Minimizing risk in video hyperlinking

Presented by

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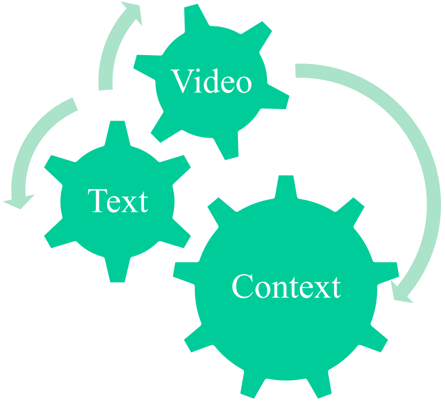


Video

Text

Context

VIREO Video Retrieval Group

What make a video “link target”?

- Supplementing anchor
- Serendipity
- User experience by *minimizing*
  - false link
  - redundancy

  } *risk*

Prefer popular and “easy” targets

Popularity – Hubness

A point x is popular if many other points regard x as "friend".

Hub score of a point x

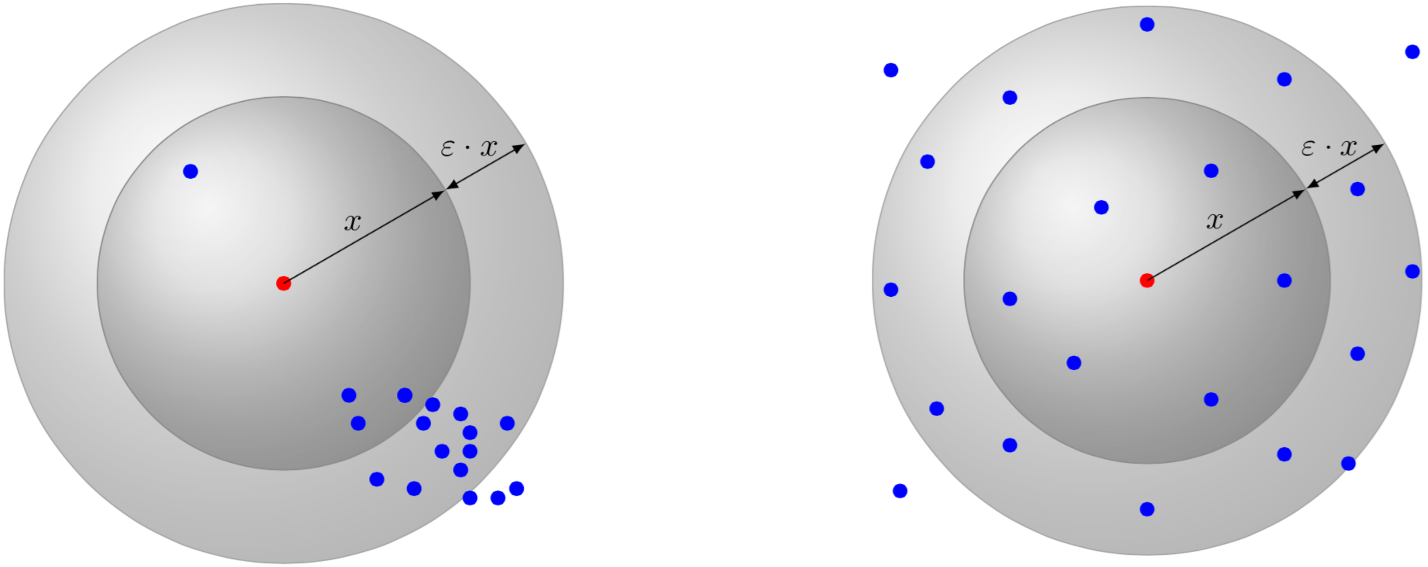
$$N_k(x) = \boxed{\sum_{i=1}^{n} \boxed{P_{i,k}(x)}}$$

x is hub if $N_k(x) > k$

M. Radovanović, A. Nanopoulos, and M. Ivanović. Hubs in space: Popular nearest neighbors in high-dimensional data. Journal of Machine Learning Research, 2010.

Easiness – Local Intrinsic Dimension (LID)

The minimal number of dimensions required to describe a point w.r.t to its local neighborhood.

