



# Commonsense Knowledge Base Reasoning

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- Facts are not stated explicitly in text.

“If you stick a pin into a carrot, it leaves a hole.”

- Facts have to be combined.

“If X is a father of Y, then Y is a child and X is older than Y.”

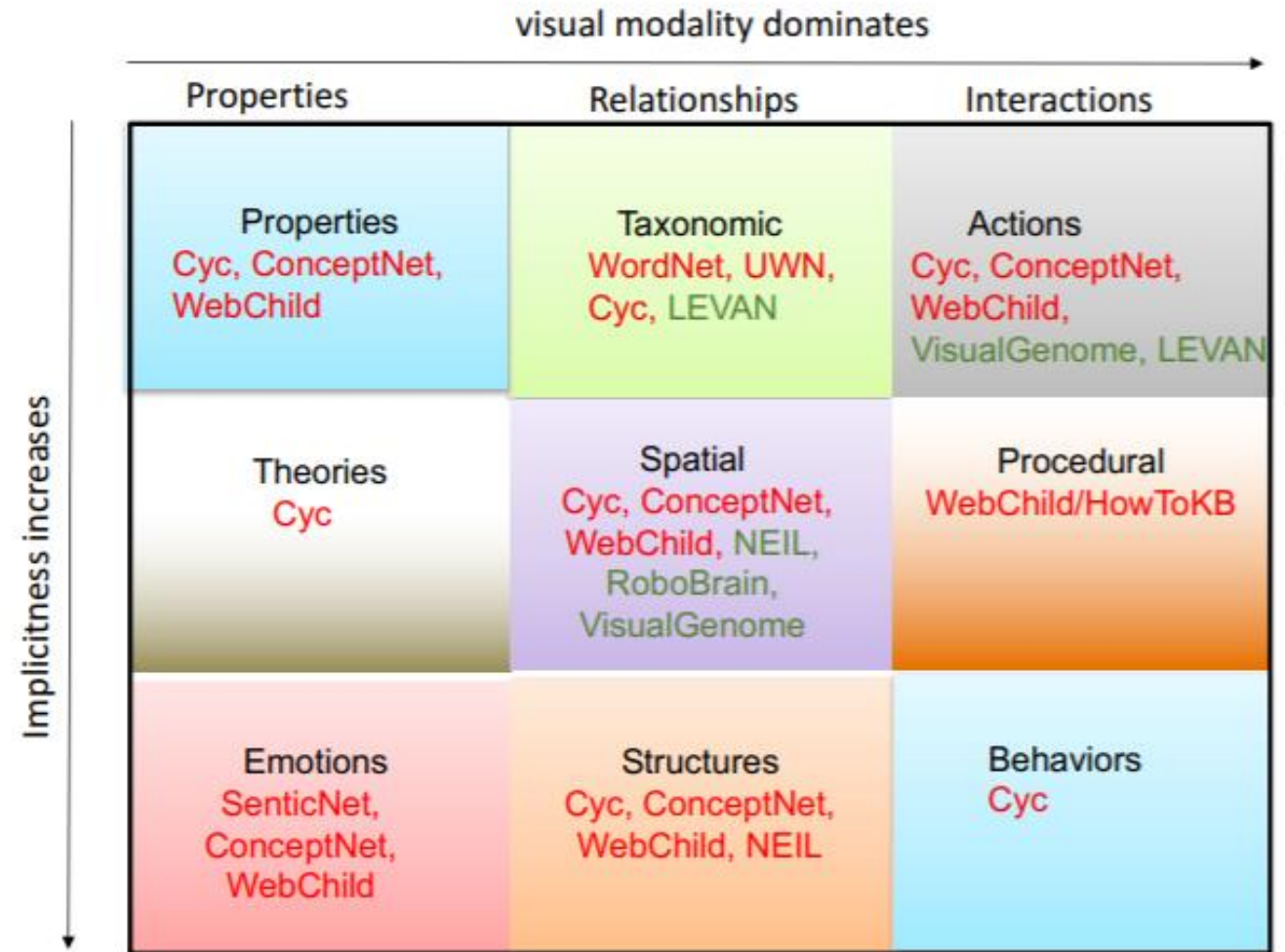
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# Why?



