



HYDERABAD

Introduction

Goal: Our aim is to extract a multimodal "*story*" summary (video and text) from a given episode of a TV Show, which typically lasts around 40 minutes.



Motivation

- 1. Typical video summarization focus on generating keyframes, skims, video storyboards or synopses. While in space of text, focus is on text-summary.
- 2. There are multimodal (input) to unimodal / multimodal (output) approaches too, but we significantly differ in the type of video (stories vs. creative/ documentary).
- 3. Leveraging *recap* (as our supervising signal), we tried to capture the overall story-arc of an episode (~40 mins) where temporal video/text signal may not align semantically, making this task even more challenging.

2 famous crime-thriller TV Shows: (i) 24, (ii) Prison Break

- Why action thrillers? Challenging than rom-/sit-coms and captivating plot-lines (story-arc).
- Key Idea: Use Recaps from next episode to extract story-summaries from the current one.
- Label Extraction: (i) shot-matching, (ii) smoothing
- Data Stats: Altogether, 10 Seasons with 205 episodes.

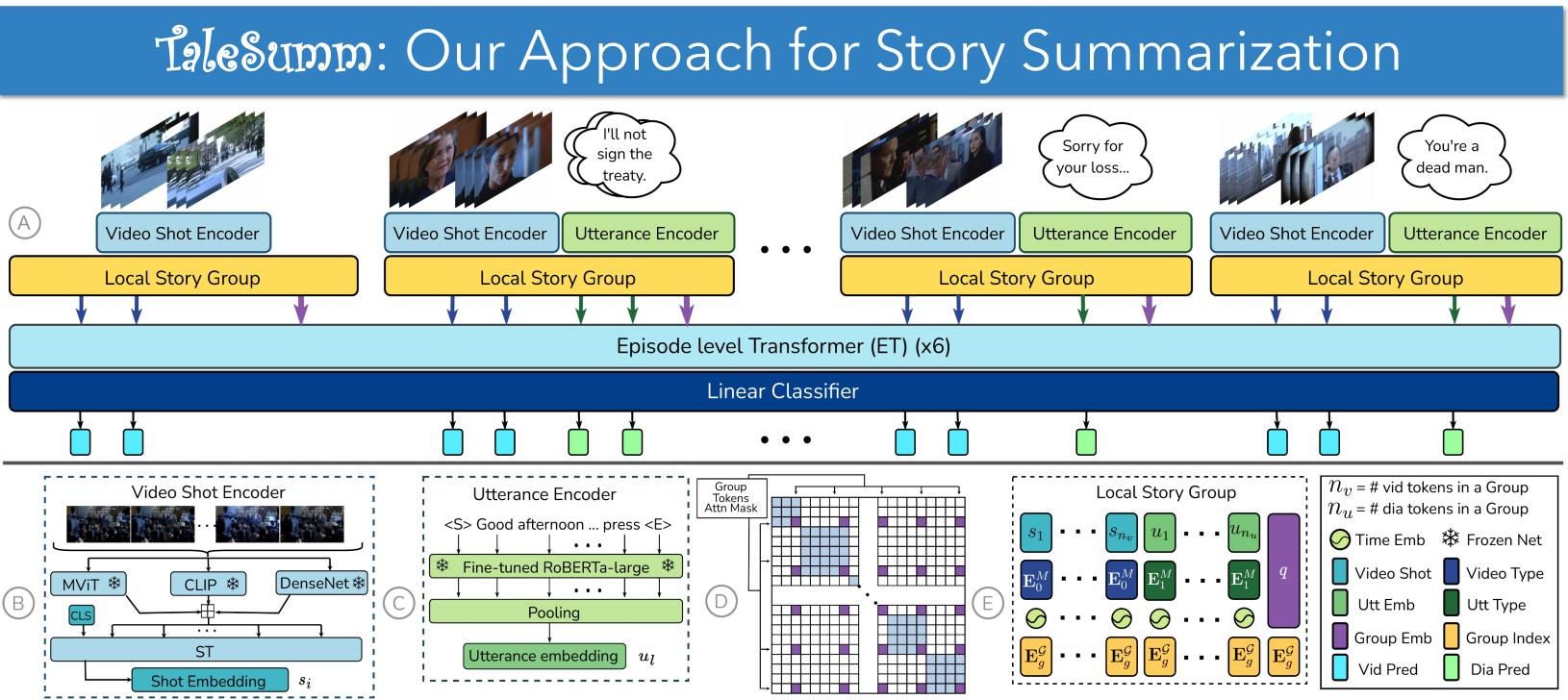
Acknowledgments: We thank Bank of Baroda for partial travel support, IIIT-H Faculty seed grant and Adobe Research India for student funding. # of Seasons # of Episode Dataset dura Avg episode

