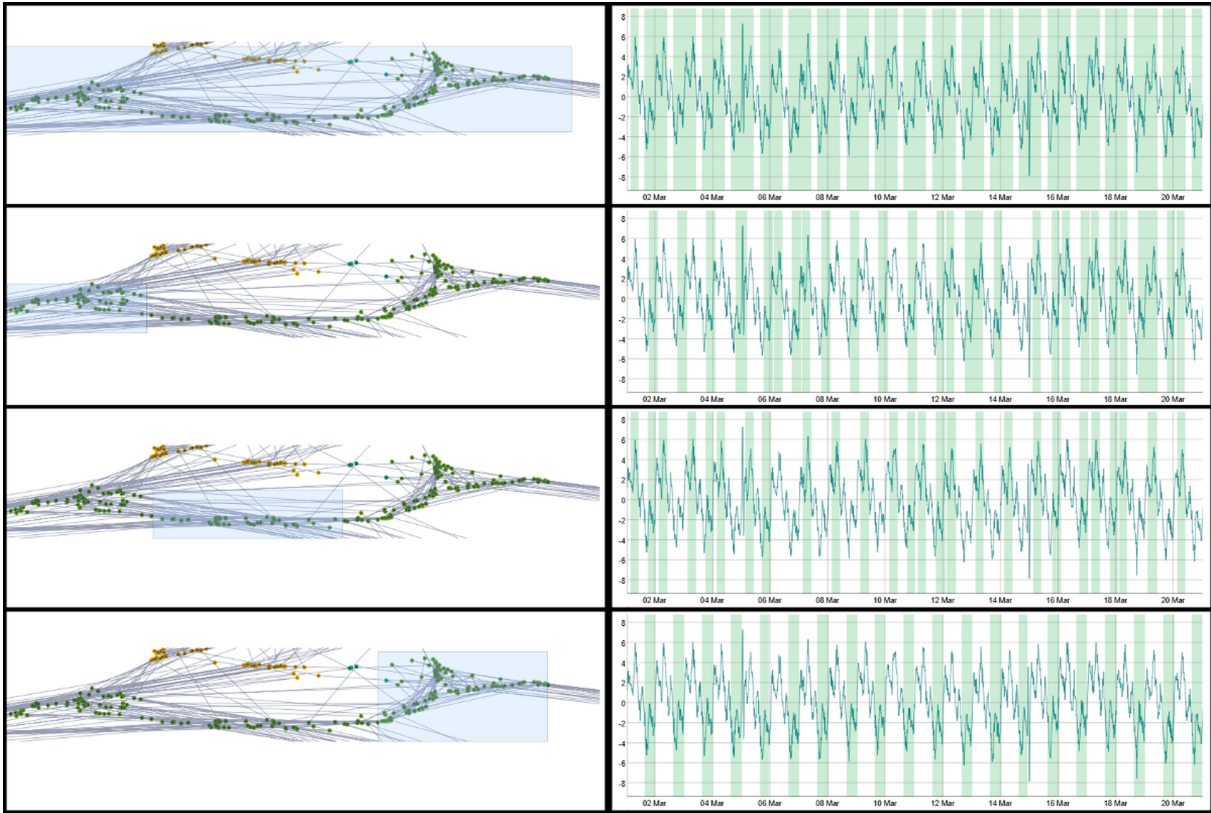
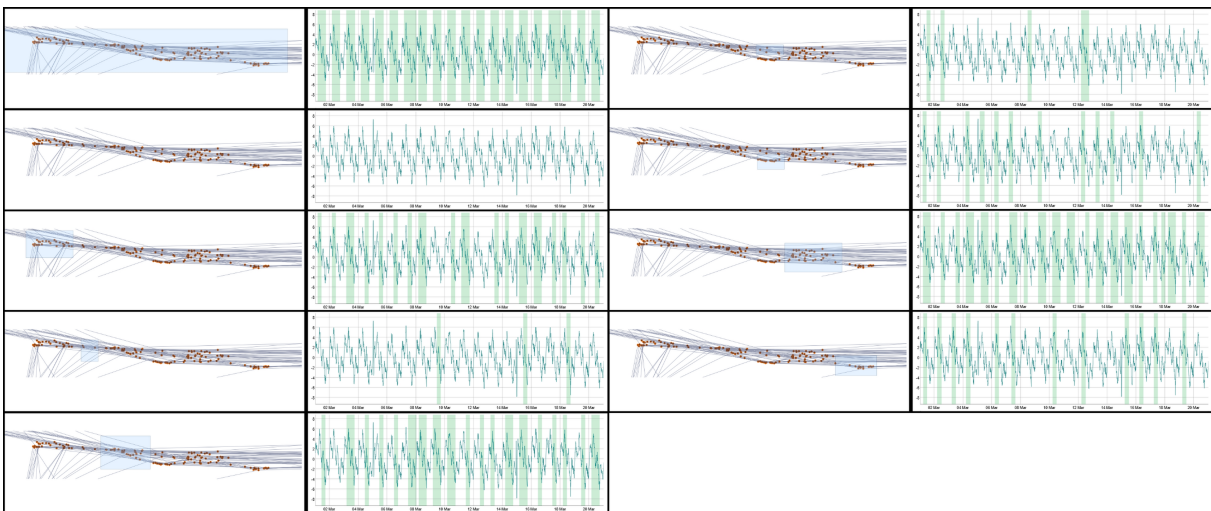