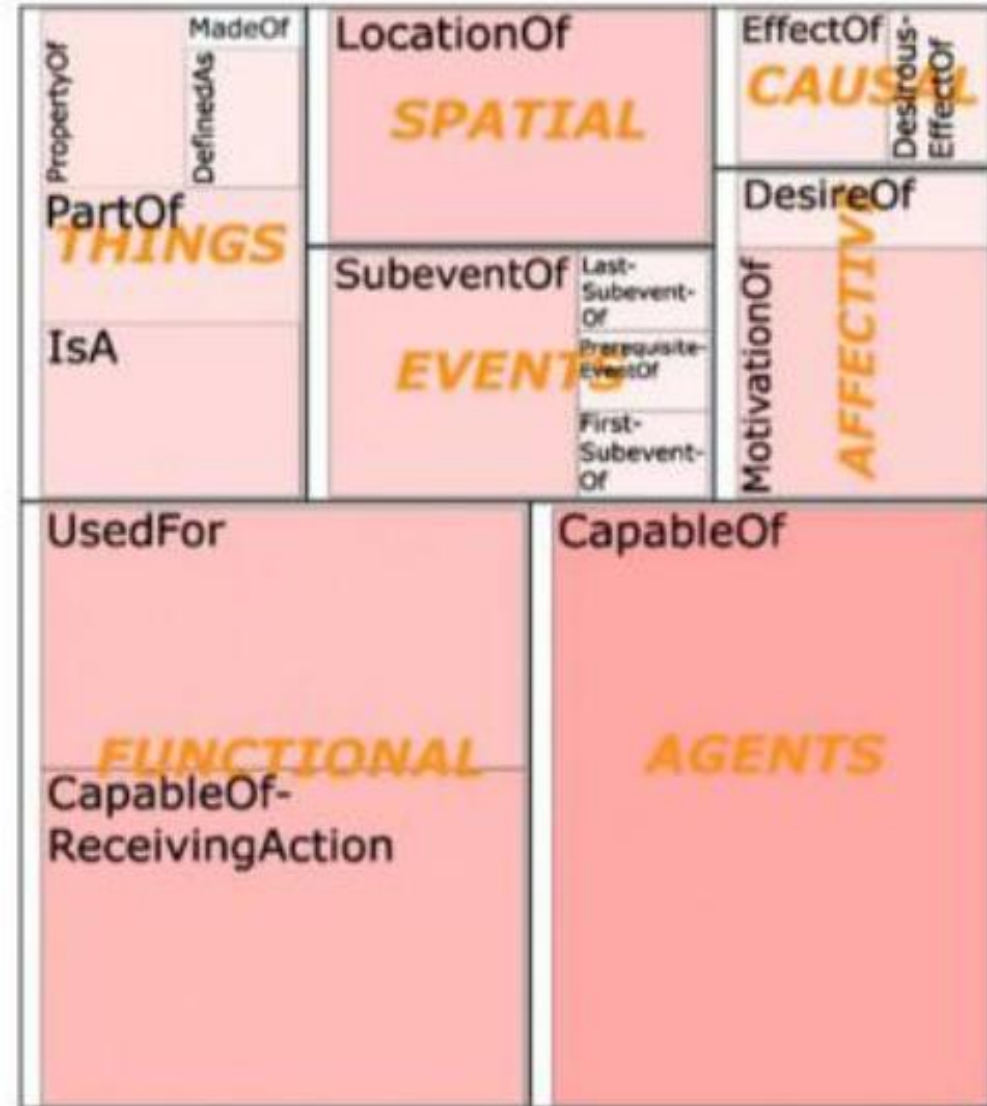
How we  
can represent  
it?

