A Study of Zero-shot Adaptation with Commonsense Knowledge

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Background and Problem statements

Background:

Zero-shot evaluation is Important for evaluating common sense

Self-supervision with Knowledge Graphs brings good zero shot performance

Problems to explore:

Unclear impact of knowledge training to models

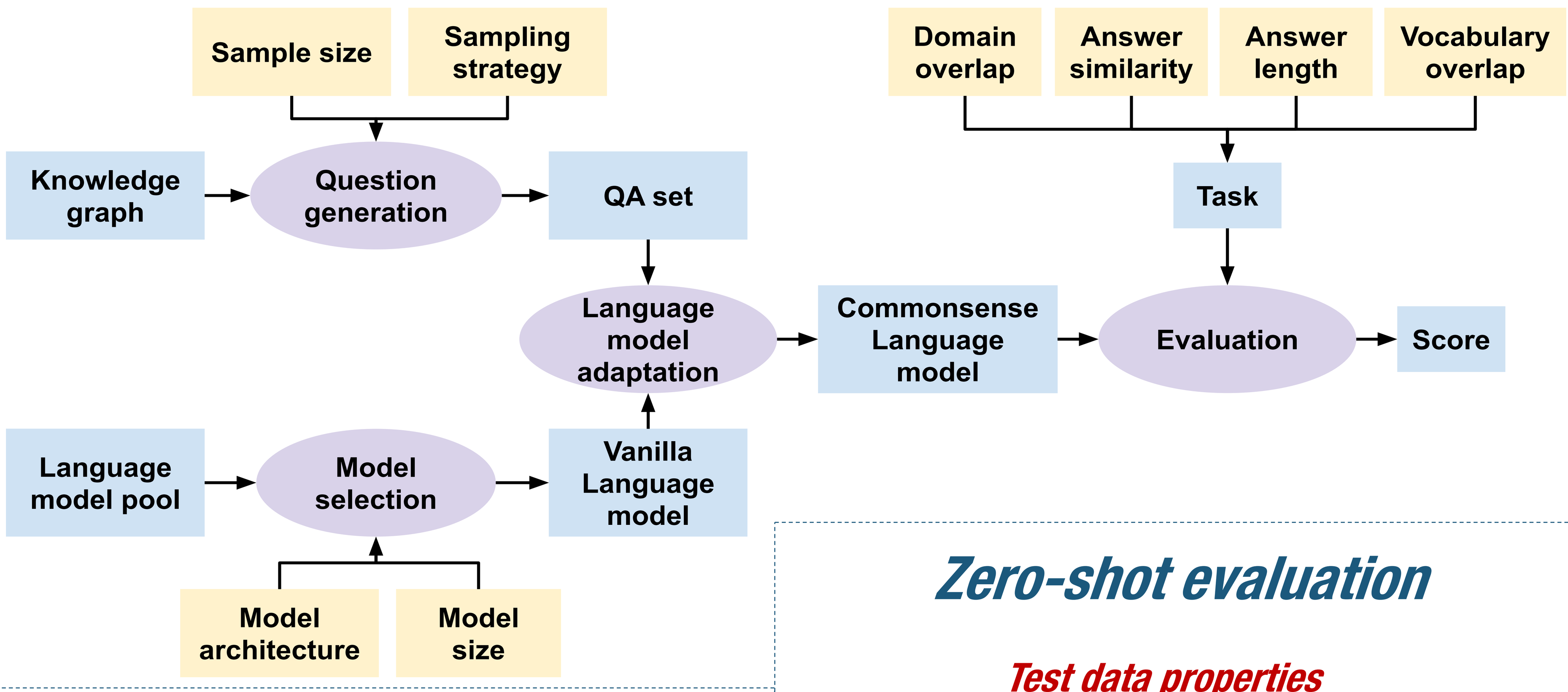
Uncertain optimal knowledge data size

Best training data sampling strategy

LMs' ability of generalizing the knowledge

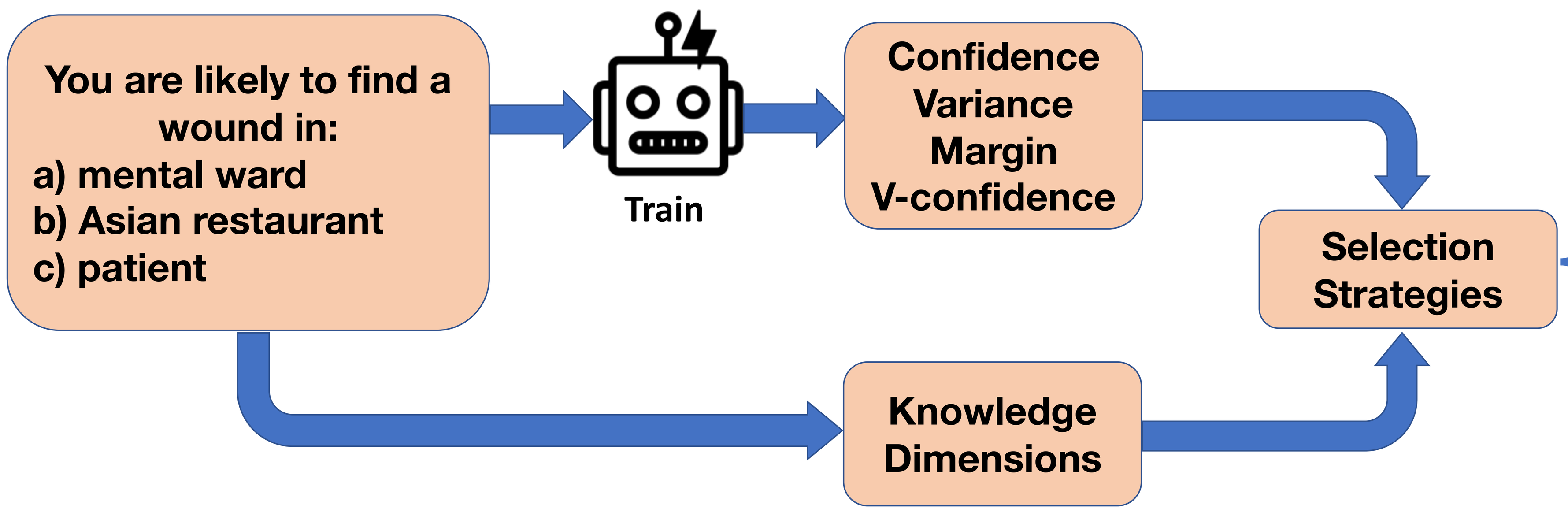
The connection between model's performance and properties of the task

Research Framework



Data Generation & Selection

