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Behavior-Tree Embeddings for Robot Task-Level Knowledge

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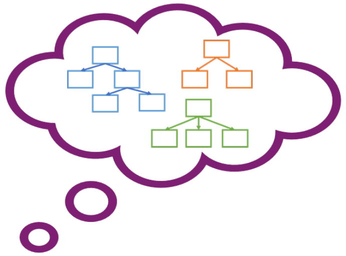
Task-Level Knowledge

- Manual design of robot tasks remains a cumbersome work.
- Consider a knowledge base consisting a collection of behavior-tree tasks.



A way to utilize task-level knowledge?

1. Query a desired task from the knowledge base?

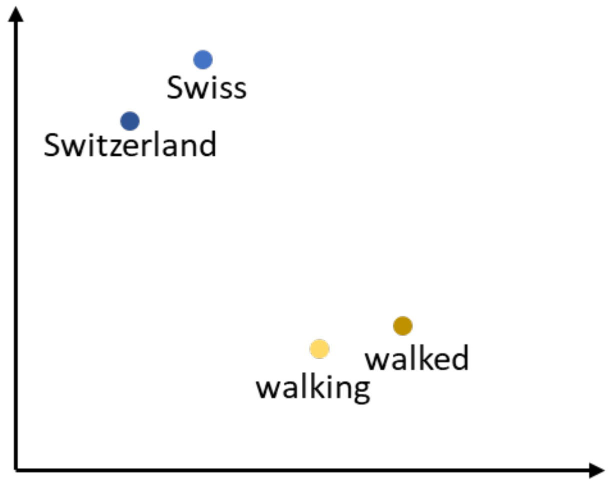
2. Enable machine learning on symbolic tasks?

Symbolic tasks → Numerical form? → Machine learning

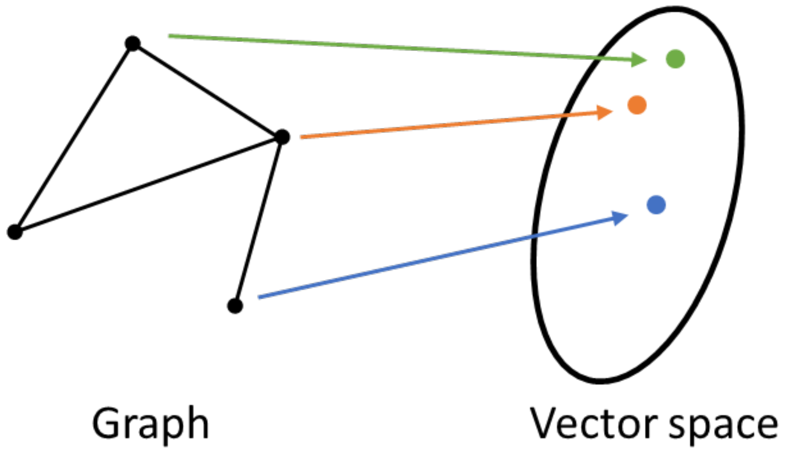
Background: Embeddings

- Embedding: Mapping an entity into a fixed length vector.

document, word, sentence, node, waveform, …(Entity2Vec)