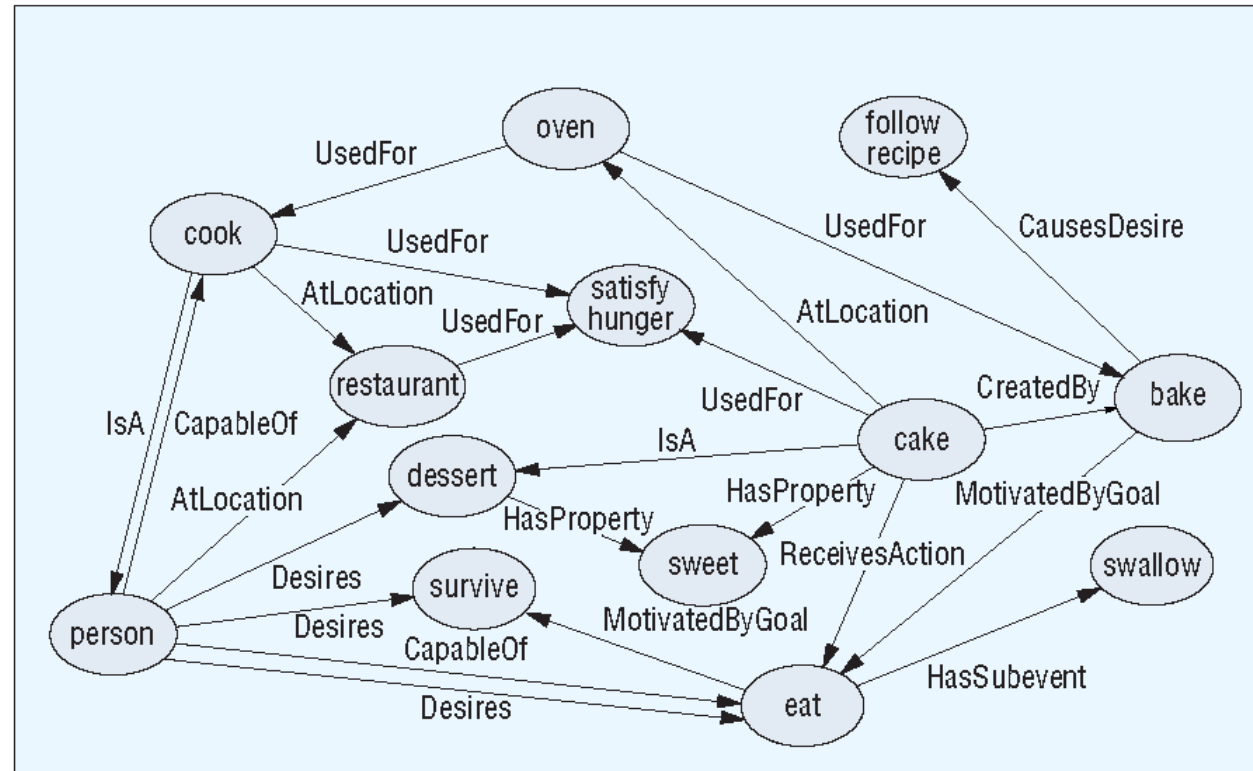
# Commonsense KBs



# ConceptNet

- Freely available commonsense knowledge base.
- Supports many practical textual reasoning tasks over real-word documents.
- 1.6 million assertions, 34 relation types.

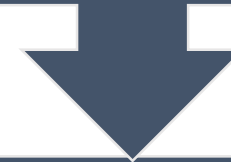




# ConceptNet

# Project

Commonsense  $\leftrightarrow$  ConceptNet KB.



Objective: Increase coverage of ConceptNet by inferring missing entries.



How: Score tuples in ConceptNet using KB Completion methods.