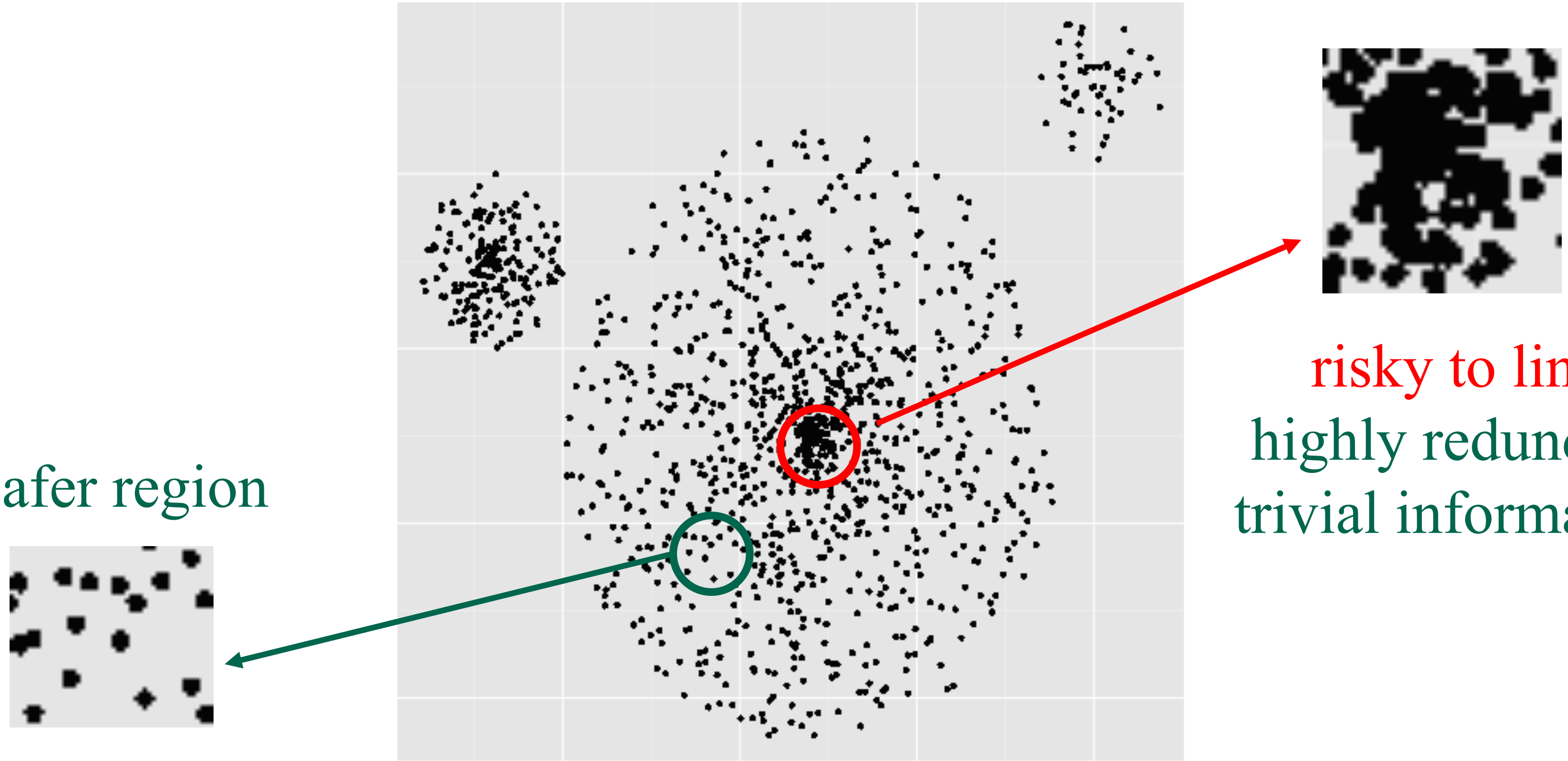


volume expansion → LID → Risk

M. E. Houle. Inlierness, outlierness, hubness and discriminabiliy: An extreme-value-theoretic foundation. Technical Report, NII. 2010.