Avg # of sho Avg duration Avg # of utte Avg # of wor

Avg recap du Avg # of sho Avg # of utte

"Previously On ..." From Recaps to Story Summarization

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1. Level 1: Shot/Dialog Representation

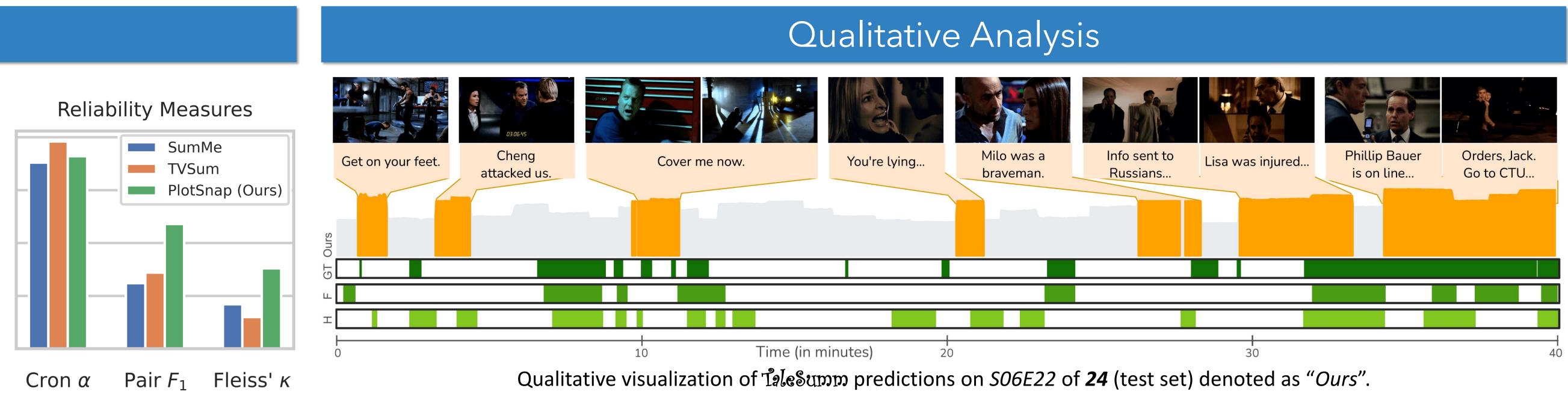
- a. Prep **Shot/Dialog encodings**: Raw video shots and dialogs pass through **B** and **C**, respectively.
- b. Form Story Groups from temporally arranged V/D tokens with an appended group token.