- $\forall (h, r, t) \in \text{ConceptNet}$ 
  - $h = [\text{word}_1, \text{word}_2, \dots, \text{word}_n]$
  - $t = [\text{word}_1, \text{word}_2, \dots, \text{word}_m]$

ex:

*(listen to radio, HasPrerequisite, tune in station)*

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# KB Completion: ConceptNet



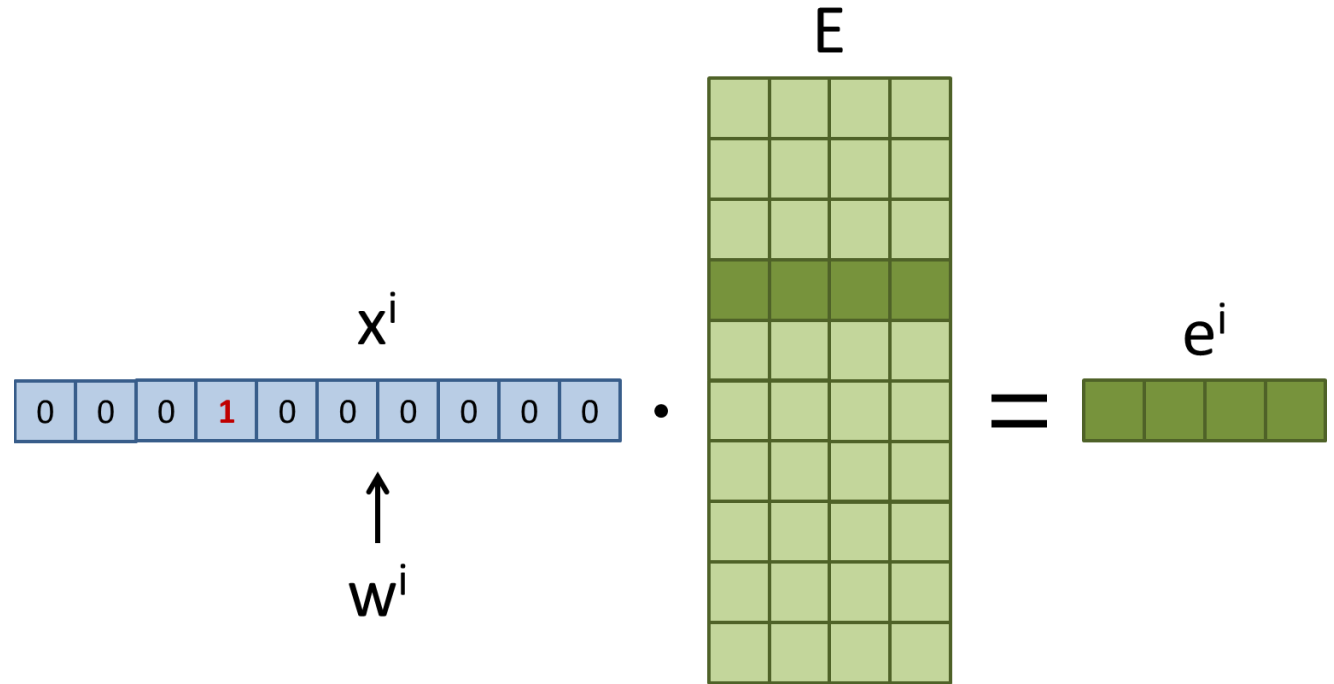
# Bilinear Averaging

- $\forall (h, R, t) \in \text{ConceptNet}$

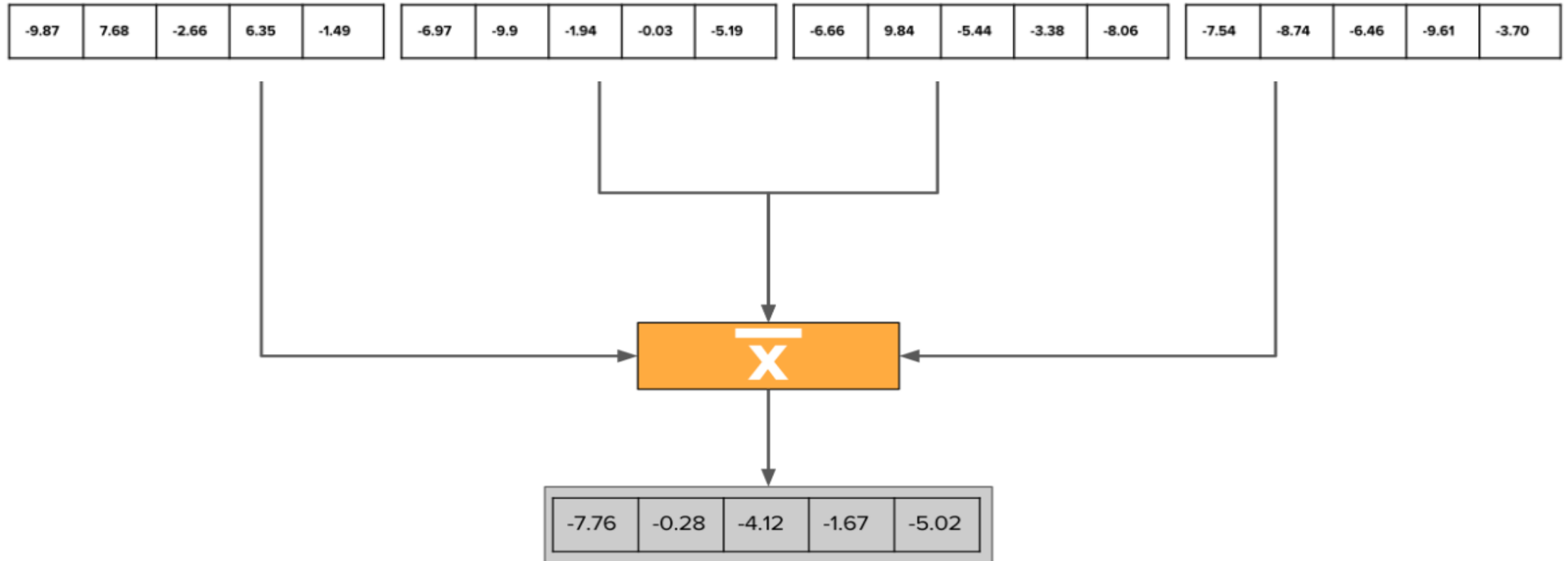