Easiness – Diversity

Average pairwise distance between a target and its *k*-nearest neighbors



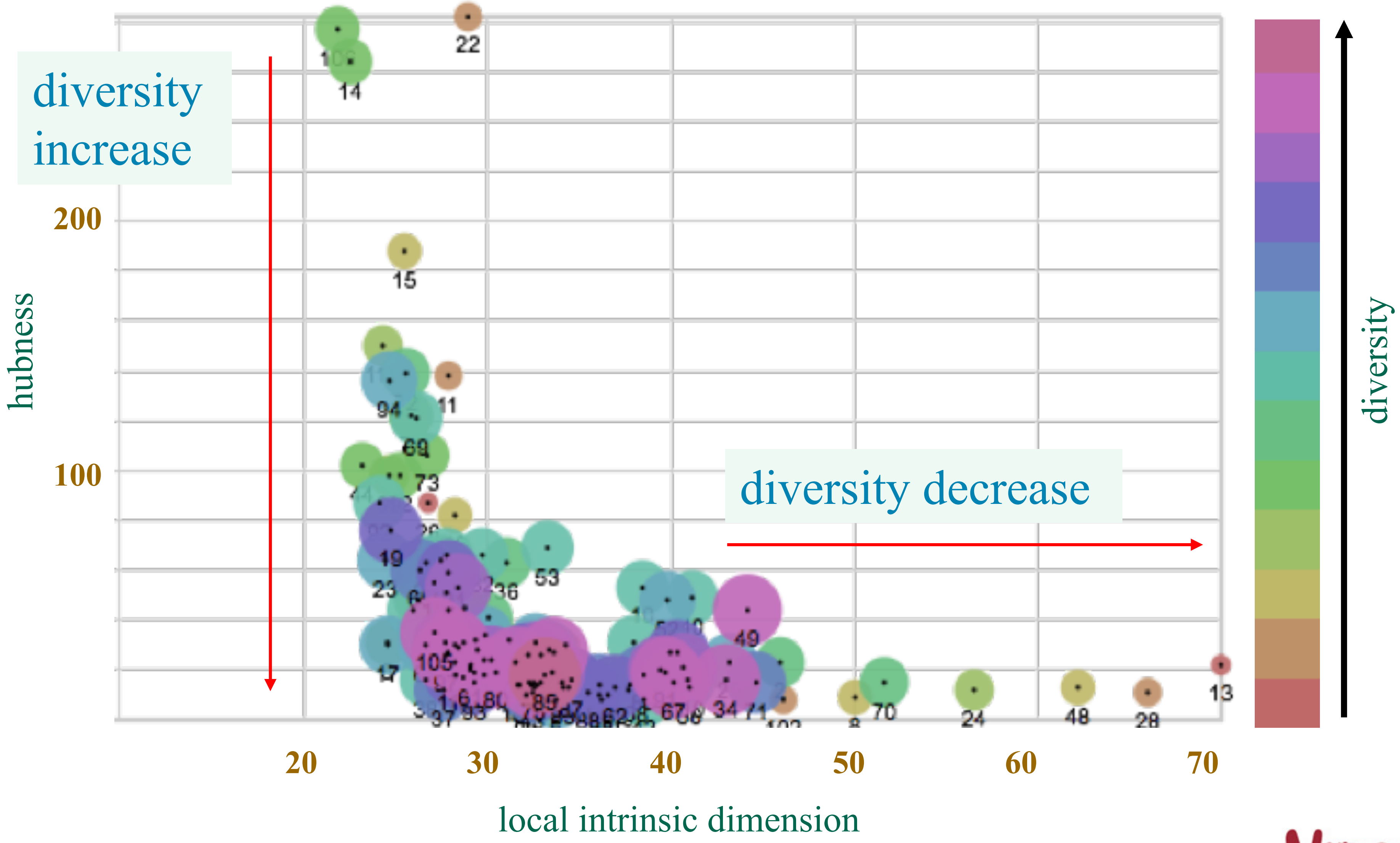
safer region

risky to link

highly redundant

trivial information

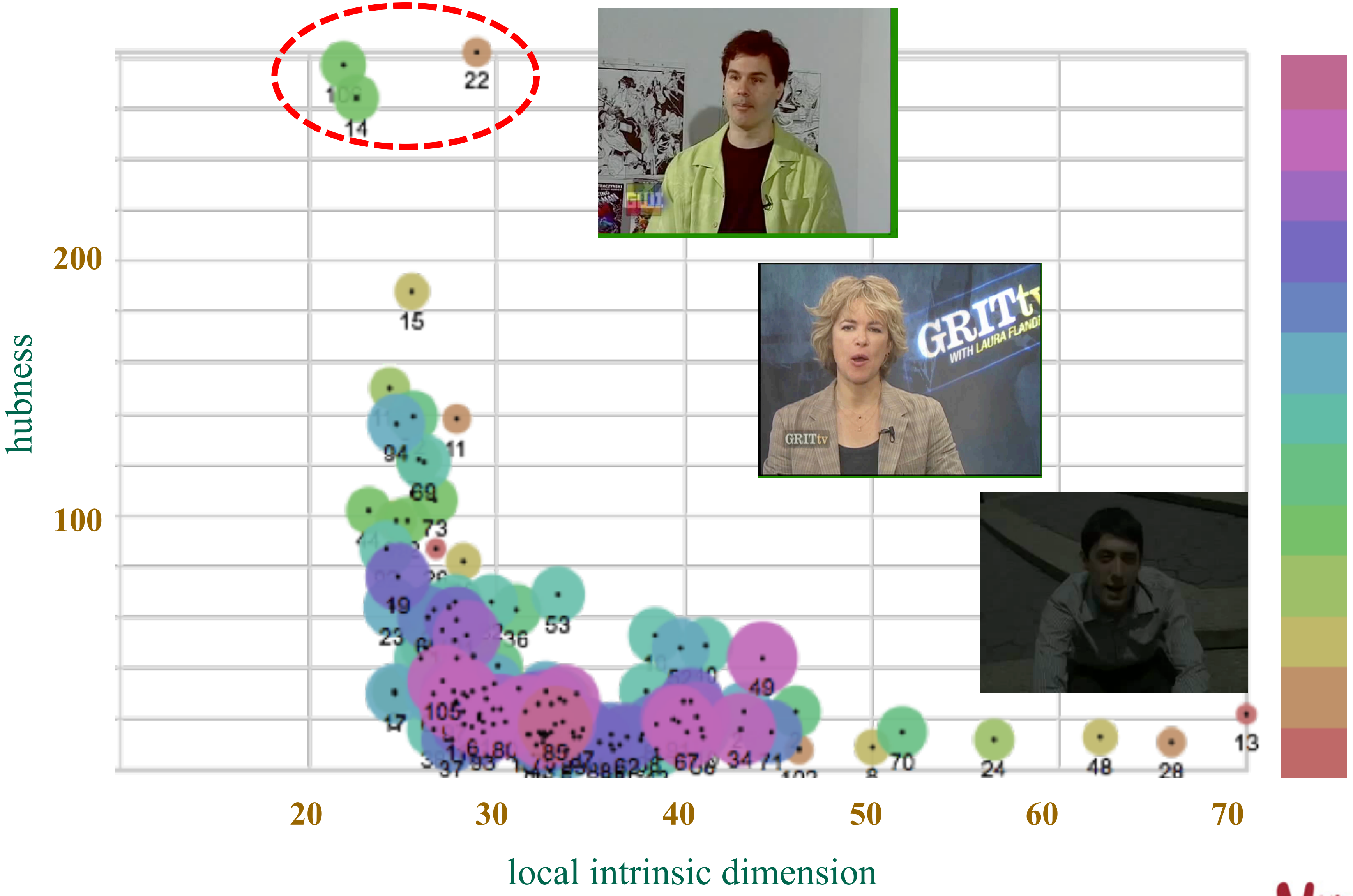
Insights of 122 anchors on development set