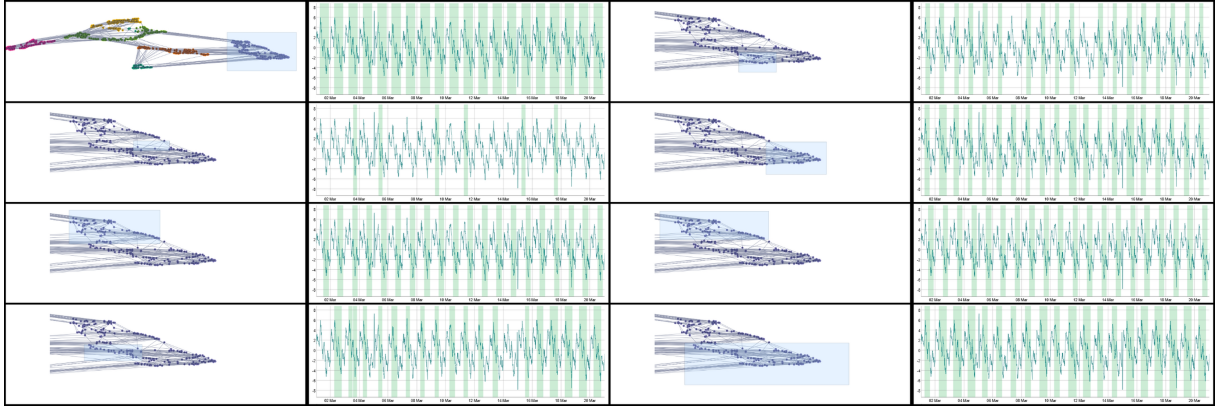
**Figure A.17:** Cluster II: Analysis of the second cluster in the embeddings projections of the zero-shot version of MOMENT-large applied to S2.



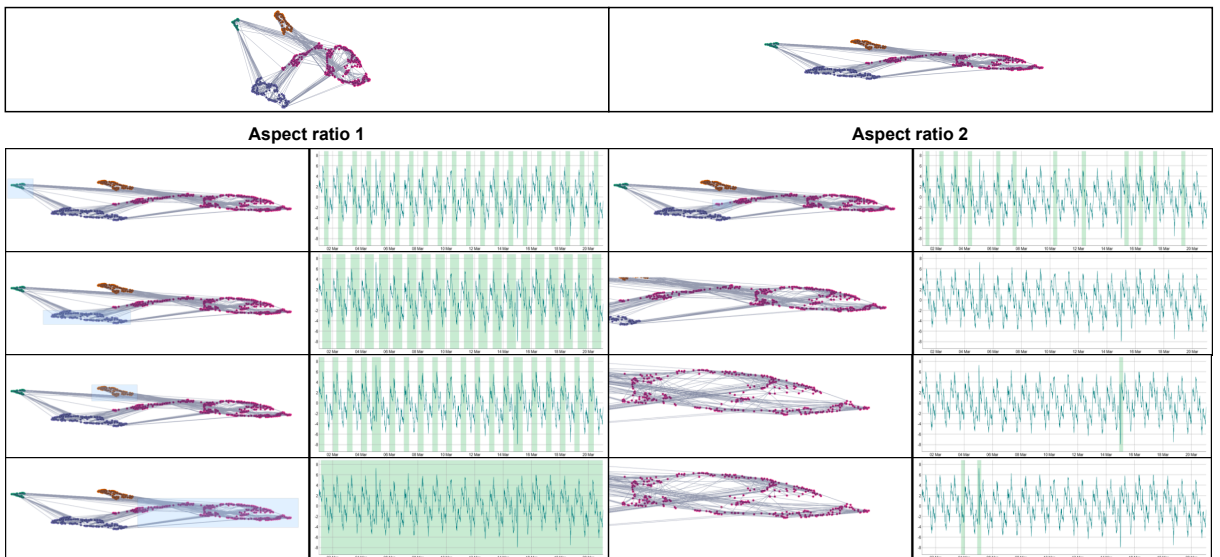
**Figure A.18:** Cluster III: Analysis of the third cluster in the embeddings projections of the zero-shot version of MOMENT-large applied to S2.