- $h = [h_1, h_2, \dots, h_n]$

- $t = [t_1, t_2, \dots, t_m]$

- $R = [r]$



# Word Averaging

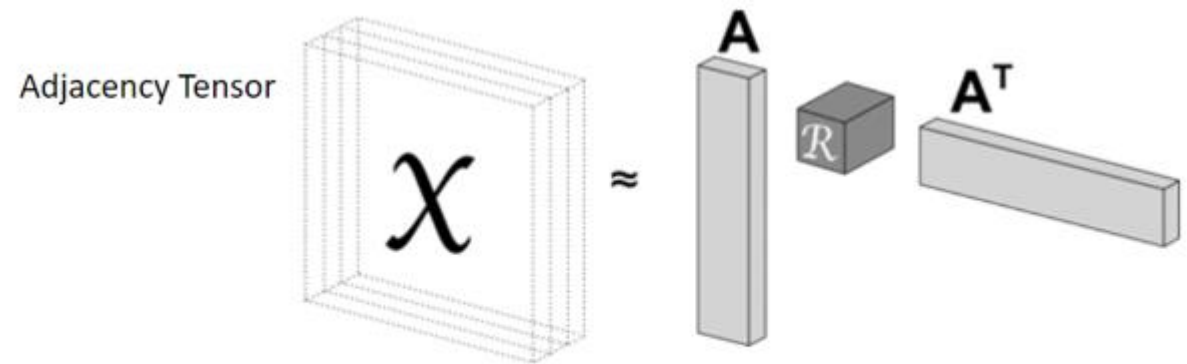


# Bilinear Model

$$f_{ijk}^{\text{RESCAL}} := \mathbf{e}_i^\top \mathbf{W}_k \mathbf{e}_j = \sum_{a=1}^{H_e} \sum_{b=1}^{H_e} w_{abk} e_{ia} e_{jb}$$

$$A = [e_i^1, e_i^2, e_i^3, \dots, e_i^n] \in E^m$$

$$W = R = [r_i^j] \in E^{m \times m}$$



- Problem:
  - $R$  grows quadratically with term vectors.

