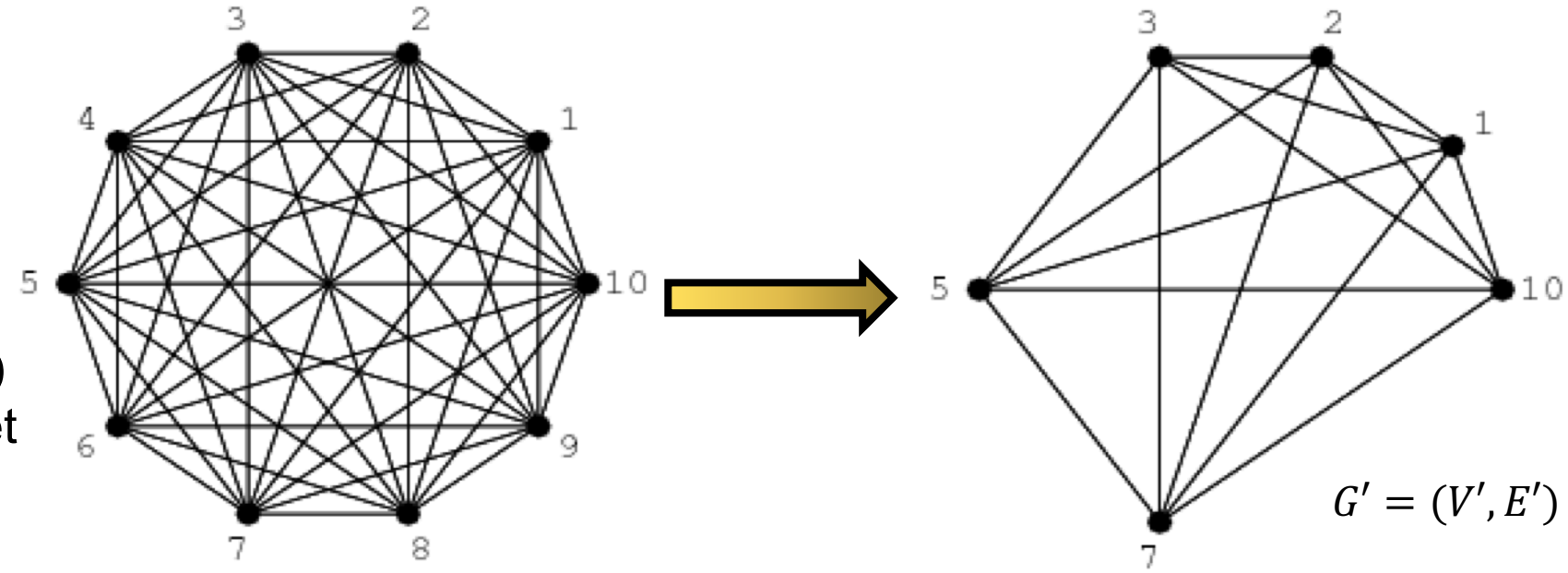


$$V' = V' \cup (help, spirit, discourage, motivate, cheer, inspiring)$$

Induced Subgraph

Construct a connected subgraph $G' = (V', E')$ from V' by defining E' as the set of ConceptNet edges that directly connect any pair of concepts.

$G = (V, E)$
ConceptNet



$G' = (V', E')$

Vertex-Induced Subgraph

Ranking and Selecting Multi-hop Paths

- Hypothesis: The most useful commonsense relation paths should include vertices that are ***important*** with respect to the ***entire extracted subgraph***.

- Collect all shortest paths between concepts from the text and human needs.

Scoring Measures

- **Vertex score:**
  - **Closeness Centrality (CC):** Importance of a vertex is measured by how *close a vertex is to all other vertices* in a given graph.
  - **PageRank (PR):** Importance of a vertex is reflected by the *number of incoming edges*.
  - **Personalized PageRank (PPR):** Vertex should hold importance with respect to *the pair of vertices that are been connected*: concepts from the text and human needs.