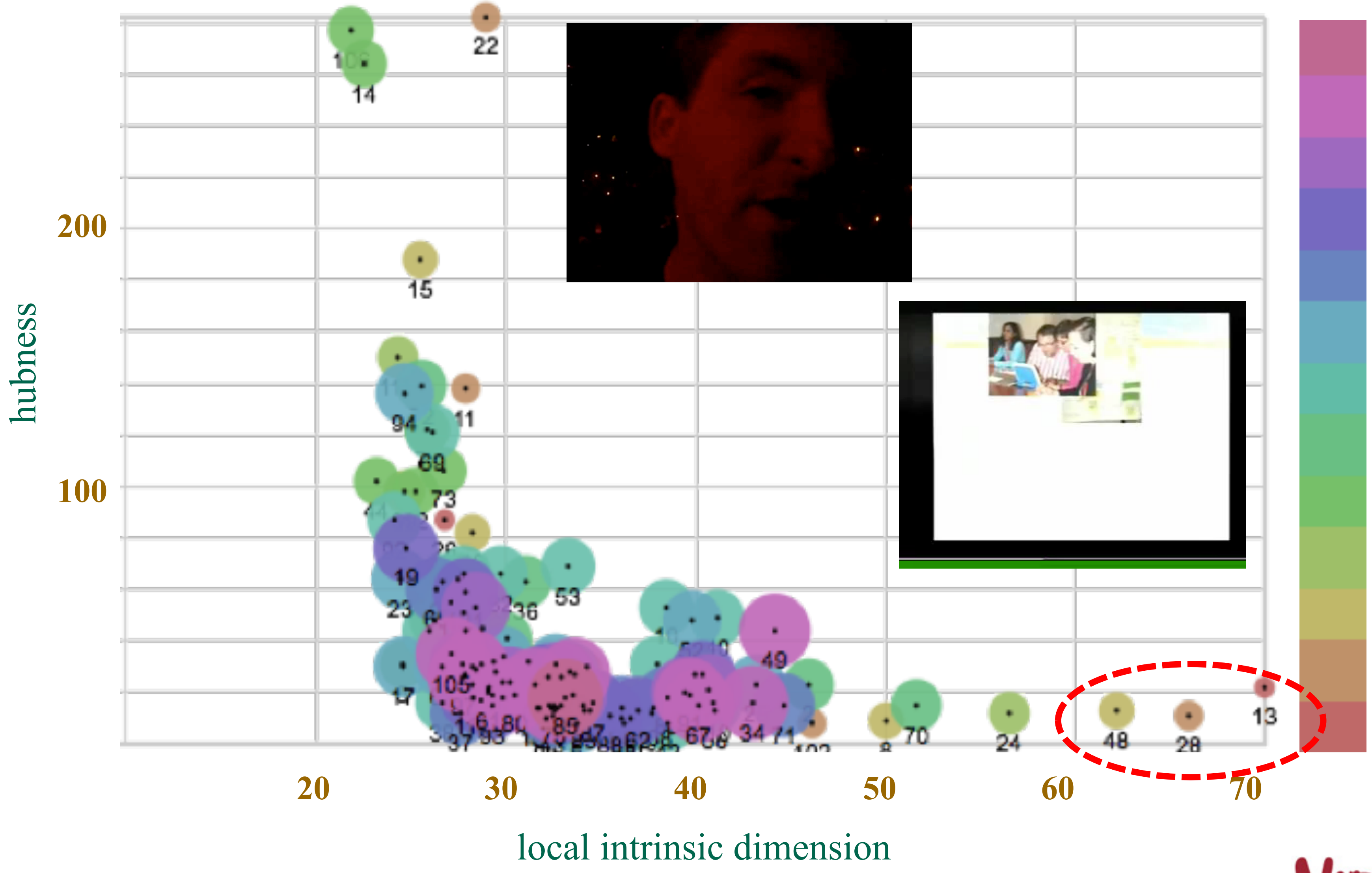
diversity increase

diversity decrease

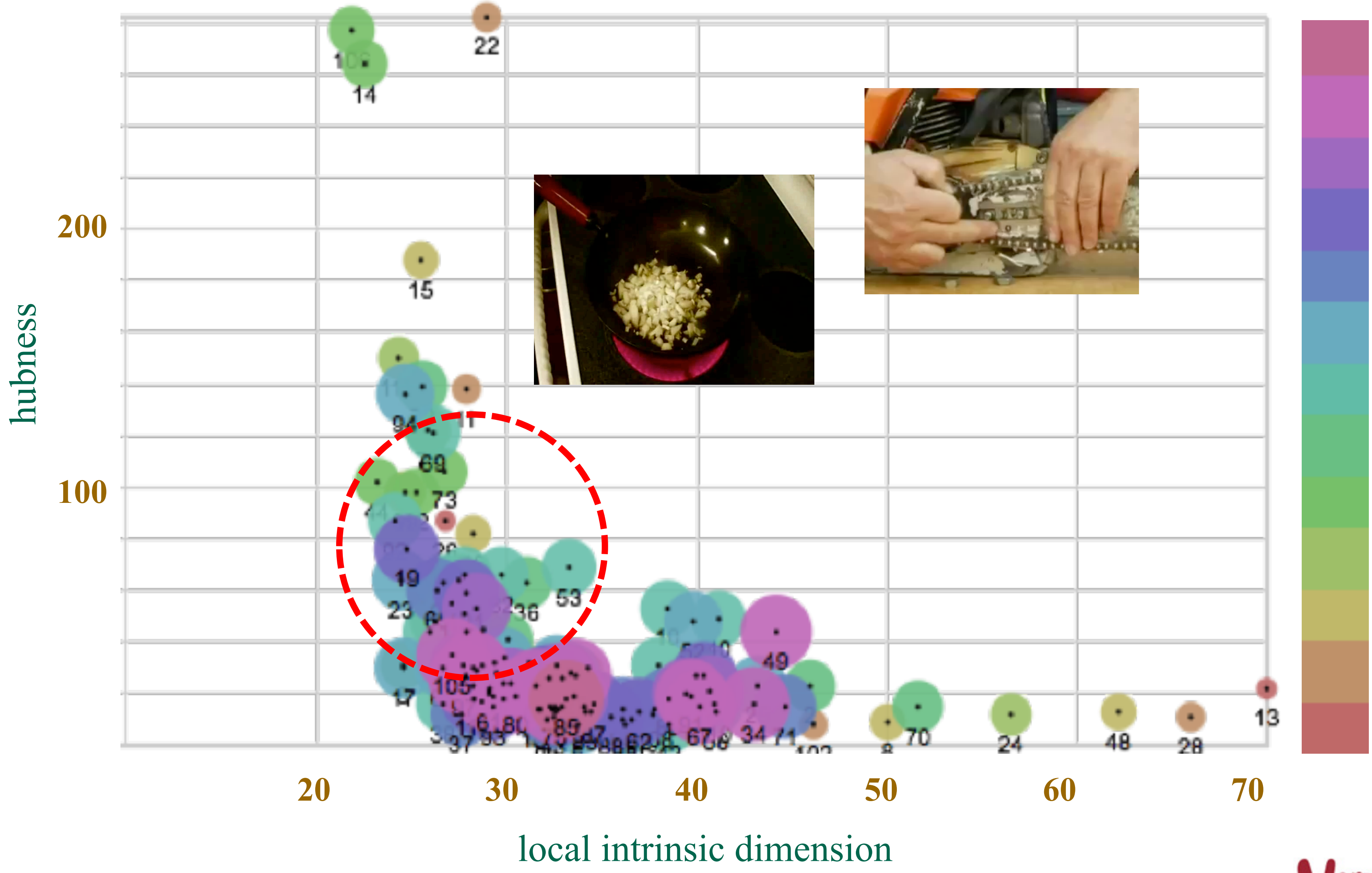
Insights of 122 anchors on development set



