Extracting Action Hierarchies from Action Labels and their Use in Deep Action Recognition

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Problem Statement

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- **HAR datasets** smaller and less diverse compared to image recognition datasets
  -> *training data bottleneck in deep neural network learning*
- **Data limitation**: Multi-modal model designs utilizing language, audio or other sensory information
- **Language- infused designs**:
  - Script data introduced to speech recognition models
  - Constrained to a limited action set ->Action datasets with script data are scarce
- **Action/ activity labels**: source of linguistic information *present in every dataset*
  - Contain motion motif(s), object presence, visual relationships
  - Motion motif commonalities -> common verbs or verbs with high semantic similarity
  - Object commonalities -> common nouns or nouns with high semantic similarity

Proposed method:
Define Action Granularity Tree from Action Labels

- **Part-of-speech detection**: use a part-of-speech (POS) tagger from the Natural Language ToolKit (NLTK), to classify words into lexical categories

- **Tag refinement**: refine with *syntax rules* to account for words with multiple semantic interpretations (e.g. screw : *noun/verb*, take off & take out)

  - ***Verbs***: discriminate between cases of the same verb when followed by an ad-position or a particle (at, on, out, over, etc.)

  - ***From noun to verb***: acceptable action description format

    verb + adposition/particle + noun

- **Cluster** label sentences based on POS commonalities or high semantic content similarity.

  - Similarity : defined with a form of distance between the verb word embeddings in WordNet.

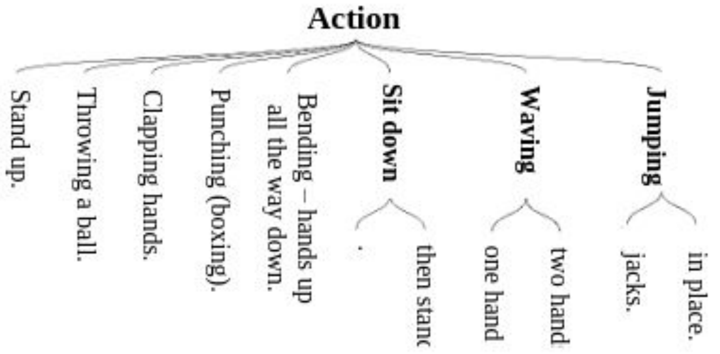


Fig. : Action hierarchy generated with the application of the proposed verb-centered lexical analysis on the class labels of the MHAD dataset, [*Jumping in place, Jumping jacks, Bending - hands up all the way down, Punching, Waving - two hands, Waving - one hand, Clapping hands, Throwing a ball, Sit down then stand up, Sit down, Stand up.*]

Incorporate Action Hierarchy in DNN designs

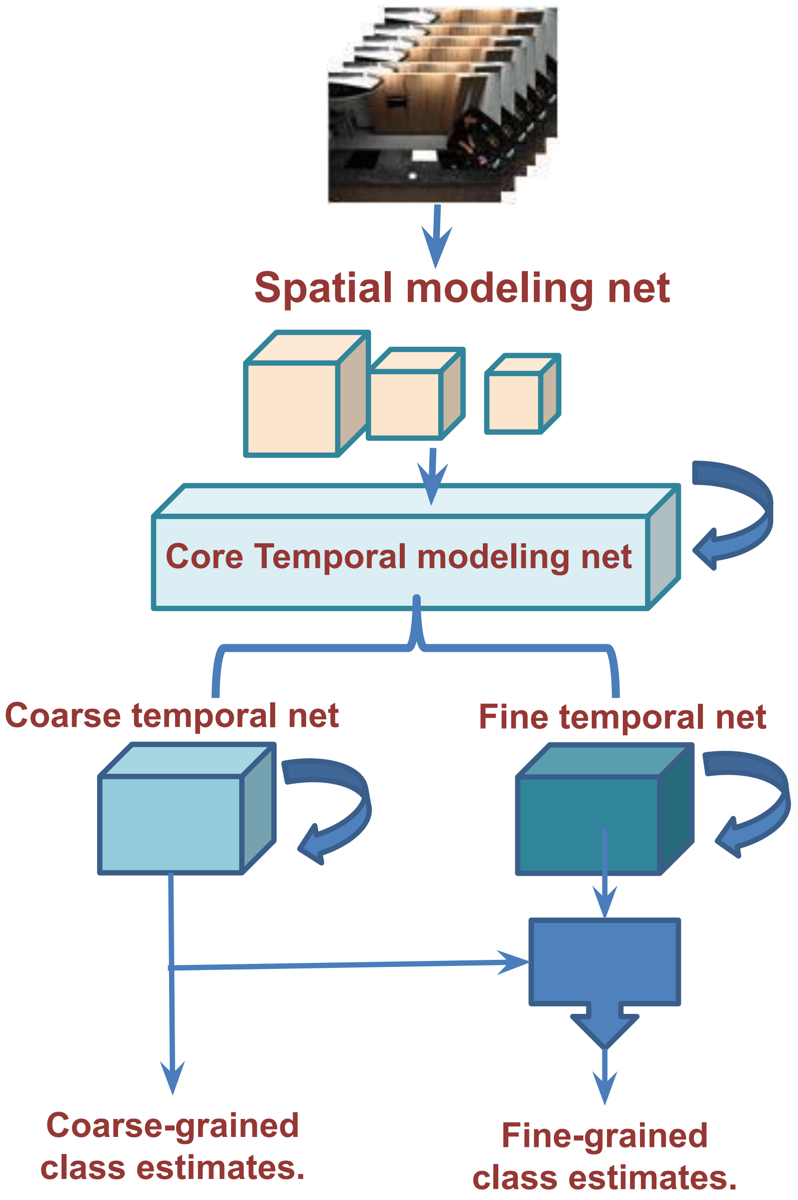
- **DNN design directions:**
  - <u>Modify</u> the temporal modelling sub-network.
  - <u>Mimic</u> the *N*-level action granularity with a set of subnets, one for each level (coarse-to-fine).
  - <u>Introduce</u> the learned representations of the coarser ones to finer sub-nets, using
    - *Skip-connections & feature vector concatenations*
- **Shallow action hierarchy** cost function:

$$C = -\frac{1}{N}\sum_{n=1}^{N}\left[\sum_{k=1}^{K} T_{n,k}^{gn} log\left(Y_{n,k}^{gn}\right) + \sum_{l=1}^{L} w_l T_{n,l}^{fn} log\left(Y_{n,l}^{fn}\right)\right]$$

with w_l : vector of label associations of the fine-grained action classes,

(T_n^{gn}, T_n^{fn}) : ground-truth labels for coarse- and fine-grained actions sets,

(Y_n^{gn}, Y_n^{fn}) : the estimated action classes



Experimental Results

- **Datasets:** MHAD (11-actions), J-HMDB (21-actions), MPII Cooking Activities (64-actions)

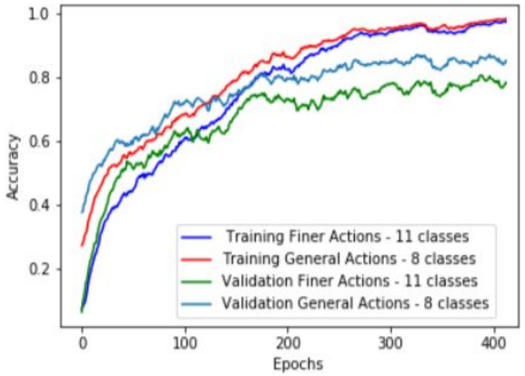
	Datasets		
	MHAD	*J-HMDB*	*MPII Cooking*
Num unique verbs	9 verbs	19 verbs	42 verbs
Avg num verbs/lbl	1.128 verb/lbl	1.0 verb/lbl	1.188 verbs/lbl
Avg lbl length	3.182 PoS/lbl	1.333 PoS/lbl	2.297 PoS/lbl
Avg asc via verb	0.545 asc/lbl	0.286 asc/lbl	1.656 asc/lbl
Max/min asc verb	1/0 asc	2/0 asc	5/0 asc
Num finer labels	11	21	64
Num Gen labels	8	18	36

- **Accuracy:**

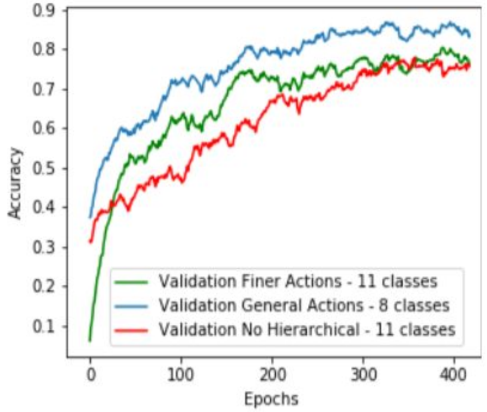
Architecture Design	**Datasets** (mAcc. (Coarse, Fine)%)		
	MHAD	*J-HMDB*	*MPII Cook*
NH-BiLSTM	(-, 64.17)%	(-, 36.28)%	(-, 29.45)%
H-BiLSTM	(82.50, 70.25)%	(45.68, 42.61)%	(60.70, 35.40)%
NH-I3D	(-, 89.61)%	(-, 72.38)%	(-, 48.18)%
H-I3D	(98.75, 96.38)%	(78.47, 76.10)%	(70.47, 54.30)%

TABLE: Action recognition performance for MHAD, JHMDB and MPII datasets between hierarchical (H) and non-hierarchical (NH) deep architecture designs.