**Figure A.19:** Cluster IV: Analysis of the fourth cluster in the embeddings projections of the zero-shot version of MOMENT-large applied to S2.



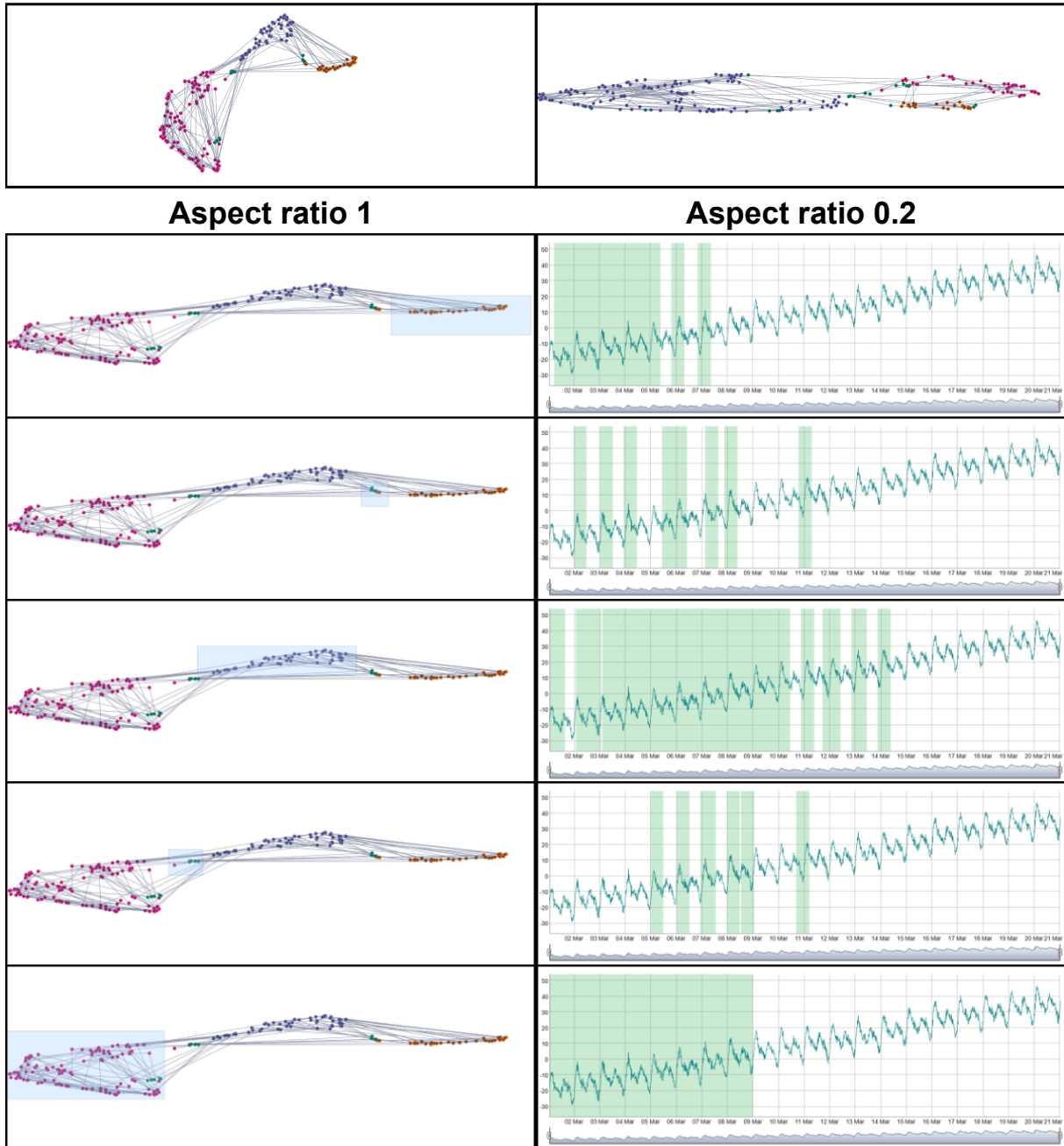
**Figure A.20:** Cluster V: Analysis of the fifth cluster in the embeddings projections of the zero-shot version of MOMENT-large applied to S2.