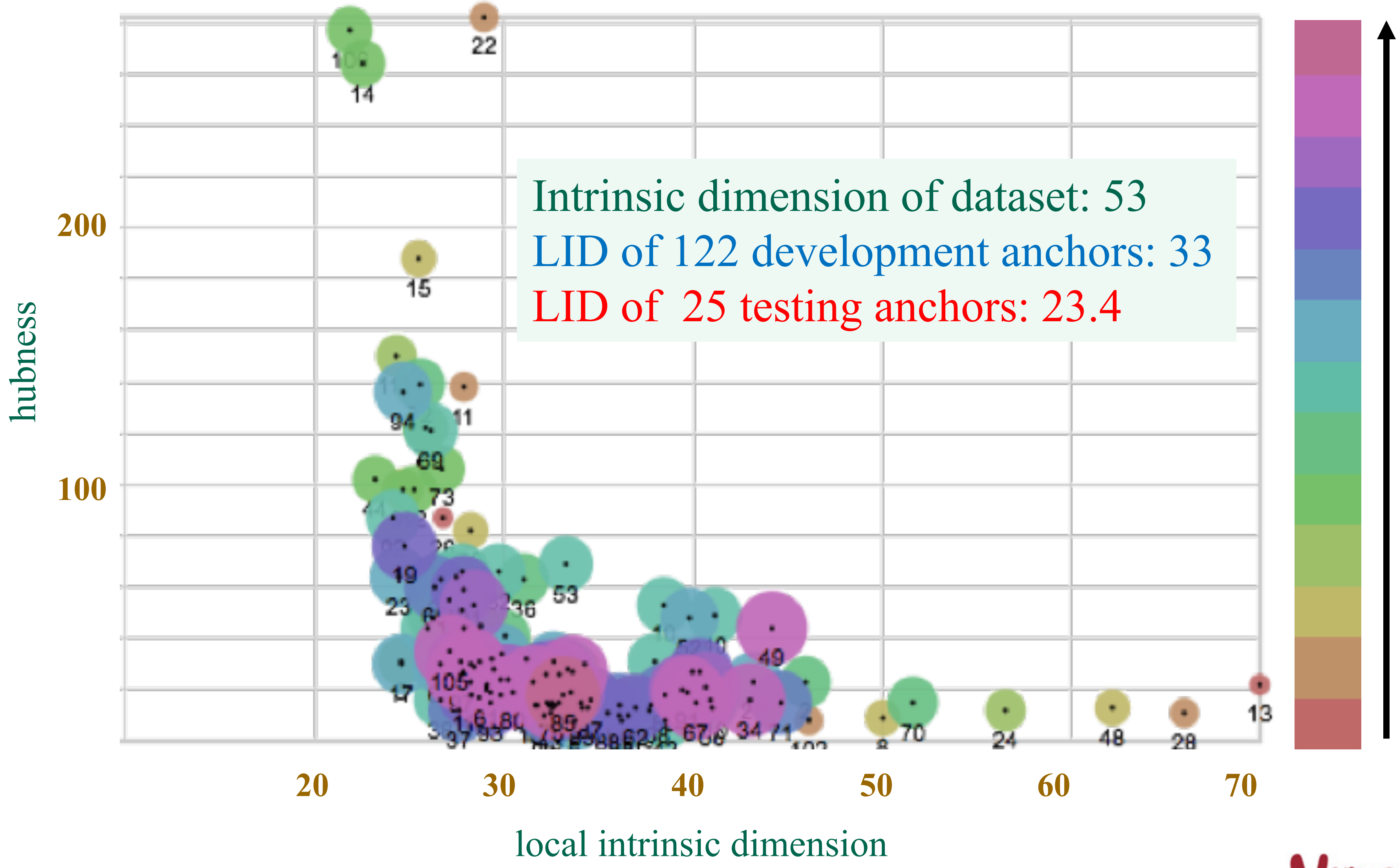
Insights of 122 anchors on development set



Insights of 122 anchors on development set



Insights on dataset



Intrinsic dimension of dataset: 53

LID of 122 development anchors: 33

LID of 25 testing anchors: 23.4

Algorithm – the art of compromise

Hub 👆
Local intrinsic dimension (LID) 👇
Diversity 👆

Optimization: Select *k* out of *n* candidate targets

0-1 assignment vector hub LID distance matrix

$$max_Y\left\{\frac{\boxed{Y}^t\boxed{H}}{k}-\frac{Y^t\boxed{D}}{k}+\frac{Y^t\boxed{A}Y}{k(k-1)}\right\}$$

Solution

- Relax the {0,1} constraint to [0,1]
- Similar to quadratic programming problem

On the selection of anchors and targets for video hyperlinking, in ICMR 2017

Variants of algorithm

Depending on the initialization of assignment vector *Y*

Hub-first
Initialize the first *k* targets with largest hub scores to 1

LID-first
Initialize the first *k* targets with largest LID scores to 1

<u>Intuition</u>

- Hub-first for anchor selection — Popular content
- LID-first for target selection — Specific content

Submissions

Run-1: Visual baseline

Run-2: Run-1+ LID-First (re-rank top-100)

Run-3: Multimodal baseline

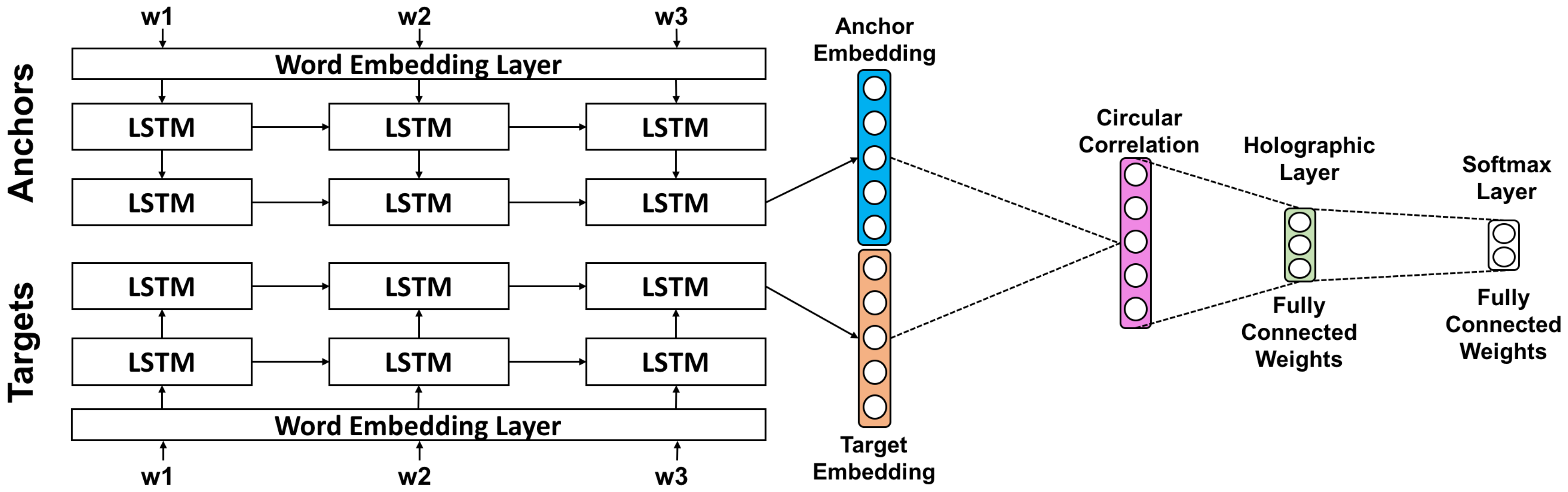
Run-4: Run-3 + LID-First (re-rank top-100)