- **Learning speed difference:**



(a) Hierarchical DNN

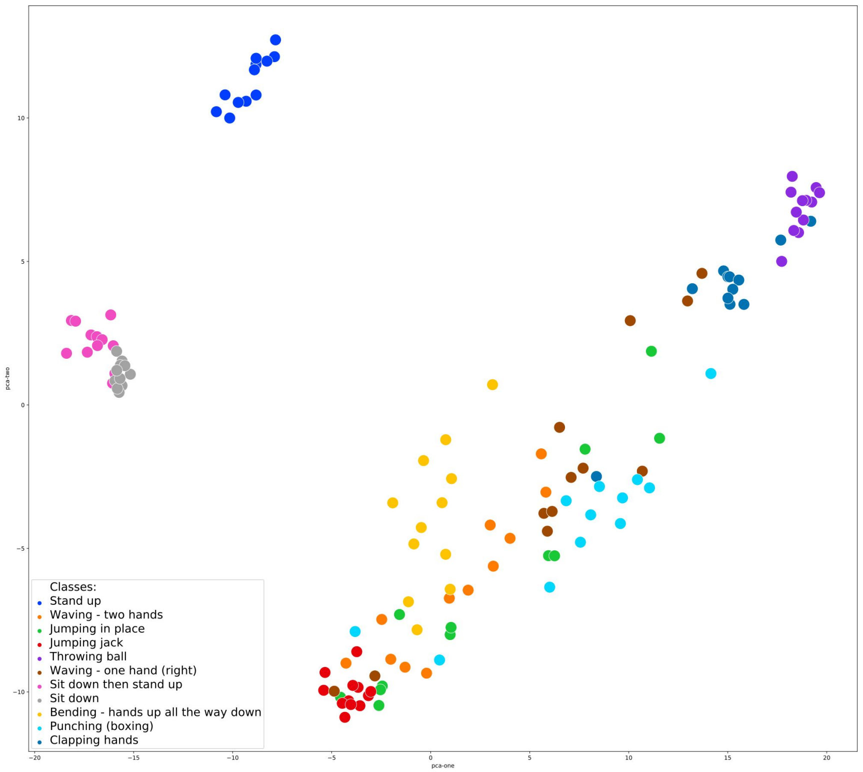


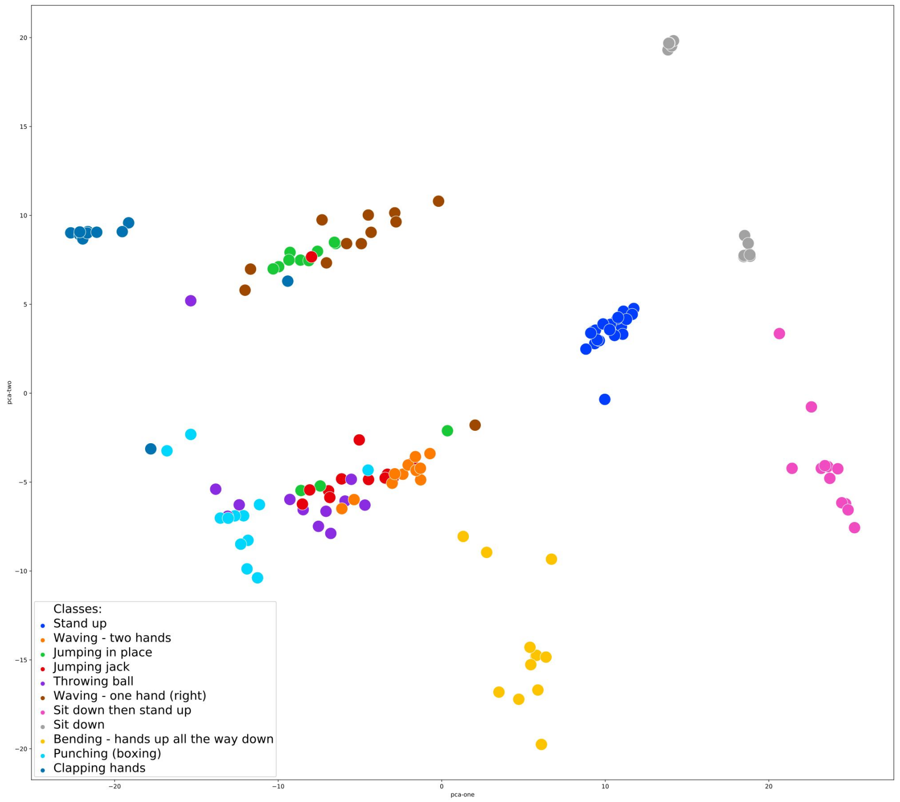
(b) Hierarchical and Non-Hierarchical DNN

- **Observations on the impact of hierarchical design:**
  - 4-6% score improvement in every deep model & dataset case
  - Increases learning speed in the earlier epochs of learning

Experimental Results

- **Visualization of learned representations with PCA:**





Classification layer, MHAD dataset (a) Non-Hierarchical , (b) Proposed Hierarchical model design

Conclusions & Future Work

Conclusions:

- **Action labels** contain a considerable amount of **action-related information**.
- Identifying action class similarities a priori using the linguistic description provides useful insights regarding action complexity and hierarchy.
- Mimicking this hierarchical structure in a deep model design, **leads to learning speed and accuracy improvement (up to 6%)**, compared to a non-hierarchical design.
- Despite the increase in the number of hyperparameters (+20-24%), learning at early stages is faster compared to a non-hierarchical design.

Future Work:

- Datasets with **complex actions require elaborate linguistic analysis** to capture the semantics contained in the action labels.
- Investigate the effect of increasing the levels of action granularity in
    - accuracy and learning speed
    - layer level fusion selection

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Thank you!

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