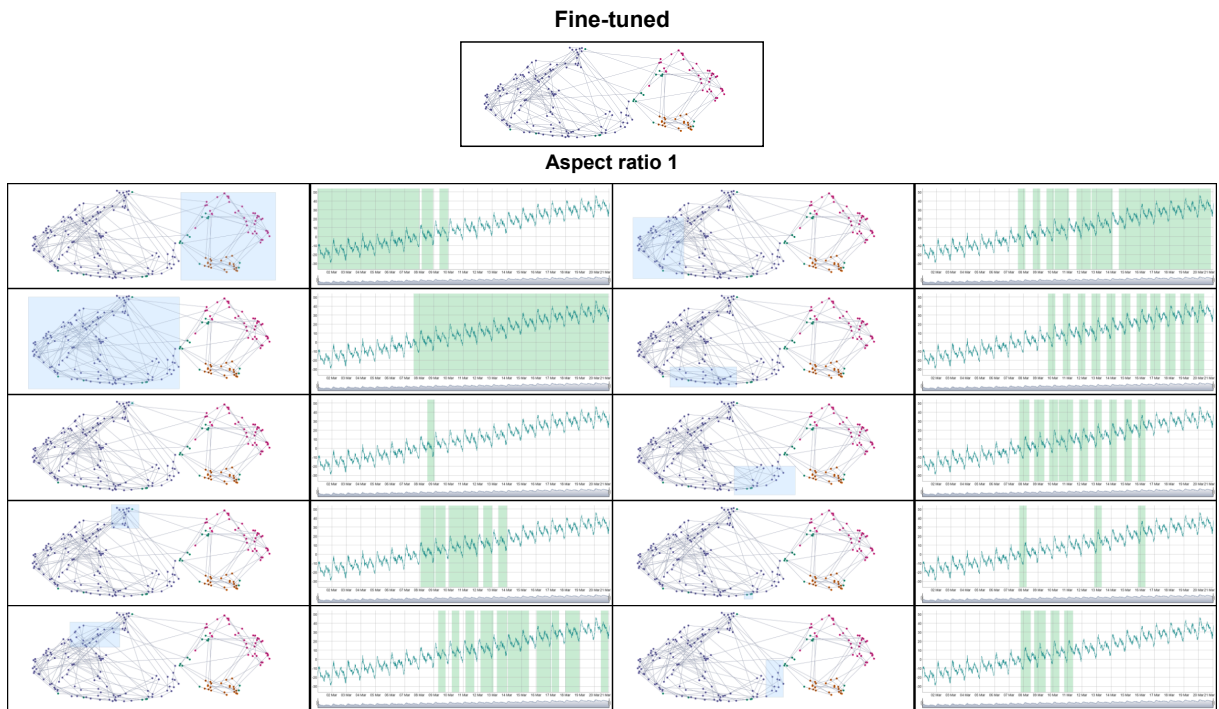
**Figure A.21:** Embeddings projections of the fine-tuned version of MOMENT-large applied to S2.

Figures A.22 and A.23 show the latent space of the MOMENT-base applied to S3 in the zero-shot and fine-tuned versions, respectively.

