Motivation

Most Human Action Understanding models **do not understand the action -> fragile** and **unable to adapt** to new settings.

To gain more in-depth knowledge about human actions -> new action understanding task: which actions are likely to occur in the same time interval.

Most **human actions are interconnected** , as an action that ends is usually followed by the start of a related action, not a random one.

Interconnection of human actions is **very well depicted in lifestyle vlogs**, vloggers record their **everyday routine** .







Human Action Co-occurrence in Lifestyle Vlogs using Graph Link Prediction

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Our Contributions:

- 1. Novel task: Human Action Co-occurrence Identification.
- 2. ACE (Action Co-occurrencE) **Dataset**: a graph of ~12k co-occurring pairs of actions & video clips.
- 3. Graph link prediction Models: use visual & textual information to infer if two actions are co-occurring.
 - a. Graphs are particularly well suited to capture relations between human actions.
 - b. Graph representations capture novel and relevant information across different data domains.



make bed

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Heuristics-based Graph Topology

(e.g. Common Neighbours):

score_A1A2 = node_A1 & node_A2 #common score_A1A2 > thresh. -> A1 & A2 co-occur

Embedding-based:

cosine-similarity (emb_A1, emb_A2) > thresh A1 & A2 co-occur

Learning-based (SVM): Input: emb_A1 + emb_A2 + score_A1A2

Data Representation Action Embeddings: Sentence-BERT Transcript Embeddings: Sentence-BERT

Action Embeddings: CLIP (Text Transformer) Sequence-level: CLIP (Vision Transformer ViT-

Action Embeddings: Average of neighbour node/ action embed. (Sentence-BERT or CLIP)

Downstream Task: Similar Action Retrieval

- Novelty vs. Relevance in Action
- Retrieval.
 Diversity in Action Representations.

• Location in Action Representations.

7	INPUT REPRESENTATIONS		
k	Textual	Graph	
	DIVERSITY/ OVERLAP SCORE 4		
3	0.35	0.12	
5	0.31	0.11	
10	0.26	0.10	
Dataset	LOCATION / RECALL SCORE ↑		
Breakfast	0.16	0.22	
COIN	0.23	0.60	
EPIC-KITCHENS	0.14	0.26	

Tab. 4: : Scores measuring the difference of information, diversity, and location, between the action kNNs using different types of embeddings: textual and graph-based

rub fin	bu	
dab stain	remove stain	build hous
rubs	stain	
use baking soda	use water	use

use hydrogen peroxide pu

Fig. 2: Top 3 action neighbors, obtained from textual and graph-based representations, for 3 random action queries from our dataset: "rub stain", "build desk", "chop potato".

Models & Evaluation

	Model	Accuracy			
	BASELINE				
neighbours	Random	50.0			
	HEURISTIC-BASED				
	Common Neighbours	82.9			
	Salton Index	71.2			
->	Hub Promoted Index	78.3			
	Hub Depressed Index	61.5			
	Adamic-Adar Index	82.9			
	Resource Allocation	67.3			
	Shortest Path	82.9			
	EMBEDDING-BA	ASED			
	Cosine similarity	82.8			
	attri2vec	65.7			
Tout	GCN	77.2			
Flext	GraphSAGE	78.1			
	LEARNING-BASED				
5/16) Visual	SVM	91.1			
Visual					
Cronh	Tab. 3: Results on t	test data.			
f Graph					

uild of bookshelf		bake potato in oven		
l se	build furniture	add potato	chop onion	
build desk		chop potato		
knife	add • storage	add onion	add• to pan	
It piece of wood		chop chicken		