2. Level 2: Episode-Level Interactions

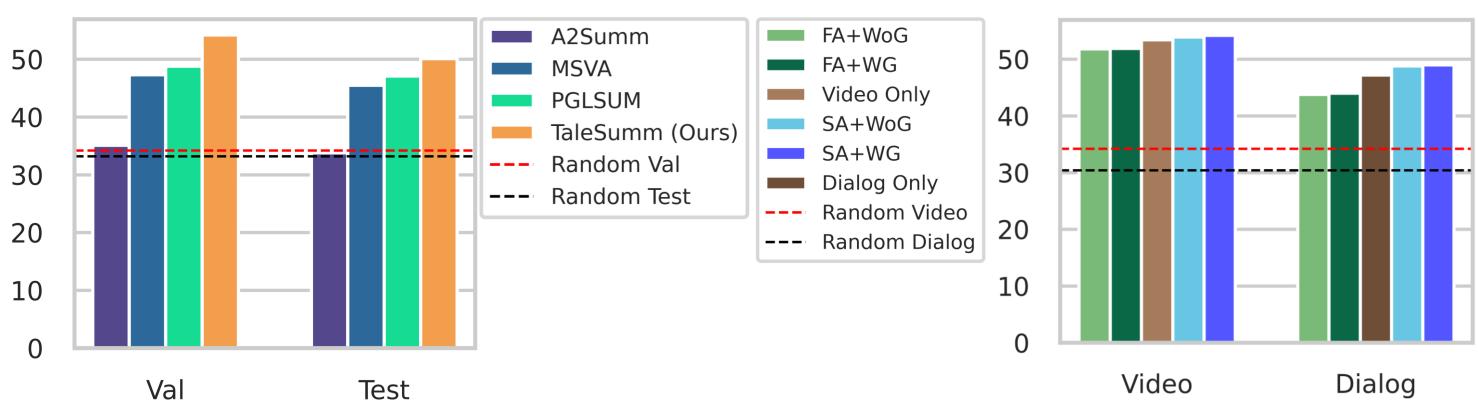
- a. Capture video/dialog tokens interactions within their corresponding story groups.
- b. Pass the aggregated info inside each SG across every SGs via GT with special attention mask.
- c. A shared linear classifier at the end for video-shot/dialog to predict their importance.
- d. Our approach TaleSumm is trained in an end-to-end fashion with BCE loss.

PlotSnap: Our Multimodal Dataset

TV Series	24	Prison Break	
S	8	2	1.00
es	172	33	
ation (hours)	125.9	24.0	0.75
e duration (s)	2635 ± 72	2615 ± 39	
ots per episode	825 ± 101	999 ± 117	ຍ 0.50 S
on of shots (s)	3.2 ± 2.5	2.6 ± 2.3	
terances per episode	564 ± 54	529 ± 59	0.05
ords/tokens in utterance	7.9 ± 5.4	7.4 ± 5.8	0.25
luration (s)	104 ± 28	62 ± 20	0.00
ots in recap	55 ± 12	43 ± 9	
terances in recap	33 ± 6	22 ± 5	

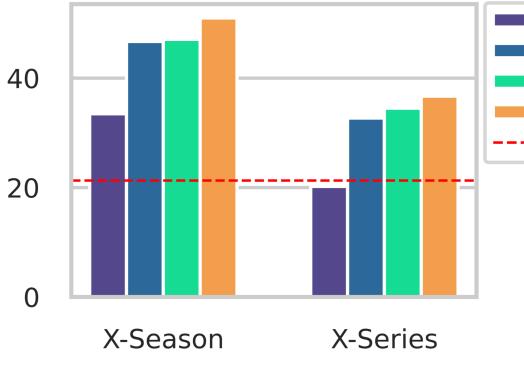


Video SoTA



TaleSumm outperforms SoTA models adapted for our task.

Generalization (On Test)



GT: Ground-Truth; **F**: A fan site (Fandom) inspired labels; **H**: Human annotated



https://katha-ai.github.io/projects/recap-story-summ/

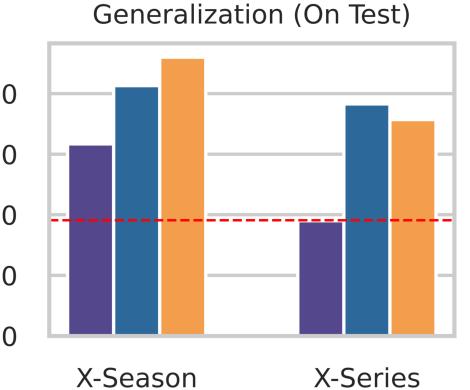


Experiments (Metric: AP)

Architecture Ablation

Video A2Summ 40 PGLSUM TaleSumm (Ours) 30 Dialog --- Random X-Series 20 A2Summ PreSumm 10 TaleSumm (Ours) --- Random X-Series

Special Attention with Group Token setting is **BEST**.



TaleSumm generalizes better on X-Season/Series (an entire season/series in test)