### Zero-shot

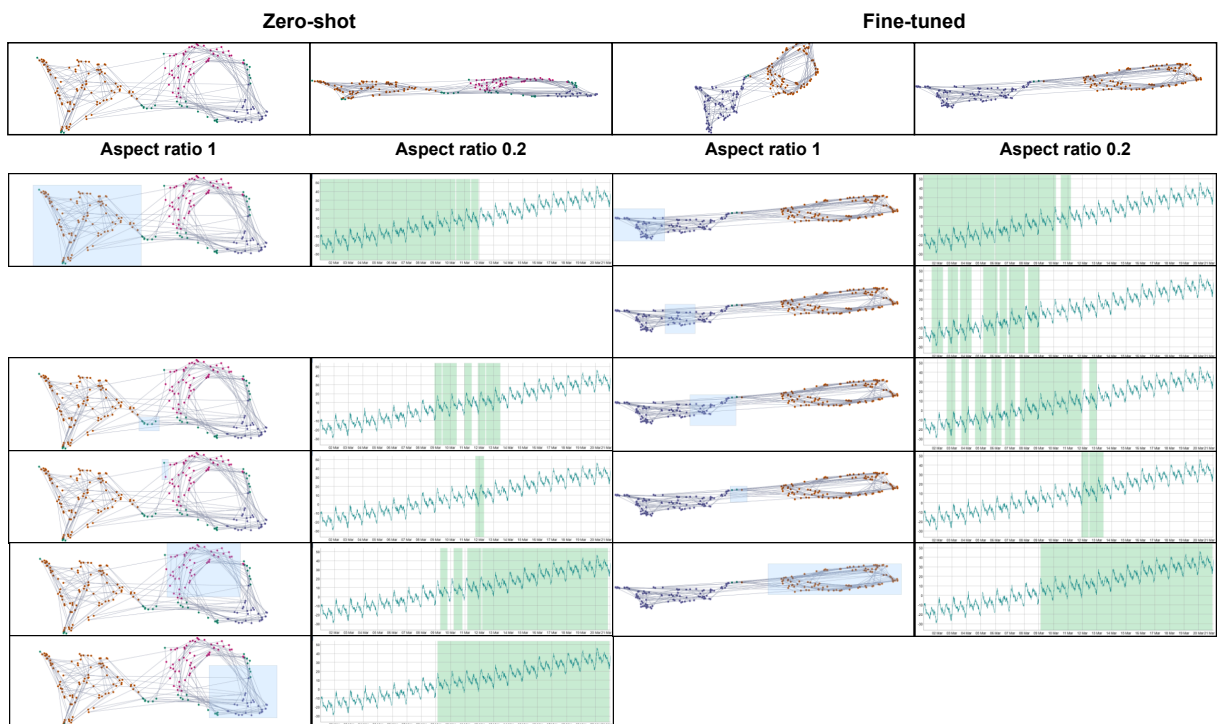


**Figure A.22:** Embeddings projections of the zero-shot version of MOMENT-base applied to S3.



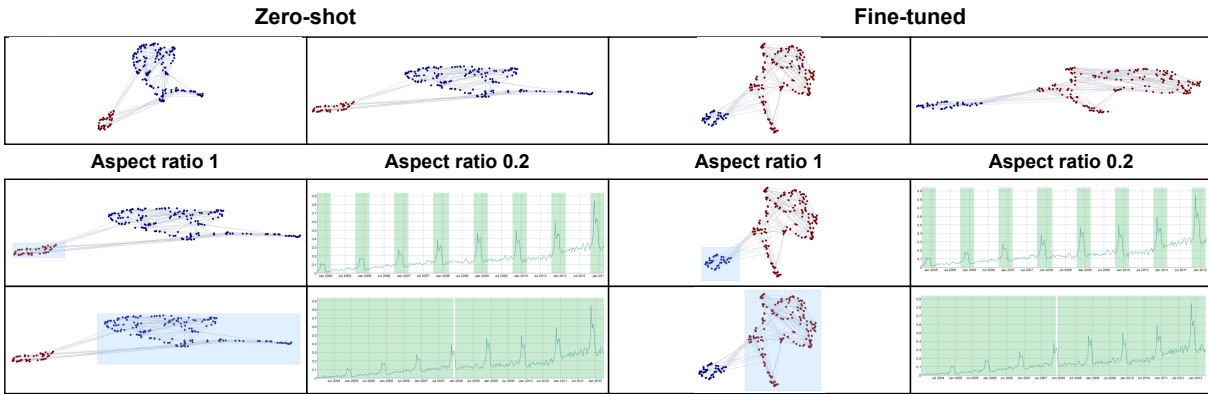
**Figure A.23:** Embeddings projections of the fine-tuned version of MOMENT-base applied to S3.

Figure A.24 shows the latent space of MOMENT-large using S3 as input.