Implementation

- Exclude 2,719 testing videos without speech – *intuitively not suitable as targets?*
- Use LDA-based model for video fragmentation (*ACL* 2017)
- Visual run based on 14K concepts
  - ImageNet, ImageNet-Shuffle, SIN, RC, Places
- Use LIMSI ASR
- Multimodal run based on the fusion of cosine similarity and Siamese network

Cross-modal evaluation

Siamese recurrent architecture – train using 122 anchors of development set



Feed different input pairs
- visual, visual
- text, text
- text, visual
- visual, text

Softmax has two nodes – Probability of similarity and dissimilarity

Average fusion of pair similarities

Learning to rank question answer pairs with holographic dual LSTM architecture in SIGIR 2017

Result

	P@5	P@10	P@20	MAP	MAiSP	
Run-1	0.864	0.852	0.502	0.1848	0.1113	visual run
Run-2	0.864	0.860	0.530	0.1849	0.1128	
Run-3	0.856	0.852	**0.582**	**0.1951**	**0.1199**	multimodal
Run-4	0.856	0.852	0.710	0.2392	0.1473	

Conclusion-1: Multimodal run brings some improvement for search depth @ 20 and beyond

Result

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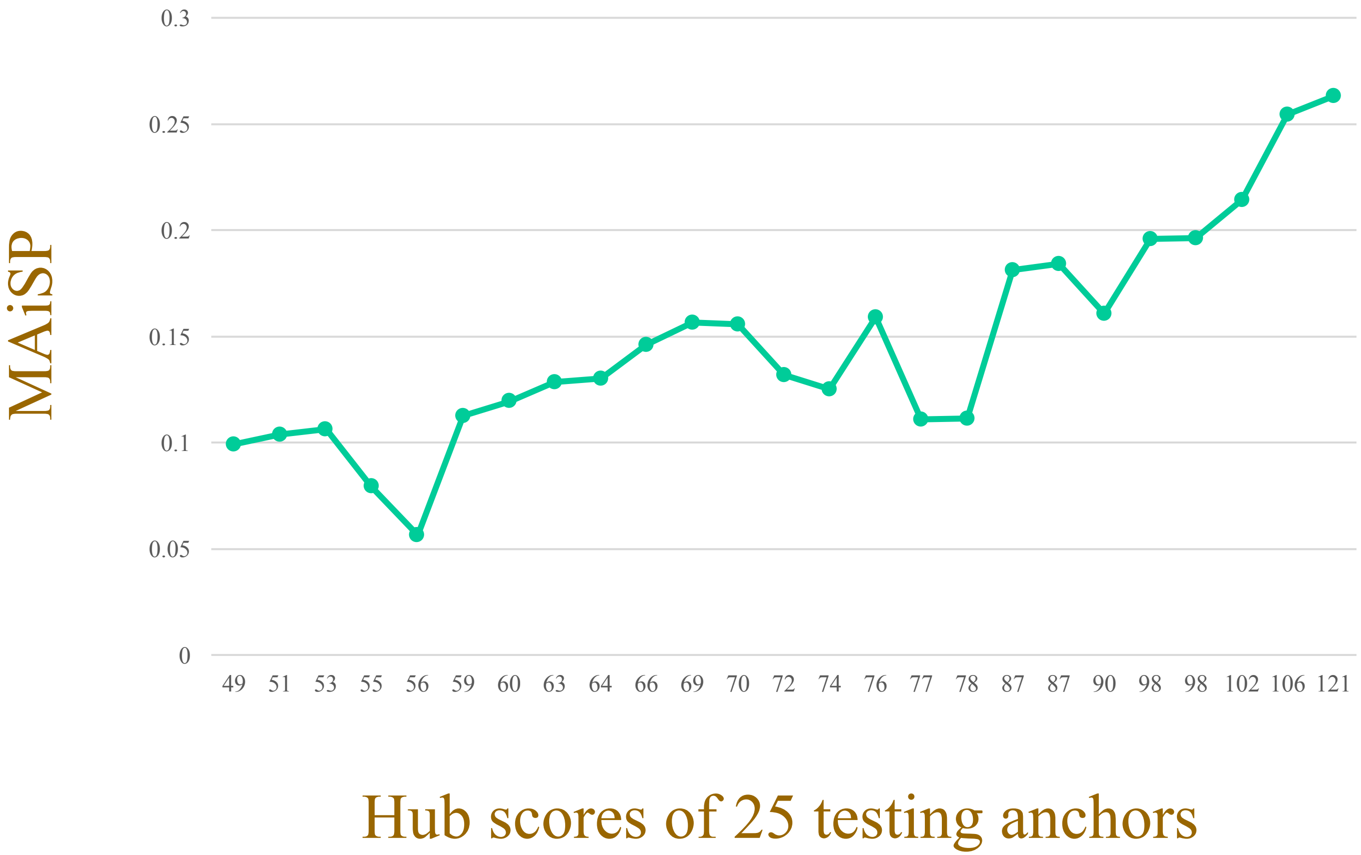
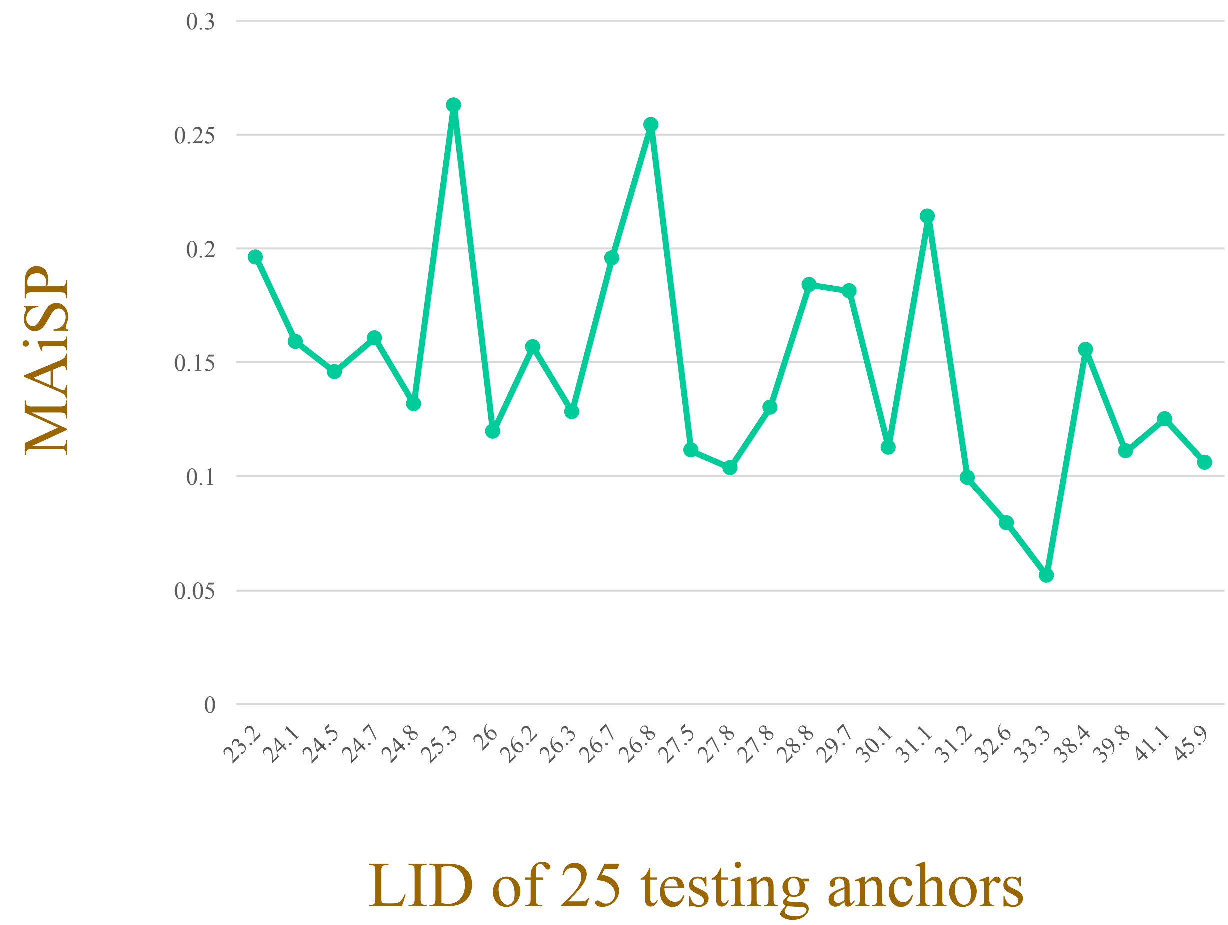
Multimodal + LID-first