- **Path Score** $= \frac{\sum Scores\ of\ the\ each\ node\ in\ the\ path}{Number\ of\ nodes\ in\ the\ path}$

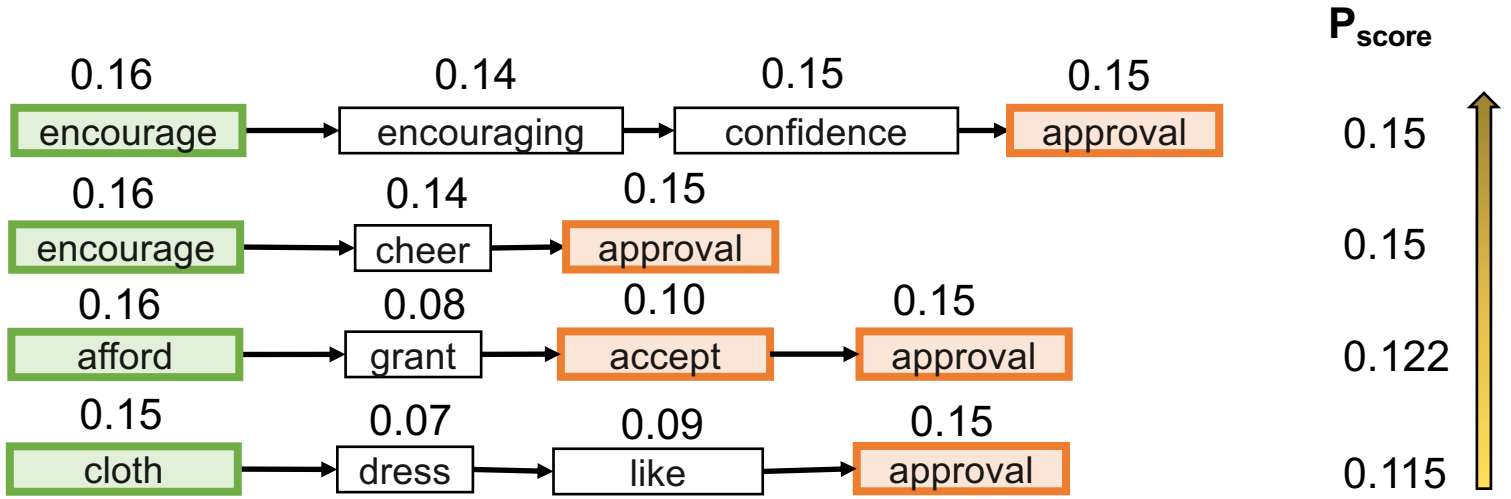
Path Selection

Narrative Story Meg was invited to a fancy dinner party.

Previous Sentence But she could not **afford** any **fancy clothing** to **wear**.

Sentence Her mom **encouraged** her to **go** anyways

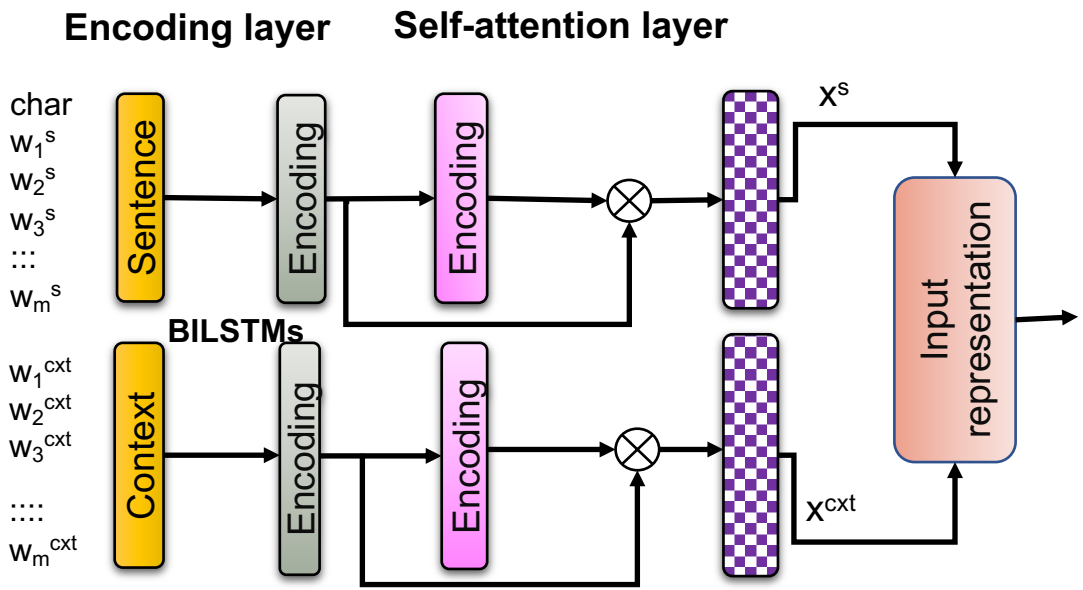
Paths connecting human needs (h) and concepts (c) with V_{score} and P_{score}