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# Bilinear Model

- Problem:
  - $R$  grows quadratically with term vectors.
- Solution:
  - Apply non-linear transform on each term.
    - $u_i = \tanh(W^{(B)}v_i + b^{(B)})$
    - $\text{score}(h, R, t) = u_h^T W_R u_t$

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# Bilinear Model

## ConceptNet Tuples

```
[['ReceivesAction', 'hockey', 'play on ice', '3.4594316186372978'],  
 ['AtLocation', 'restroom', 'rest area', '3.4594316186372978'],  
 ['HasPrerequisite', 'eat breakfast', 'make breakfast', '3.4594316186372978'],  
 ['AtLocation', 'book', 'table', '3.4594316186372978'],  
 ['AtLocation', 'dust', 'refrigerator', '3.4594316186372978'],  
 ['UsedFor', 'letter', 'communication', '3.4594316186372978'],  
 ['UsedFor', 'dynamite', 'blow thing up', '3.4594316186372978'],  
 ['AtLocation', 'shade', 'window', '3.4594316186372978'],  
 ['HasA', 'cat', 'eye', '3.4594316186372978'],  
 ['AtLocation', 'cat', 'bag', '3.4594316186372978']]
```

# Preprocessing

- Word to index

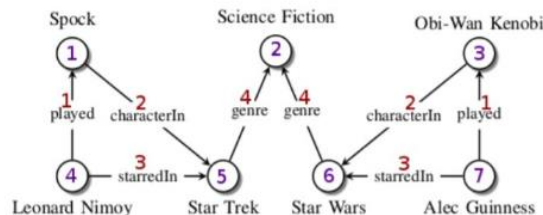
```
[[13, [630], [64, 36, 317]],  
 [1, [3333], [391, 314]],  
 [5, [80, 434], [75, 434]],  
 [1, [105], [166]],  
 [1, [1223], [668]],  
 [2, [235], [1104]],  
 [2, [5351], [1340, 46, 74]],  
 [1, [2103], [469]],  
 [8, [227], [676]],  
 [1, [227], [334]]]
```

# Preprocessing

- Padding

```
(array([[ 630,    0,    0, ...,    0,    0,    0],
       [3333,    0,    0, ...,    0,    0,    0],
       [  80, 434,    0, ...,    0,    0,    0],
       ...,
       [  44,    0,    0, ...,    0,    0,    0],
       [1588, 805, 1936, ...,    0,    0,    0],
       [ 189,    0,    0, ...,    0,    0,    0]]),
array([[  64,   36,  317, ...,    0,    0,    0],
       [ 391,  314,    0, ...,    0,    0,    0],
       [  75,  434,    0, ...,    0,    0,    0],
       ...,
       [68029,    0,    0, ...,    0,    0,    0],
       [  332,    9,  805, ...,    0,    0,    0],
       [    3,   54,  738, ...,    0,    0,    0]]),
array([13,  1,  5, ...,  1,  2,  9]))
```





$(e_4, r_1, e_1)$  exists     $(e_1, r_1, e_4)$  does not  
 $(e_1, r_2, e_5)$  exists     $(e_1, r_3, e_5)$  does not  
 $(e_4, r_3, e_5)$  exists     $(e_6, r_3, e_5)$  does not  
 ... and so on

$$BCE = -\frac{1}{N} \sum_{i=0}^N y_i \cdot \log(\hat{y}_i) + (1 - y_i) \cdot \log(1 - \hat{y}_i)$$

# KB Completion as a Triple Classification

- Random Sampling
  - For every positive example generate negatives by:
    - randomly perturb head.
    - randomly perturb tail.