<u>Conclusion-2</u>: LID-first boosts multimodal run and shows the best improvement for search depth @ 20 and beyond

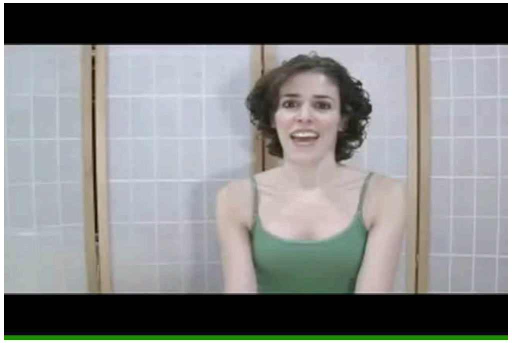
Correlation between hub & performance



Correlation between LID & performance

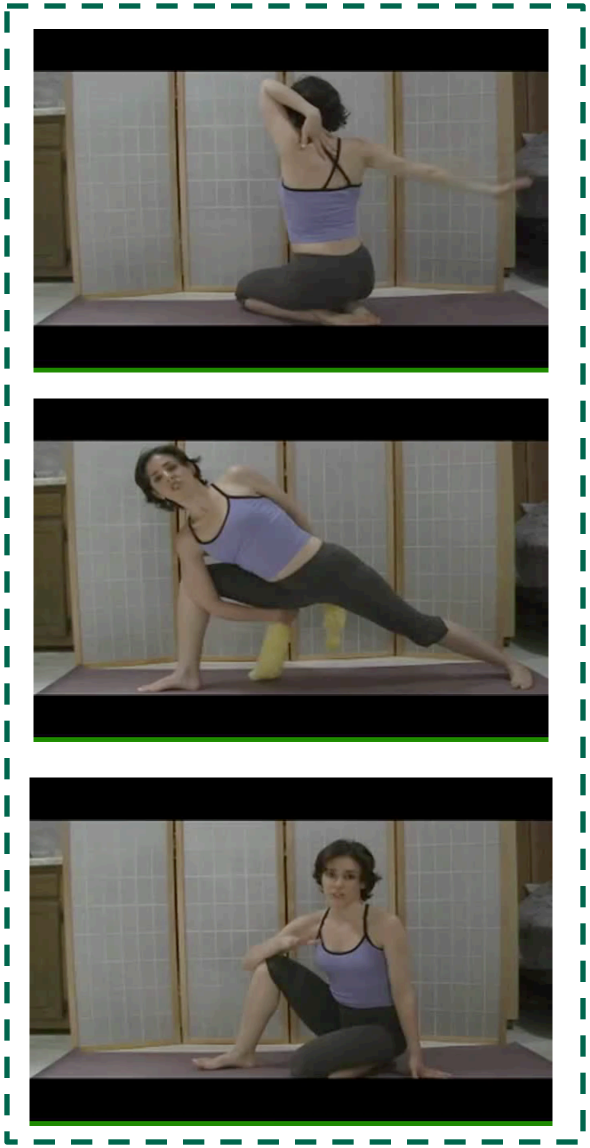


Anchor 145
Yoga practice



shower,0.970
shoji,0.941
window screen,0.456
television, television system,0.404
ballet dancer,0.341
dress,0.313
home,0.270
balance beam, beam,0.232
Adult_Female_Human,0.220
Speaking_To_Camera,0.209
leotard, unitard, body suit, cat suit,0.180