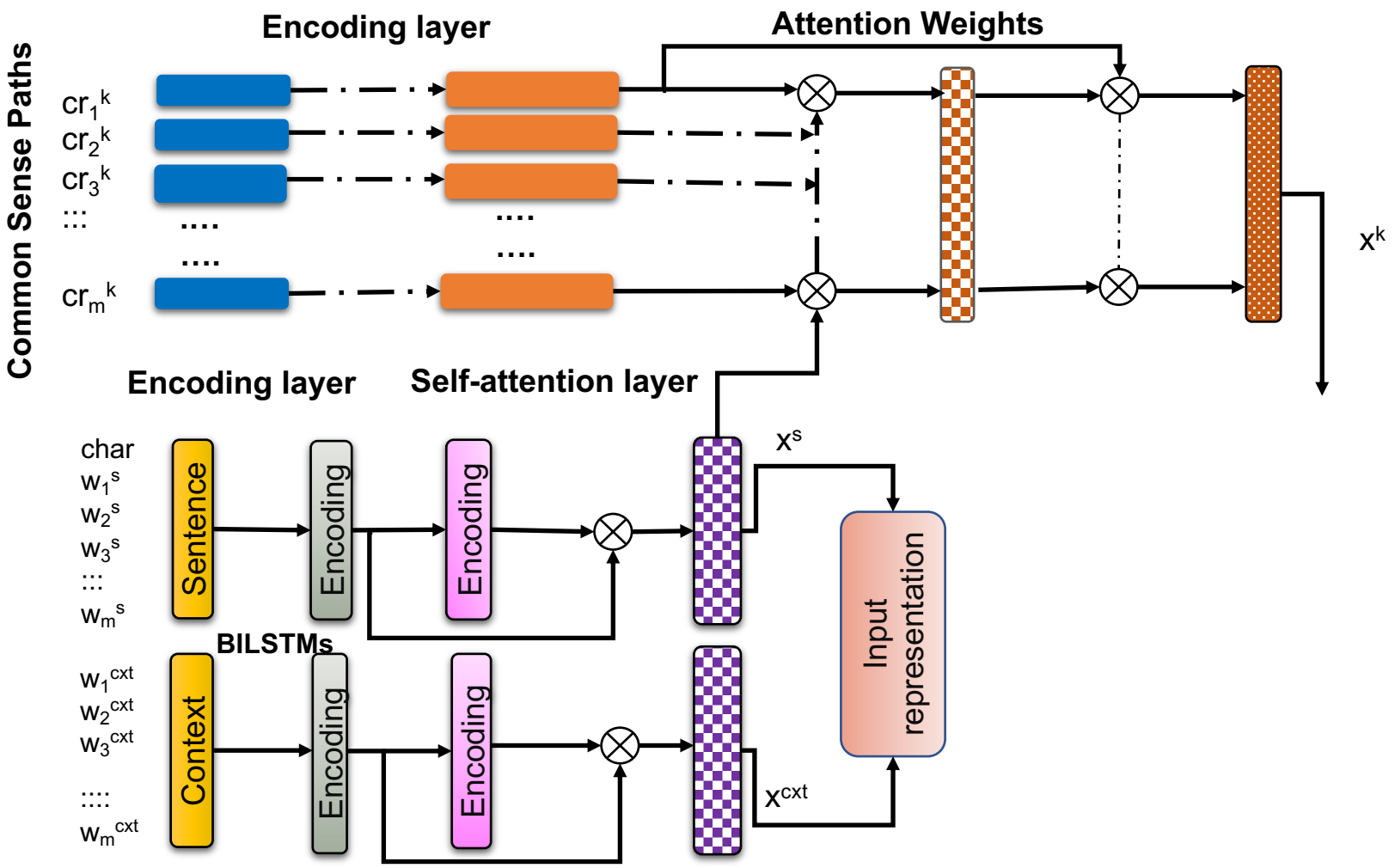
Select: top-k paths per human need

Gated Attention Model with Knowledge

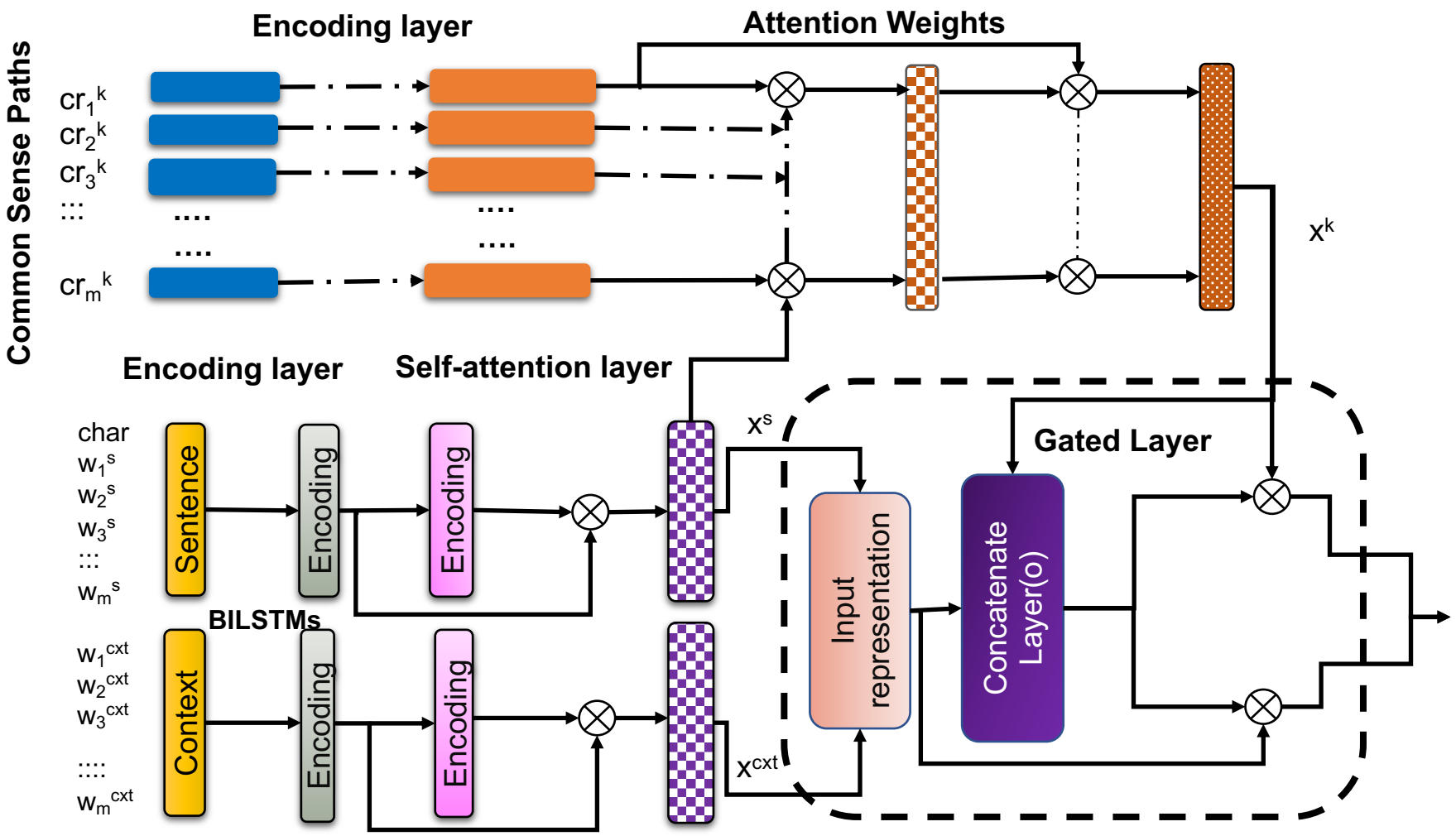
Gated Attention Model with Knowledge



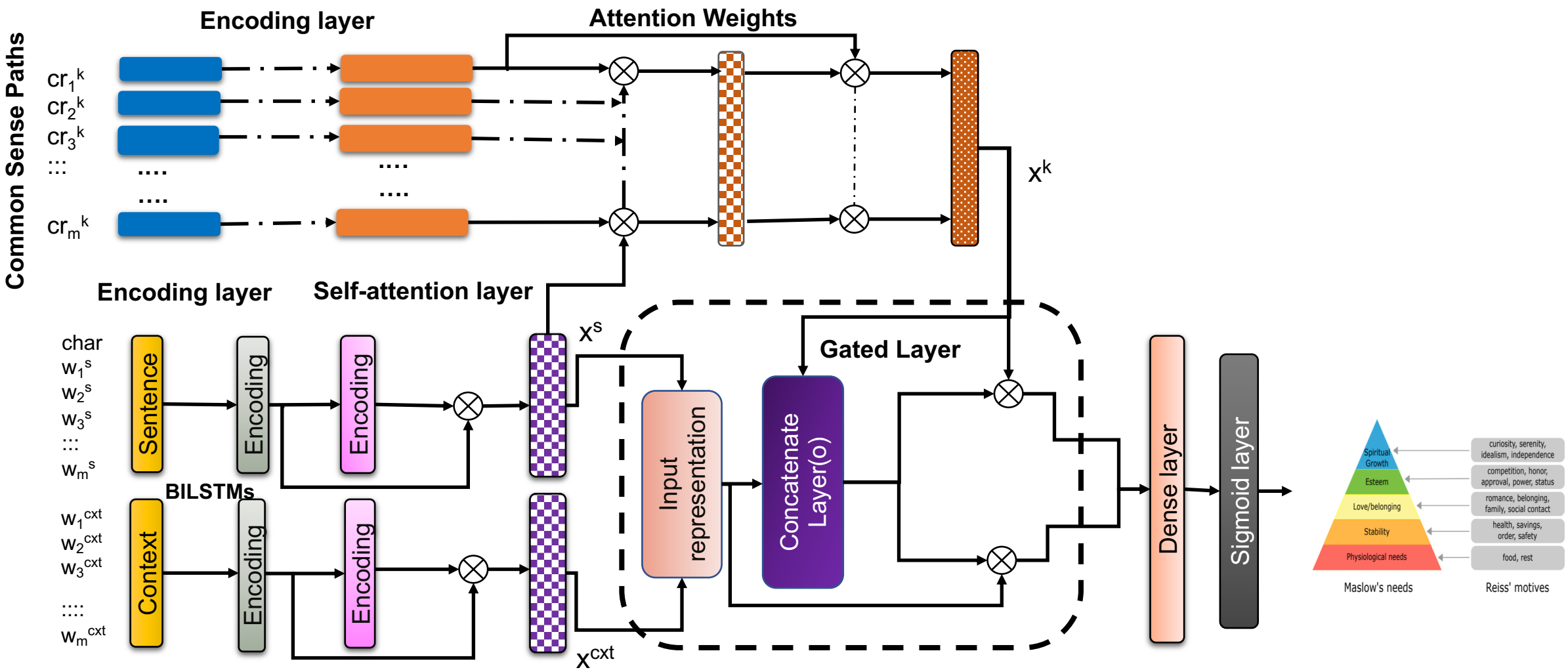
Gated Attention Model with Knowledge



Gated Attention Model with Knowledge



Gated Attention Model with Knowledge



Results

		Reiss			Maslow		