Over 1M QA sets from CSKG



- Random
- Uniform (same size each dimension)
- Temporal (knowledge dimension)
- Desire (knowledge dimension)
- Taxonomic(knowledge dimension)
- Quality(knowledge dimension)
- Rel-other(knowledge dimension)
- High vanilla confidence
- Low vanilla confidence
- High confidence
- Low confidence
- High variability
- Low variability
- High margin loss
- Low margin loss

Zero-shot evaluation

Test data properties

Length $AL(q) = \sum_{i=1}^{n} |T_{A_i}|$

Similarity $AS(q) = \frac{|T_{A_i} \cap T_{A_j}|}{|T_{A_i} \cup T_{A_j}|}$

Vocabulary $VO(q) = \frac{1}{m} \sum_{k=1}^{m} \frac{1}{f(t_k)}$

Benchmarks

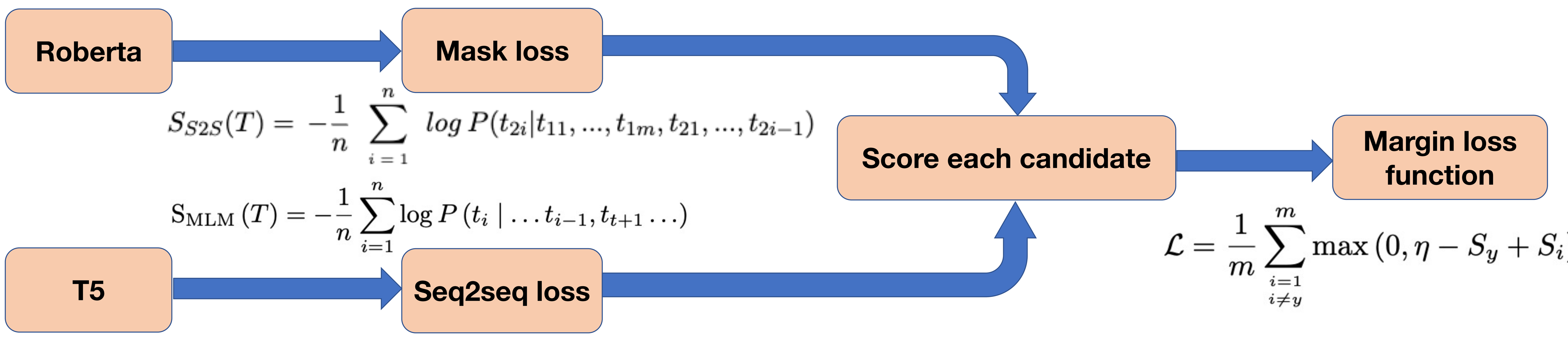
High domain overlap:

CommonsenseQA [Talmor et al., 2019] (CSQA)
SocialIQA [Sap et al., 2019b] (SIQA)

Low domain overlap:

Abductive NLI [Bhagavatula et al., 2019] (ANLI)
PhysicalIQA [Bisk et al., 2020] (PIQA)
WinoGrande [Sakaguchi et al., 2019] (WG)

Language Models



$$S_{S2S}(T) = -\frac{1}{n} \sum_{i=1}^{n} \log P(t_{2i} | t_{11}, \ldots, t_{1m}, t_{21}, \ldots, t_{2i-1})$$

$$S_{MLM}(T) = -\frac{1}{n} \sum_{i=1}^{n} \log P(t_i \mid \ldots t_{i-1}, t_{t+1} \ldots)$$

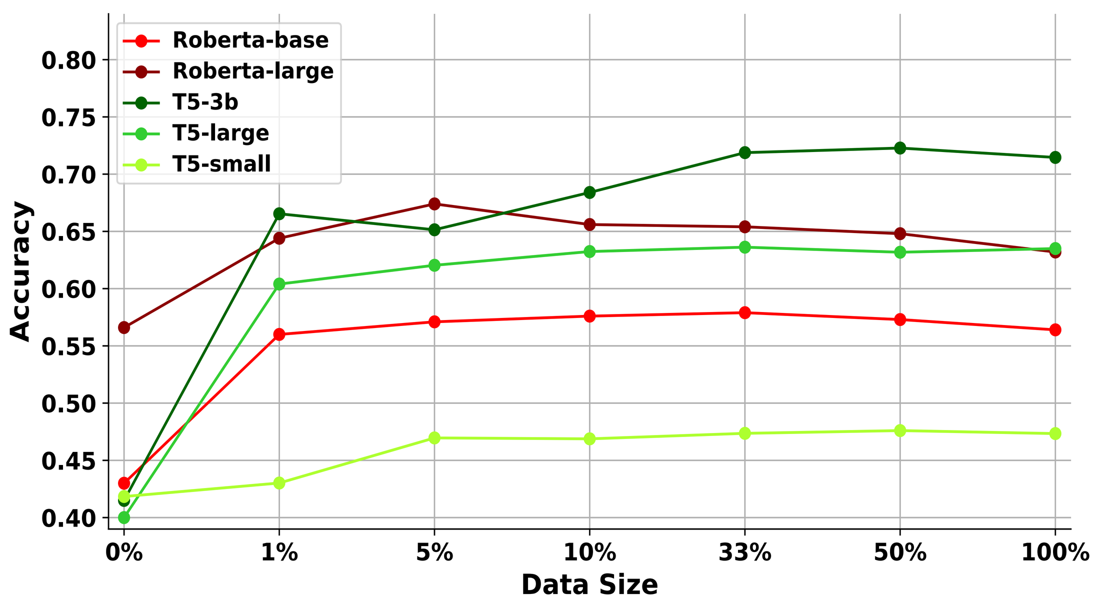
$$\mathcal{L} = \frac{1}{m} \sum_{\substack{i=1 \\ i \neq y}}^{m} \max(0, \eta - S_y + S_i)$$