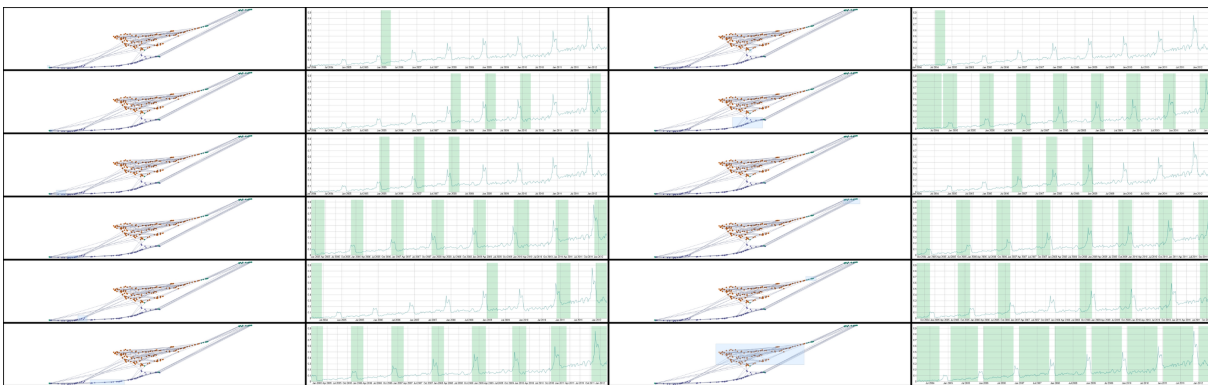


**Figure A.24:** Embeddings projections of MOMENT-large applied to S3.

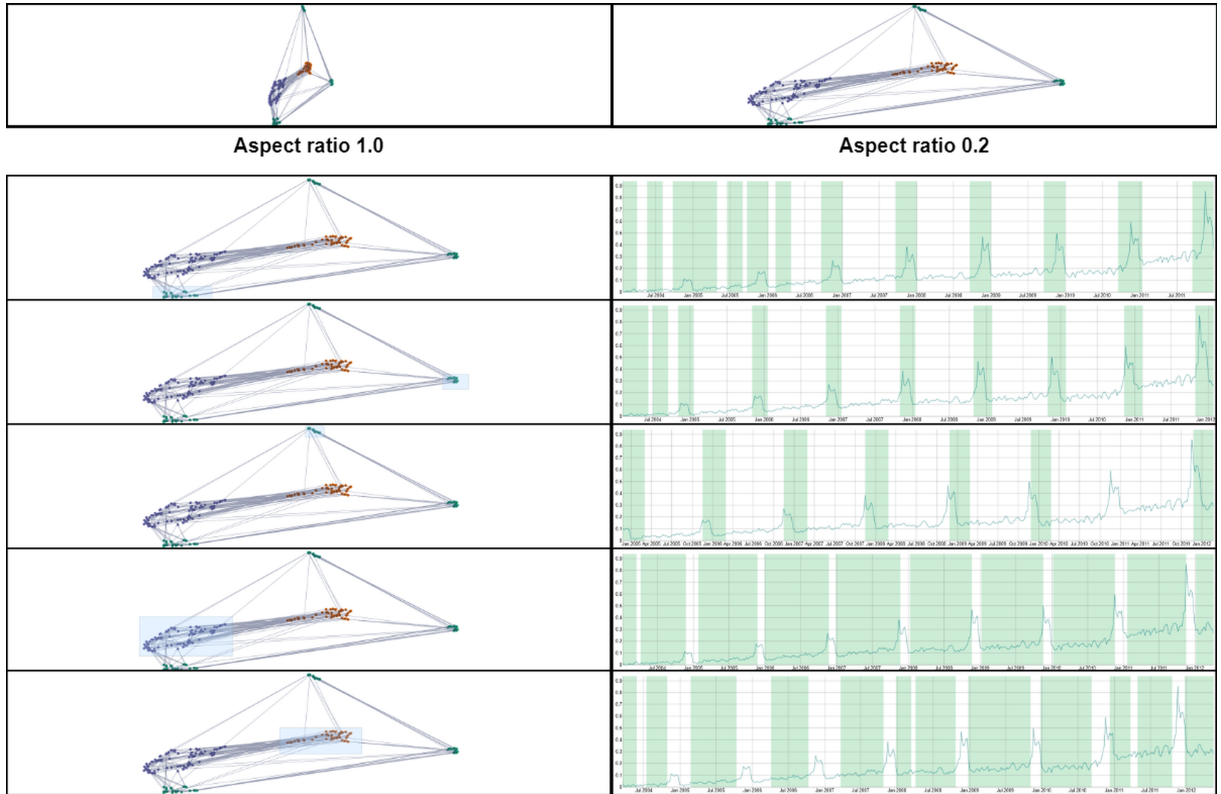
Figure A.25 shows the embedding projection of MOMENT-base applied to Koh1 's in the zero-shot modality. Figure A.26 presents the zero-shot projection of MOMENT-large for the same dataset, while Figure A.27 displays the latent space after fine-tuning MOMENT-large.