Model	**Embedding**	**P**	**R**	**F1**	**P**	**R**	**F1**
BiLSTM	Glove 100d	18.35	27.61	22.05	31.29	33.85	**32.52**
CNN	Glove 100d	18.89	31.22	**23.54**	27.47	41.01	32.09
REN (Henaff et al. 2016)	Glove 100d	16.79	22.20	19.12	26.24	42.14	32.34
NPN (Bosselut et al. 2017)	Glove 100d	13.13	26.44	17.55	24.27	44.16	31.33

[Rashkin et al., 2018]

Results

		Reiss			Maslow		
Model	**Embedding**	**P**	**R**	**F1**	**P**	**R**	**F1**
BiLSTM	Glove 100d	18.35	27.61	22.05	31.29	33.85	32.52
CNN	Glove 100d	18.89	31.22	23.54	27.47	41.01	32.09
REN (Henaff et al. 2016)	Glove 100d	16.79	22.20	19.12	26.24	42.14	32.34
NPN (Bosselut et al. 2017)	Glove 100d	13.13	26.44	17.55	24.27	44.16	31.33
BiLSTM + Atten	Glove 100d	25.08	28.25	26.57	47.65	60.98	53.54
BiLSTM + Atten + Knowledge	Glove 100d	28.47	39.13	**32.96**	50.54	64.54	**56.69**