Results: Overall

Model	LDO aNLI	LDO WG	LDO PIQA	HDO SIQA	HDO CSQA	Avg(LDO)	Avg(HDO)	Avg
Majority [Ma et al., 2021a]	50.8	50.4	50.5	33.6	20.9	50.6	27.25	41.2
RoBERTa-large [Liu et al., 2019b]	65.5	57.5	67.6	47.3	45.0	63.5	46.1	56.6
COMET [Bosselut et al., 2019]	-	-	-	50.1	-	-	*50.1	*50.1
Self-Talk [Shwartz et al., 2020]	-	54.7	70.2	46.2	32.4	*62.5	39.3	50.9
SMLM [Banerjee and Baral, 2020]	65.3	-	-	48.5	38.8	*65.3	43.7	50.9
Ma et al. [Ma et al., 2021a]	70.5	60.9	72.4	63.2	67.4	67.9	65.3	66.8
Dou & Peng [Dou and Peng, 2022]	-	-	-	59.9	67.4	-	63.6	63.6
RoBERTa-base (ours)	59.9	53.1	65.7	54.6	53.6	59.6	54.1	57.4
RoBERTa-large (ours)	71.5	60.0	72.6	63.6	66.4	68.0	65.0	66.8
T5-small (ours)	50.6	51.6	56.2	42.3	36.4	52.8	39.4	47.4
T5-large (ours)	66.1	58.7	70.8	57.5	63.1	65.2	60.3	63.2
T5-3b (ours)	**76.6**	**71.0**	**76.7**	**65.3**	**69.9**	**74.7**	**67.6**	**71.9**
RoBERTa-large (supervised)	85.6	79.3	79.2	76.6	78.5	81.4	77.5	79.8
T5-3b (supervised)	87.5	84.4	76.3	78.6	81.5	82.7	80.1	81.7

Careful Knowledge Sampling and Model design leads to Consistent Improvement across tasks

Optimal training data size Depends on LM size and architecture



Results: Sampling Strategies

Strategy		LDO aNLI	LDO WG	LDO PIQA	HDO SIQA	HDO CSQA	Avg(LDO)	Avg(HDO)	Avg
Random	5%	65.9	56.5	70.5	55.4	61.9	64.3	58.7	62.0
Dimension	temporal	66.6	56.4	**71.2**	54.9	**63.4**	**64.7**	**59.2**	**62.5**
	desire	64.4	57.9	69.6	55.9	62.2	64.0	59.1	62.0
	taxonomic	61.8	54.0	66.8	52.8	57.5	60.9	55.2	58.6
	quality	**66.8**	**58.4**	70.0	**56.4**	59.6	65.1	58.0	62.2
	rel-other	61.0	52.5	65.9	51.7	54.0	59.8	52.9	57.0
Uniform		65.3	57.5	69.2	56.6	62.7	64.0	59.7	62.3
Vanilla-conf	high	65.3	56.8	69.0	55.5	57.5	63.7	56.5	60.8
	low	64.0	56.0	68.1	52.0	59.6	62.7	55.8	59.9
Conf	high	62.9	53.8	66.5	53.9	57.0	61.1	55.5	58.8
	low	41.8	48.5	42.0	24.7	07.7	44.1	16.2	32.9
Varibility	high	64.0	54.6	65.1	51.1	54.5	61.2	52.8	57.9
	low	61.7	54.9	66.8	52.7	55.9	61.1	54.3	58.4
Margin	high	63.8	54.5	67.2	52.8	56.9	61.8	54.9	59.0
	low	41.5	45.0	43.7	24.1	09.1	43.4	16.6	32.7

Natural distribution Is the Optimal sampling strategy

dimension: temporal
Q:Jan went out with Quinn's friends and had a great time.What does Jan need to do before this?
A1:get dressed(*); A2:cancel her plans; A3:see Quinn's Friends again