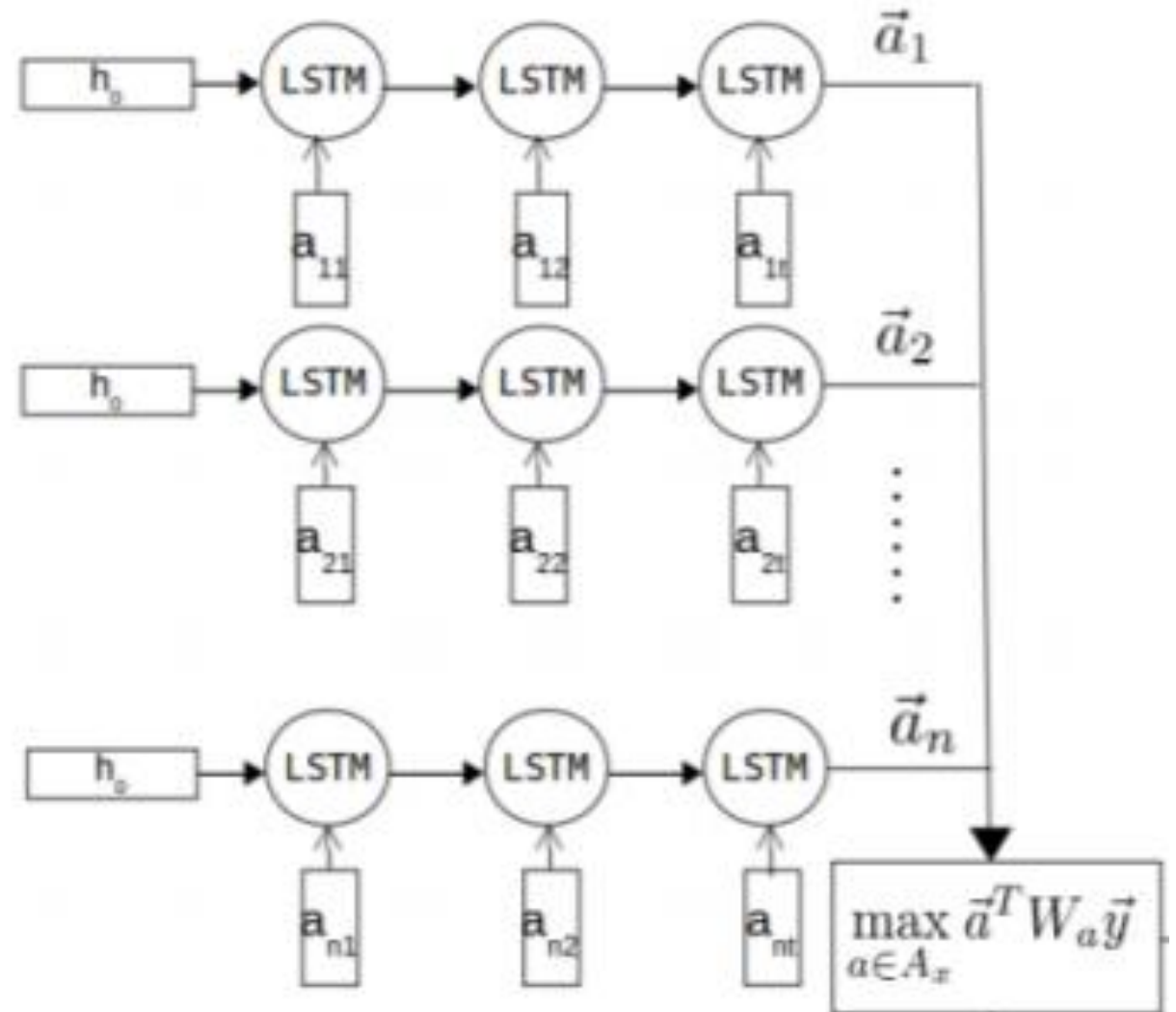
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# Negative Sampling

# Bilinear LSTM

- $\forall (h, R, t) \in \text{ConceptNet}$

- $h = [h_1, h_2, \dots, h_n]$
- $t = [t_1, t_2, \dots, t_m]$
- $R = [r]$



# Pre-training

- ConceptNet generated from OMCS.
- Normalize OMCS sentences with ConceptNet relation.

```
['If you want to eat breakfast HasPrerequisite make breakfast'],  
['Something you find on book AtLocation table'],  
['Something you find behind refrigerator AtLocation refrigerator']
```

- Merge ConceptNet tuples and their OMCS sentences.
- Train word2vec on merged corpus.