**Figure A.25:** Embeddings projections of MOMENT-base zero-shot version applied to Koh1 's

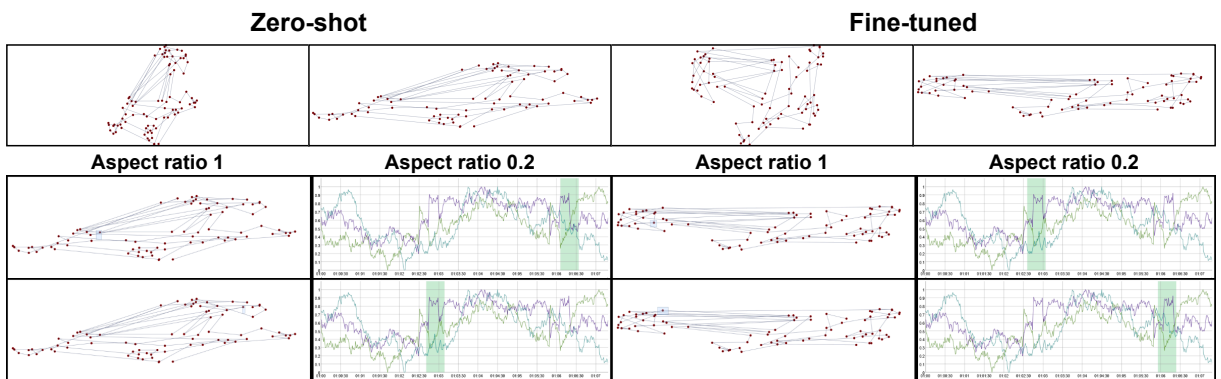


**Figure A.26:** Embeddings projections of MOMENT-large applied to Kohls.

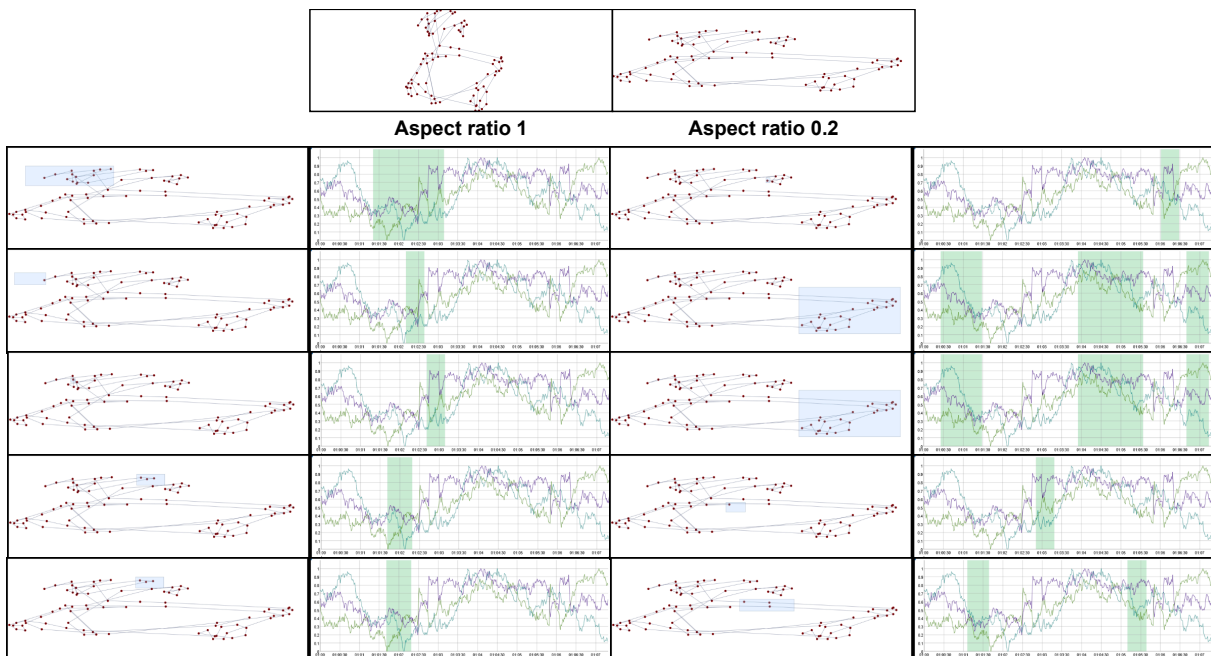


**Figure A.27:** Embeddings projections of MOMENT-large applied to Kohls.

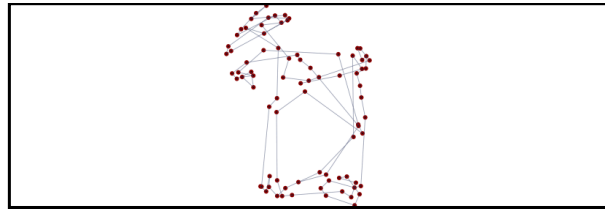
Figure A.28 shows the embedding projection of MOMENT-base applied to the M-Toy dataset. Figure A.29 displays the projection obtained using MOMENT-large in the zero-shot setting, while Figure A.30 presents the latent space resulting from fine-tuning MOMENT-large on the same dataset.