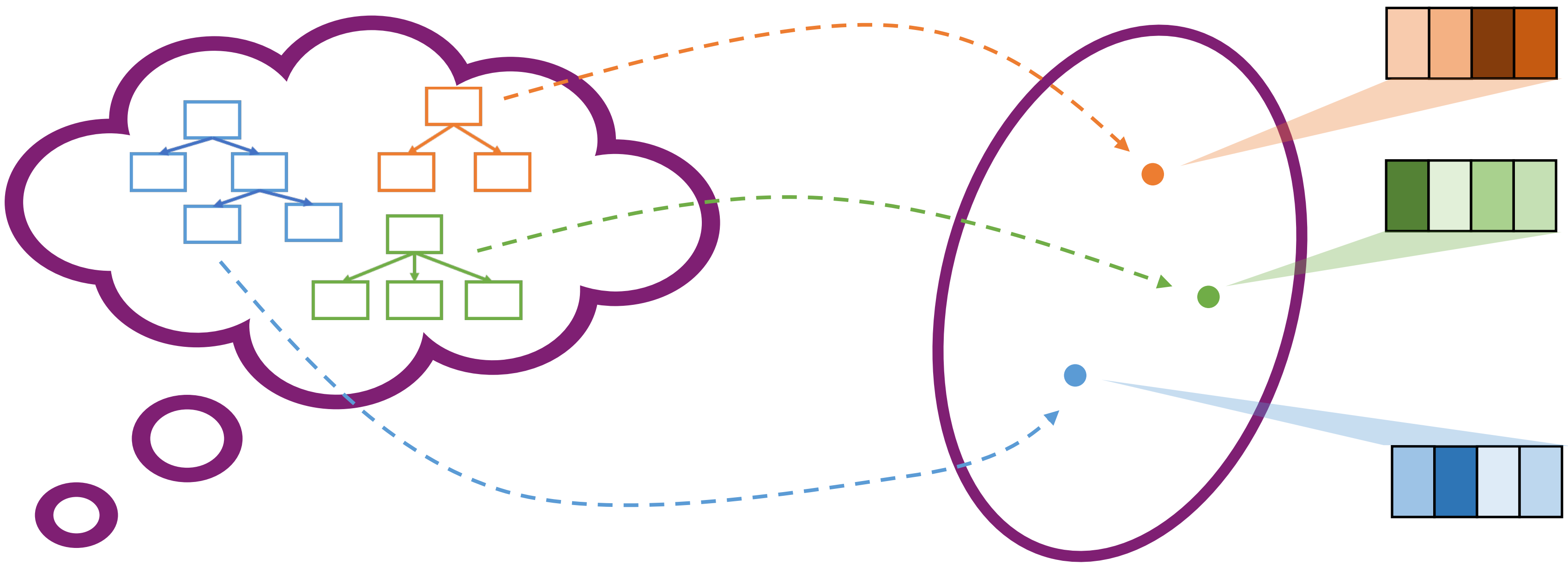


word embedding
Word2Vec, [Mikolov 2013]



node embedding
GNN, [Kipf 2016]

