We thank the reviewers for their comments and suggestions, which will help us better present our work.

In response to Reviewers 1 and 3 regarding the computational cost and comparison to NL model:

Model	Train ↑ (vids/s)	Inference ↑(vids/s)	Accuracy ↑
RSTG-to-vec	**5.23**	**17.64**	47.7
NL-I3D	4.10	13.00	44.4
RSTG-to-map res4	3.35	8.21	48.4
RSTG-to-map res3-4	2.53	7.09	**49.2**

We show the runtimes for different variants of our model and the NL-I3D model using the Resnet-50 backbone on Something-Something videos. Times are similar: our RSTG-to-vec model is the fastest and has better accuracy than the NL model, while our top performing model RSTG-to-map res3-4 is about 2x slower than RSTG-to-vec. We will include the comparisons in the camera ready, if accepted.

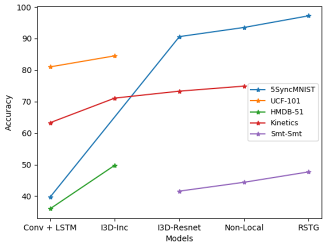
In response to Reviewers 1 and 2 regarding experiments on Charades dataset:

We agree that Charades represents a good dataset for evaluation. In the paper, considering time and computational resources constraints, we tested on two datasets. Something-Something is a large-scale, real-world dataset (newer and 10x larger than Charades), in which complex interactions in space and time are more relevant than specific object classes. Next we will perform experiments on Charades and present them in future work.

Additional responses to Reviewer 1:

More detailed analysis and discussion: We thank the reviewer for this suggestion. We will do our best to improve such analysis and discussion in the camera ready, if accepted.

Computational cost and results on Charades: Please see above our answers to Reviewers regarding computational cost as well as results on Charades. We will include computation times in the final version.



Claim L212-214 clarification: We thank the reviewer for this suggestion. We will either remove the claim or clarify it with the following experimental evidence, space permitting. What we mean is that the methods we compared against maintained the same rank order on several datasets, including ours. This affirms the consistent behaviour of the methods as well as the relevance of the datasets. In the Figure we plot the performances on different datasets, as reported in [33, 45]. There is one curve per dataset, with one point on the curve per method, shown in increasing order of performance, which is preserved across datasets.

Additional responses to Reviewer 2:

Claim to be the first space-time factorization with graph processing and comparisons to [A, B]: To our best knowledge, our work is unique by: a) proposing a message-passing, spatio-temporal graph model that incorporates differently space and time information and works with unstructured video features, s.t. nodes are not associated with distinct, semantic entities; b) our graph is recurrent in space and time, suited for online processing. It alternates messages in time with those in space. [A, B] also use space-time separation on a graph, but models are not recurrent. The nodes are associated with skeleton data or actors-object-scene info extracted with additional methods. Our model uses unstructured features provided by a convnet backbone and nodes are not associated with specific entities (e.g. objects or joints). This has an advantage: it permits independent end-to-end learning and inference, with no need external detectors. We thank R2 for the references, which we will discuss in the final version.

Comparisons to other works on Charades: Please also see our response to R1 and R2 w.r.t tests on Charades. Regarding comparisons to [B], we point out that our main task is activity recognition, whereas [B] tackles action localization. Thus, direct comparison is not as trivial. Also, method in [C] focuses on other tasks, while results on activity recognition, shown in supplementary material, are inferior to state of the art. We thank R2 for these recently published references, which we will include and discuss in the paper.

Ablation studies regarding message passing, region-split scheme and number of scales: In Section 3.1.1 we present extensive ablation studies with different types of message passing based on MLPs, which validate the relevance of recurrence with different processing over space and time. We agree with R2 that additional studies comparing to simpler space processing in the form of linear graph convolutions will bring additional insights and we will include such experiments in the final version. Also, we think that using objects as nodes is orthogonal to our approach of creating nodes from fixed regions. We argue that such a fixed organization, independent of the output of external detectors is more flexible and has certain advantages. It allows us to function independent of the exact number of objects in the scene, which could change from one moment to the next. It also relieves us from needing to detect entities and then match between nodes and entities. Thus, adapting our graph model to work with an external detector is indeed not trivial. Instead, we directly compared our method to a top performing one that uses objects as nodes [33]. We also performed ablation studies on the graph structure by varying the number of nodes and scales. We observed, for example, that the model with 30 nodes (4 scales) obtains slightly lower results (by 0.28%) while being 1.6 × slower than the model with 14 nodes (3 scales). We will include such ablation studies on number of nodes and scales if accepted.

Additional answers to Reviewer 3:

We thank the reviewer for the helpful and positive comments. We will add the time comparisons to NL-I3D, as shown in the Table above. Our RSTG-to-vec model is faster and more accurate than NL, while our top performer is slightly slower. We will add and discuss these results in the final version.