Results

		Reiss			Maslow		
Model	**Embedding**	**P**	**R**	**F1**	**P**	**R**	**F1**
BiLSTM	Glove 100d	18.35	27.61	22.05	31.29	33.85	32.52
CNN	Glove 100d	18.89	31.22	23.54	27.47	41.01	32.09
REN (Henaff et al. 2016)	Glove 100d	16.79	22.20	19.12	26.24	42.14	32.34
NPN (Bosselut et al. 2017)	Glove 100d	13.13	26.44	17.55	24.27	44.16	31.33
BiLSTM + Atten	Glove 100d	25.08	28.25	26.57	47.65	60.98	53.54
BiLSTM + Atten + Knowledge	Glove 100d	28.47	39.13	32.96	50.54	64.54	56.69
BiLSTM + Atten	Elmo	29.50	44.28	35.41$\pm$0.23	53.86	67.23	59.81$\pm$0.23
BiLSTM + Atten+ Knowledge	Elmo	31.74	43.51	**36.70$\pm$0.14**	57.90	66.07	**61.72$\pm$0.11**

Ablation Study

Model Ablations	**P**	**R**	**F1**
+Glove 300d – Attention - knowledge	23.31	34.69	27.89
+Glove 300d + Attention - knowledge	26.09	35.59	**30.11**
+Glove 300d + Attention + knowledge	28.65	39.42	33.19
+ELMo - Attention - knowledge	32.35	42.66	36.80
+ELMo + Attention - knowledge	31.45	44.29	**37.70**
+ELMo + Attention + knowledge	36.76	42.53	39.44

*without belonging class

- Using *self attention* over sentences and contexts is highly effective,
- *Knowledge-enriched* version of our model improves the performance.

Ablation Study

Model Ablations	**P**	**R**	**F1**
+Glove 300d – Attention - knowledge	23.31	34.69	27.89
+Glove 300d + Attention - knowledge	26.09	35.59	30.11
+Glove 300d + Attention + knowledge	28.65	39.42	**33.19**
+ELMo - Attention - knowledge	32.35	42.66	36.80
+ELMo + Attention - knowledge	31.45	44.29	37.70
+ELMo + Attention + knowledge	36.76	42.53	**39.44**

*without belonging class

- Using *self attention* over sentences and contexts is highly effective,
- *Knowledge-enriched* version of our model improves the performance.

Does ranking help?

Model Variants	Ranking method	P	R	F1
S+M	None	32.51	42.70	36.90
S+M	Random	31.63	43.35	36.57
Single Hop	CC+PPR	33.00	44.63	37.94
S+M	CC+PPR	36.76	42.53	**39.44**

Results for different path selection strategies; S+M: Single + Multi Hop

- Ranking and selecting relevant knowledge paths is important
- Using both single-hop and multi-hop paths improves performance