Visual run

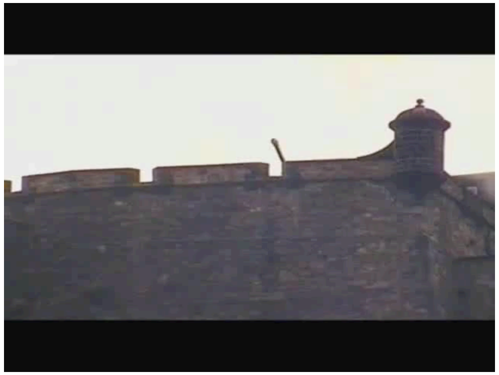


Multimodal run

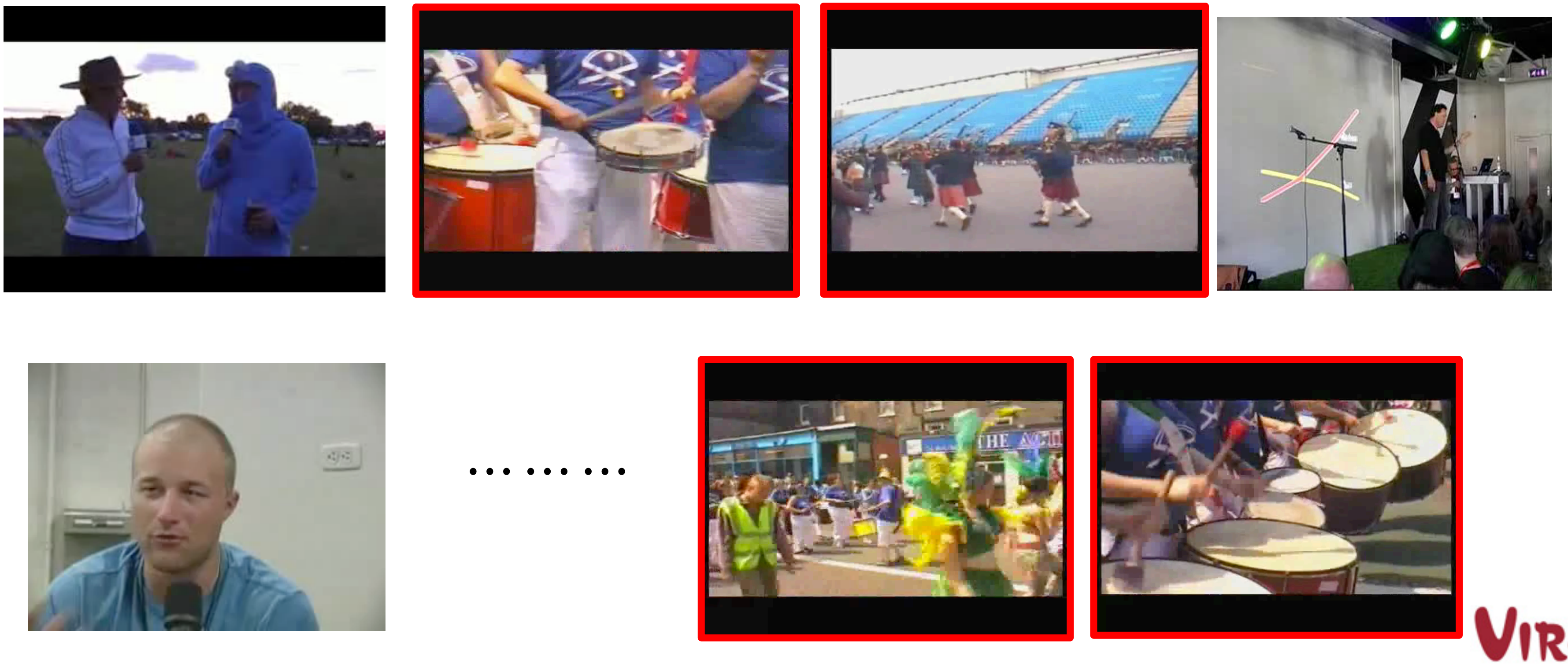
Sahaja Yoga treats drug addiction and disease

Shri Mataji started Sahaja Yoga @ India in 1970

How LID-first boosts performance



Anchor 124
University marching band



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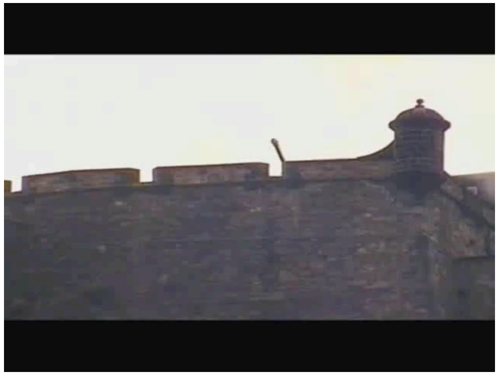
How LID-first boosts performance



Anchor 124
University marching band

… … …

When does it fail?

- Name entities in ASR are recognized incorrectly
  - anchors 124, 125, 133, 135, 140, 141, 147

- Data statistics alone is insufficient
  - May pull context-irrelevant but popular and safe fragments to a higher rank
  - Example: anchors 130 (food preparation), 139 (hat show)

Conclusion

- Multimodal run diversifies link targets
- Hub + LID + diversity improves P@20, MAiSP, MAP
- Some correlation between hub+LID of anchors and performances
- More analysis is required to understand the performance …