Our Idea: Behavior-Tree Embeddings



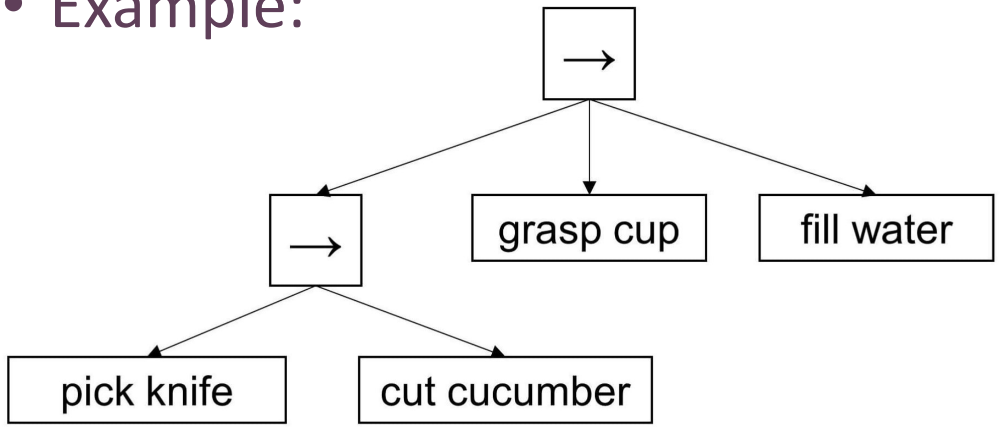
Knowledge base storing tasks

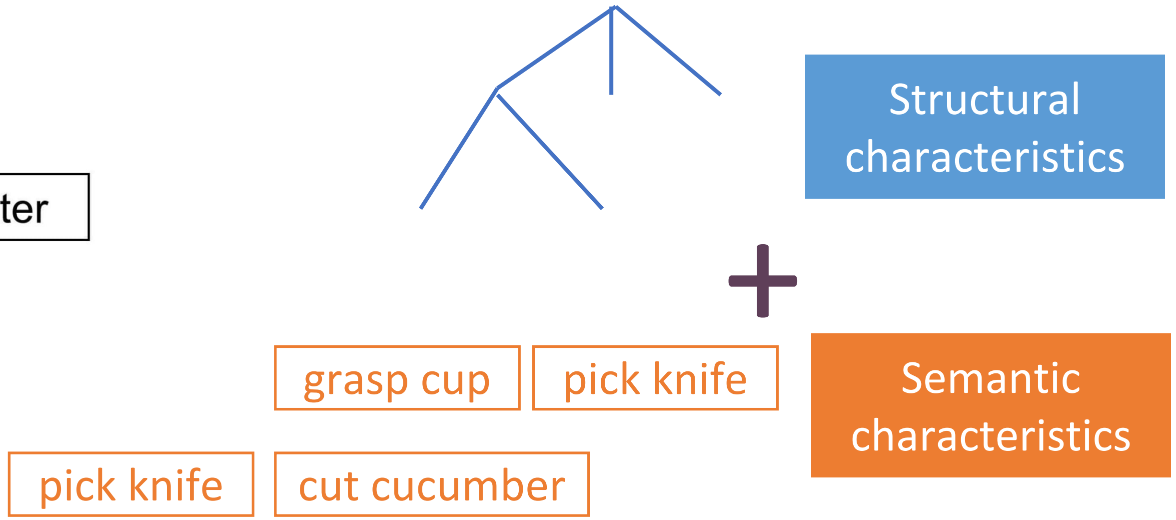
Vector space

Our Idea: Behavior-Tree Embeddings

- Principle: In the vector space, similar tasks should be close, while distinct tasks should be far away. → **Define similarity?**

- Example:





Problem Setting

- Given:
  A behavior tree that produces a single task.
- Aim:
  Encode it into a compact vector,
  while preserving semantic and structural characteristics.

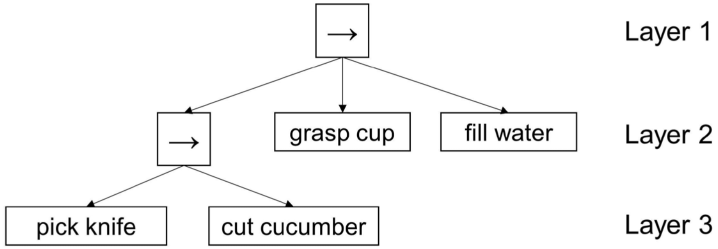
Two-stage approach:

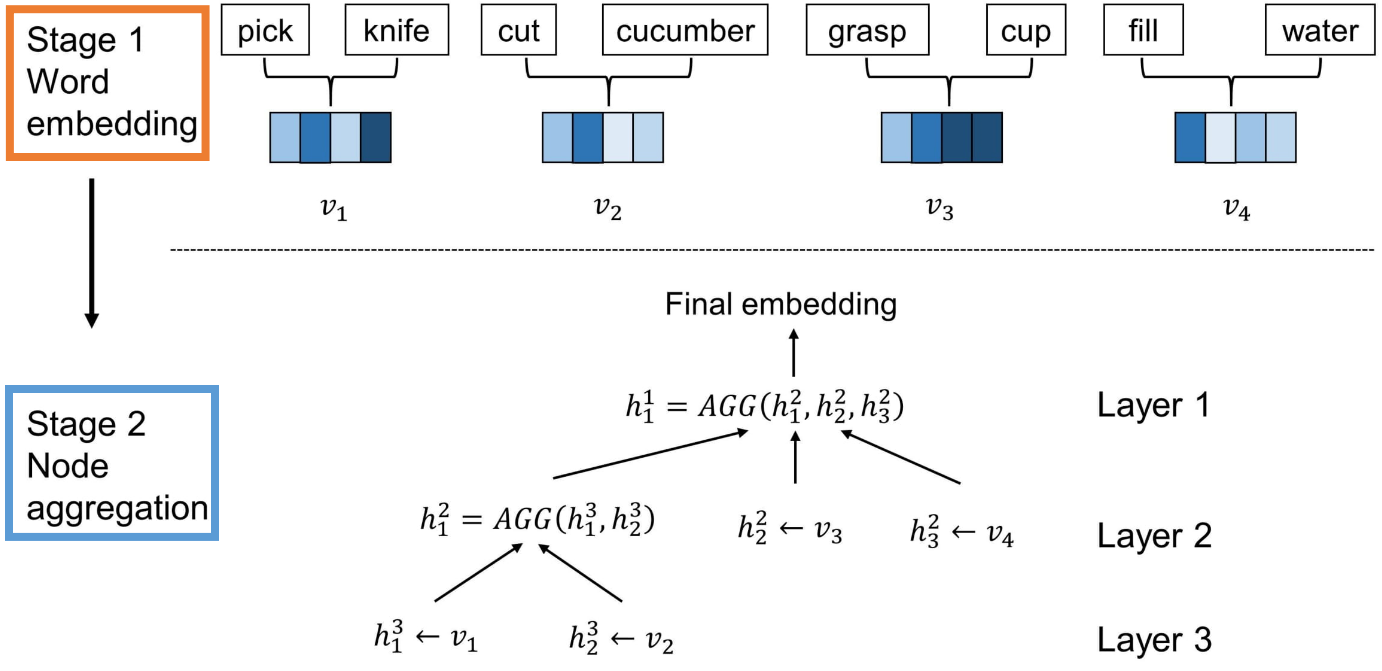
Word embedding stage → Node aggregation stage