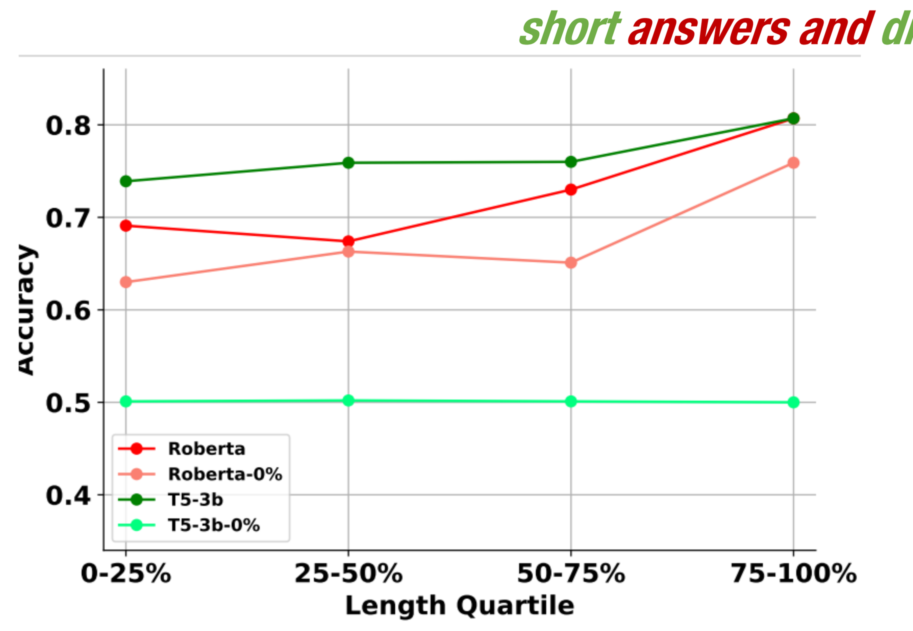
dimension: desire
Q:Robert has no regret for punching Justin in the nose because _ was the victim of injustice.
A1:Robert(*); A2:Justin

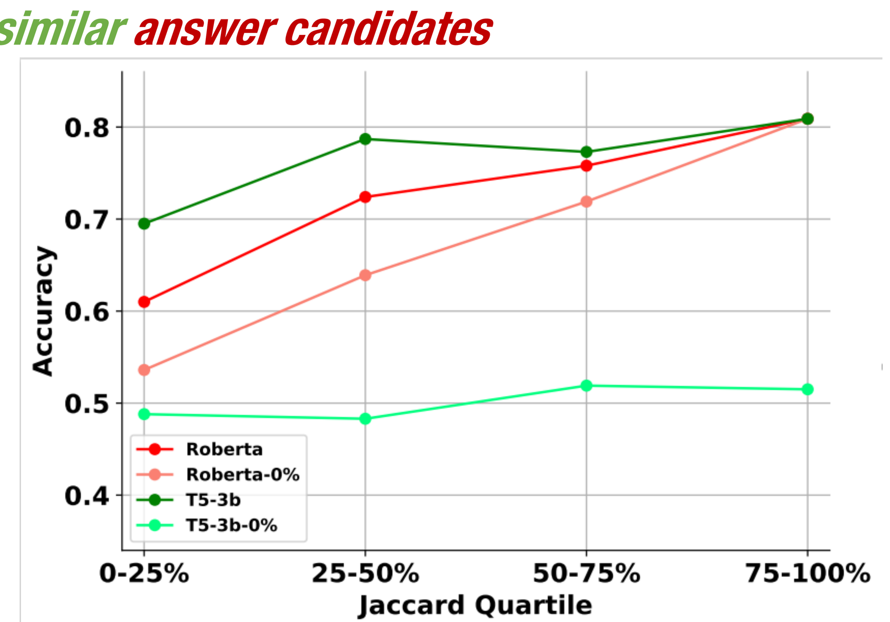
dimension: quality
Q:What can machines do that humans cannot?
A1:fail to work; A2:perform work; A3:answering questions; A4:see work; A5:fly(*)

Dimension-based strategies Makes LMs learn Complementary knowledge

Results: Test Data Properties

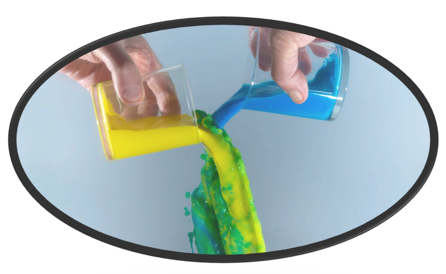
knowledge training is most effective for questions with short answers and dissimilar answer candidates

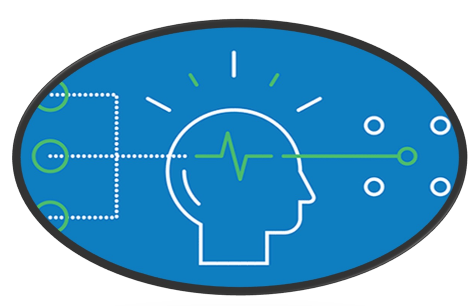




Future work:

Mixture of models





Explainable zero-shot commonsense reasoning

More realistic tasks

Code&data: https://github.com/saccharomycetes/commonsense-with-KG