**Figure A.28:** Embeddings projections of MOMENT-base applied to M-Toy.



**Figure A.29:** Embeddings projections of the zero-shot version of MOMENT-large applied to M-Toy.



Aspect ratio 1

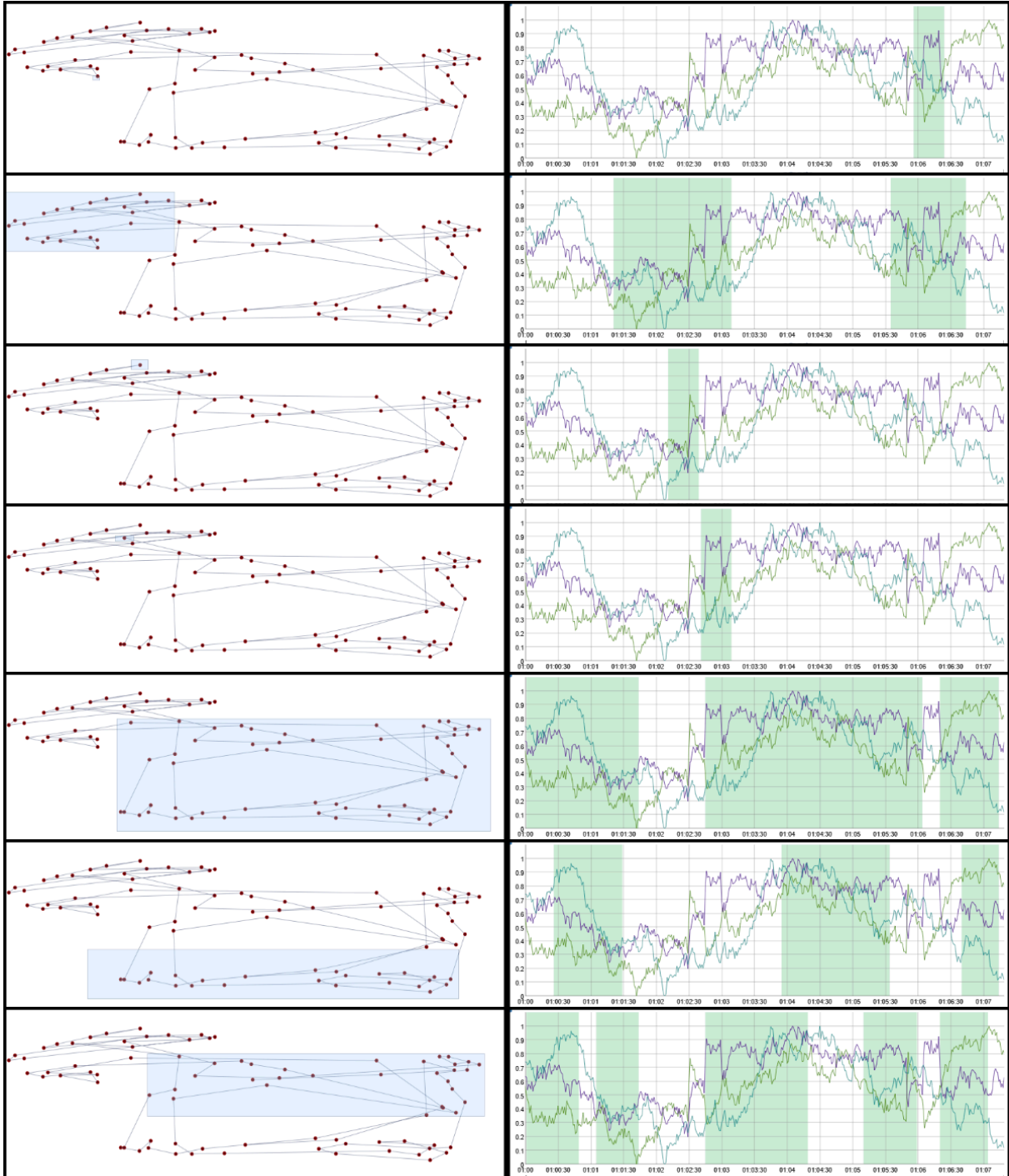


Figure A.30: Embeddings projections of fine-tuned versions of MOMENT-large applied to M-Toy.



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