Stage 1 **Stage 2**

Two-Stage Approach: An Example

- Pre-trained word-embedding model on enormous corpora
- Adaptive to different nomenclatures



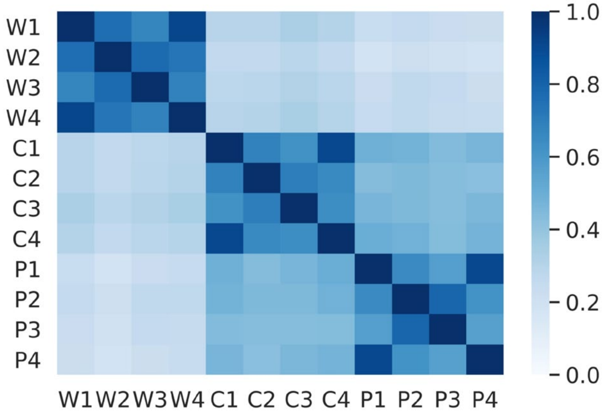


- Sum up the embeddings layer by layer:

$h_n^l \leftarrow AGG\left(\{h_u^{l+1}, \forall u \in Ch(n)\}\right)$, l layer, u child node

Evaluation 1: Similarity Measure

Semantic similarity



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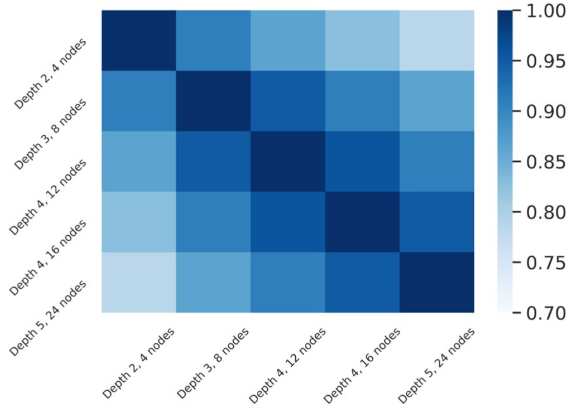
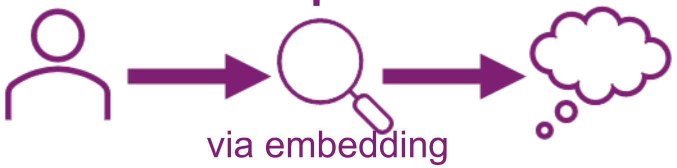
Structural similarity