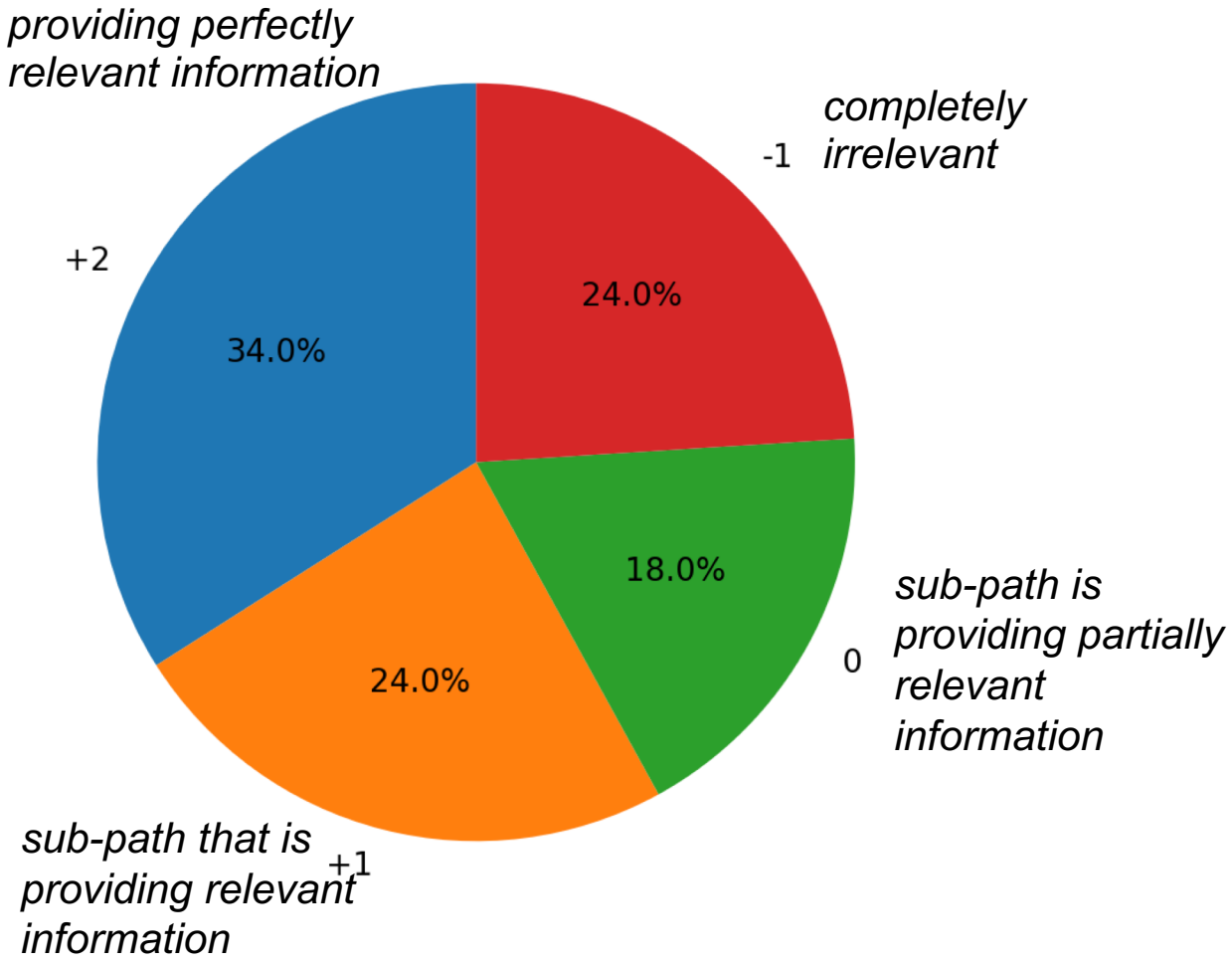
Which measure(s)?

Model	Ranking method	P	R	F1
S+M (P_{c2h}+ P_{c2c})	None	32.51	42.70	36.90
S+M (P_{c2h}+ P_{c2c})	Random	31.63	43.35	36.57
Single Hop (P_{c2h})	CC+PPR	33.00	44.63	37.94
S+M (P_{c2h}+ P_{c2c})	CC+PPR	35.30	44.11	39.21
S+M	CC	33.45	47.93	39.40
S+M	PR	35.51	42.82	38.82
S+M	PPR	36.23	43.09	39.34
S+M	CC+PPR	36.76	42.53	**39.44**

Results for different path selection strategies; S+M: Single + Multi Hop

Human evaluation

- 50 random sentence-context pairs.
- Inter annotator agreement Fless' κ= 0.76.
- Three expert evaluators scored the selected multi-hop paths.



Summary

- We show that integrating **commonsense knowledge** help the model to better predict human needs.
- Our contributions:
  - **selecting** and **ranking** multi-hop relation paths from a commonsense knowledge resource.
  - **end-to-end model** enhanced with **self-attention** and a **gated knowledge integration** component to predict human needs.
  - knowledge paths provide **interpretability**

Github: https://github.com/debjitpaul/Multi-Hop-Knowledge-Paths-Human-Needs

UNIVERSITÄT HEIDELBERG
ZUKUNFT SEIT 1386

AIPHES
ADAPTIVE INFORMATIONSAUFBEREITUNG AUS HETEROGENEN QUELLEN

Thank you for listening ! Questions?

Machine needs Commonsense to understand Human needs !!

Github: https://github.com/debjitpaul/Multi-Hop-Knowledge-Paths-Human-Needs