KBs Completion.

	<b>Bilinear-Averaging</b>
Validation Accuracy	0.7875
Validation AUC	0.8593
Test Accuracy	0.7941
Test AUC	0.8629

Words in subject found in Vocabulary ['drive', 'fast']  
Words in object found in Vocabulary ['accident']  
createdby score: 0.173436  
symbolof score: 0.163275  
haslastsubevent score: 0.149011  
causes score: 0.138195  
usedfor score: 0.128927

Words in subject found in Vocabulary ['soak', 'in', 'hotspring']  
Words in object found in Vocabulary ['relaxation']  
causes score: 0.197455  
haslastsubevent score: 0.180322  
createdby score: 0.162554  
hasprerequisite score: 0.154793  
hasfirstsubevent score: 0.152403

# Relation Discovery

## Other Models

DistMult Averaging.

DistMult LSTM.

ER-MLP Averaging.

ER-MLP LSTM.

# Implementation

- PyTorch

<https://github.com/MdAsifKhan/NLP-Project>



# Usage

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The implementation is structured as follows.

1. `model.py`

Contains implementation of different neural networks for scoring a tuple. Currently we provide following models:

- Bilinear Averaging Model
- Bilinear LSTM Model
- DistMult Averaging Model
- DistMult LSTM Model
- ER-MLP Averaging Model
- ER-MLP LSTM Model

2. `utils.py`

Implementation of preprocessing class, negative sampling and other basic utilities. Main class and functions:

- `class preprocess`

Implements method to read arbitrary phrase ConceptNet triples and convert them to token representation for training neural network models.

- `function sample_negatives`

Implements negative sampling strategy. Sampling is done by alternatively corrupting head and tail of a triple.

- `class TripleDataset`

Data class to support with pytorch batch loader.

3. `evaluation.py`

Contains implementation of different evaluation metric. For this project we mainly use accuracy and auc score.

4. `pretrained_embedding.py`

The scoring of tuple is highly dependent on initial embeddings used for training. To help model to better capture commonsense knowledge of ConceptNet we use pretraining. We create training data by combining ConceptNet tuples with natural language sentences of Open Mind Common Sense.

# Summary

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Commonsense important for general intelligence.

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ConceptNet: the largest freely commonsense database.

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Common sense enriched word embeddings, can directly be used for applications like entity resolution, pos tagging etc.



Thank you! 😊

# References

- <http://web.media.mit.edu/~minsky/E6/eb6.html>
- [https://en.wikipedia.org/wiki/Commonsense\\_reasoning](https://en.wikipedia.org/wiki/Commonsense_reasoning)
- <https://cacm.acm.org/magazines/2015/9/191169-commonsense-reasoning-and-commonsense-knowledge-in-artificial-intelligence/fulltext>
- <http://ttic.uchicago.edu/~kgimpel/papers/li+etal.acl16.pdf>
- <https://people.cs.umass.edu/~xiangl/improved-representation-learning.pdf>
- <http://web.media.mit.edu/~lieber/Publications/Understanding-Stories-Commonsense.pdf>
- [https://www.microsoft.com/en-us/research/wp-content/uploads/2016/06/Roth-Dan\\_CS-NLU.pdf](https://www.microsoft.com/en-us/research/wp-content/uploads/2016/06/Roth-Dan_CS-NLU.pdf)
- <https://github.com/commonsense/conceptnet5/wiki>
- <http://agents.media.mit.edu/projects/makebelieve/AAAI2002-makebelieve.pdf>