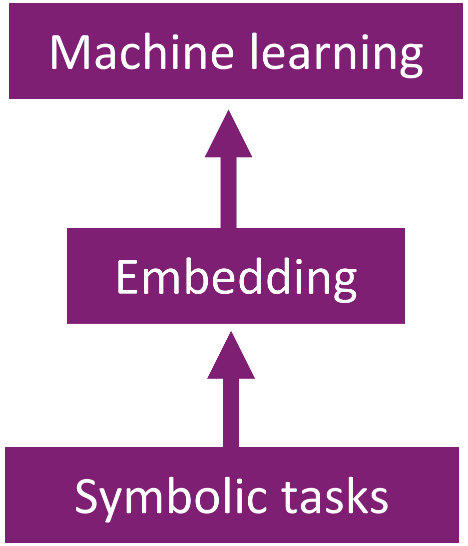


Towards efficient retrieval and reusage of tasks in knowledge base

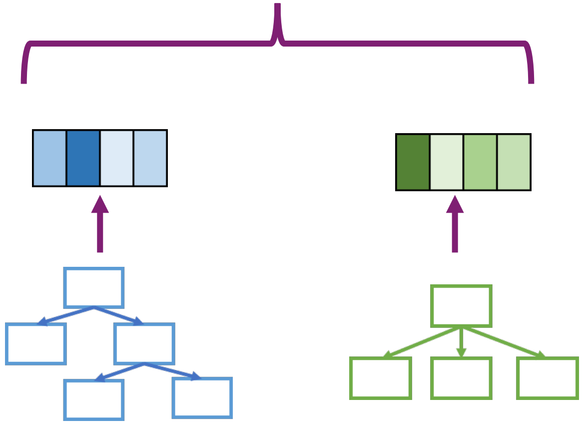
** Embeddings in all evaluations are 200-dimensional vectors*

Evaluation 2: Downstream ML Task

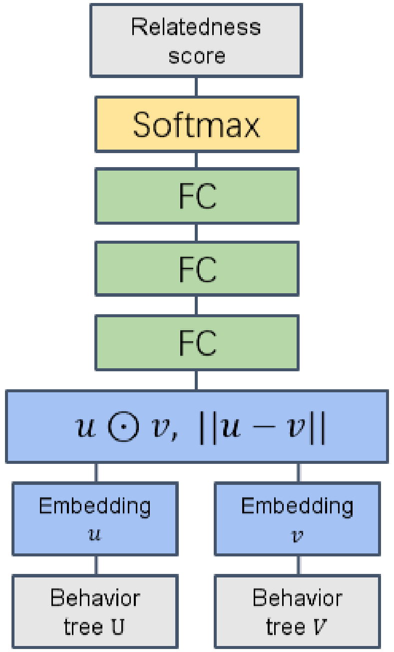
- Relatedness Prediction: A downstream machine learning task.



Predict a relatedness score

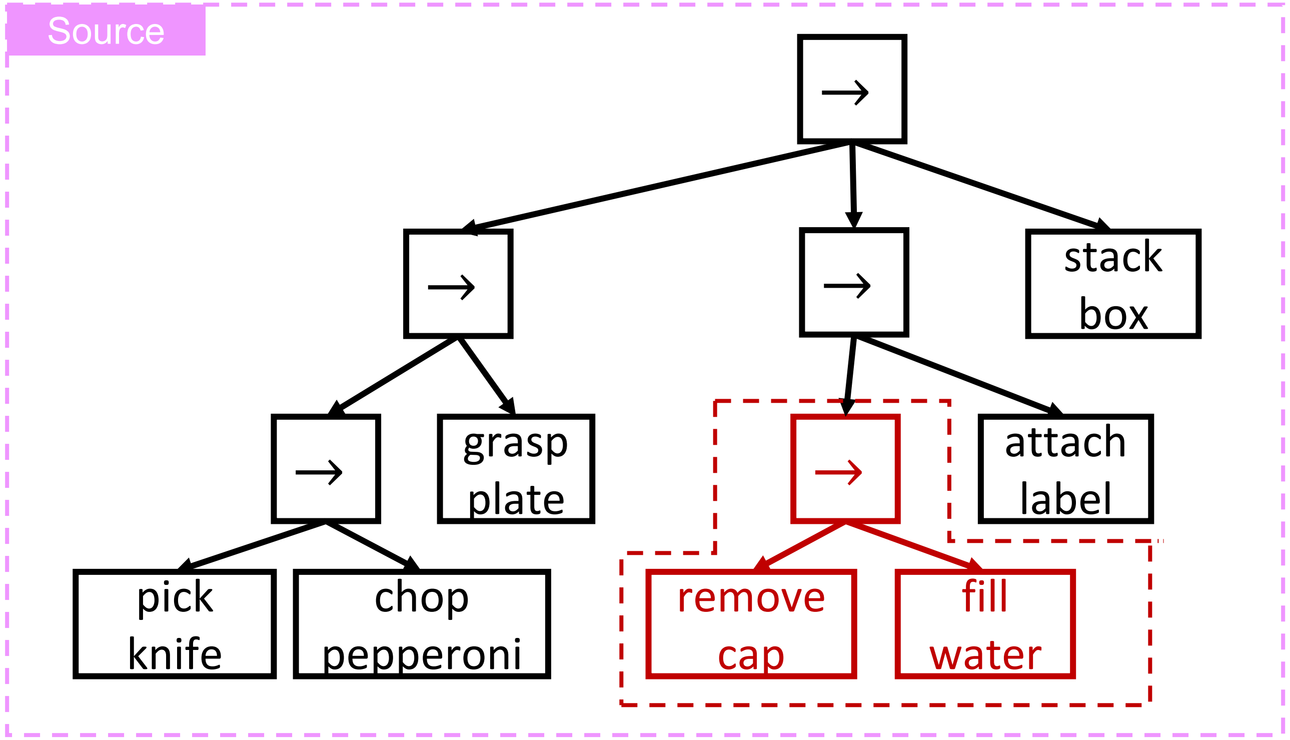


Input a pair of behavior trees



Evaluation 3: Knowledge Transfer

- Task-level knowledge transfer via vector arithmetic operations



Source:

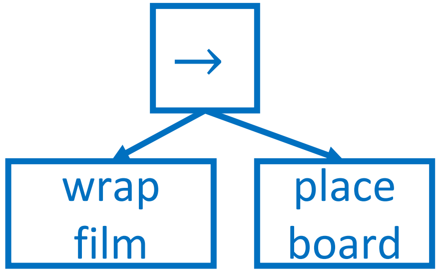
Entire task embedding: $\boldsymbol{Vec}(\text{Source})$

Sub-task embedding: $\boldsymbol{Vec}(\text{Source\_sub})$

Transfer

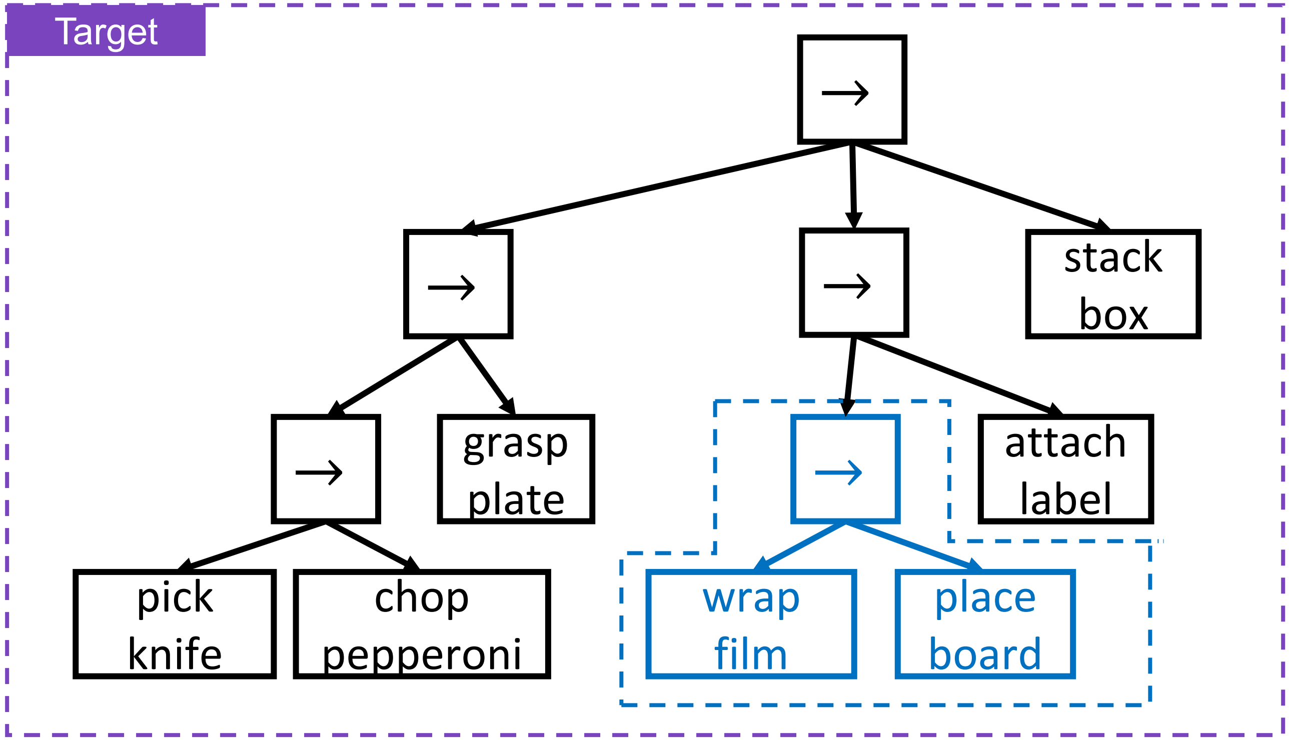
Target:

Sub-task embedding: $\boldsymbol{Vec}(\text{Target\_sub})$



Evaluation 3: Knowledge Transfer

- Task-level knowledge transfer via vector arithmetic operations



Benefit from the modularity of behavior trees

Entire target task embedding: $\boldsymbol{Vec}(\text{Target}) \approx$

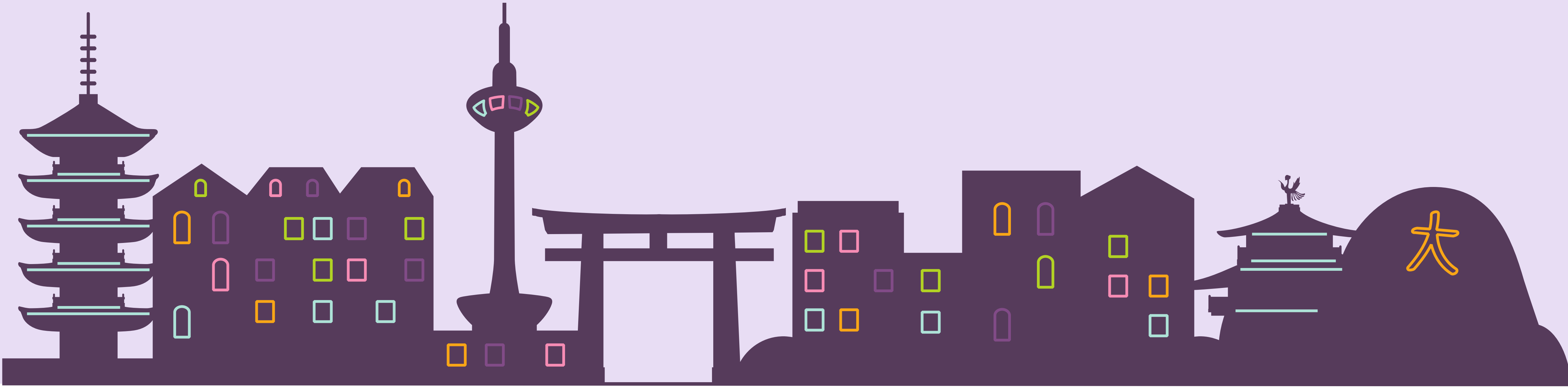
$$\boldsymbol{Vec}(\text{Source}) - \frac{1}{6}\boldsymbol{Vec}(\text{Source\_sub}) + \frac{1}{6}\boldsymbol{Vec}(\text{Target\_sub})$$

* $\frac{1}{6}$: relative position in the entire task (1 sibling node: /2; 2sibling nodes: /3)

Conclusion

- We proposed a behavior-tree embedding approach:
  - Convert symbolic task knowledge to numerical form
  - A new approach to reuse task knowledge
  - Enable machine learning on symbolic tasks

- Currently:
  Work for behavior trees consisting of *Action* and *Sequence* nodes
  In the future:
  Extend to behavior trees consisting of more node types



Thank you!

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