Token Turing Machines

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Google

THU-AM-247

A sequential, autoregressive model

A sequential, autoregressive model with **external memory**

A sequential, autoregressive model with **external memory**

designed for streaming visual data

Video representation learning

[Charades dataset, ECCV 2016]

Video representation learning

[Robotics Transformer-1, RSS 2023]









Time complexity: O(1), instead of O(T) or $O(T^2)$

Inputs

. . .

Т



Better performance, while requiring significantly less compute



Charades (temporal) Localization task

Token Turing Machine?

It is a modernization of Neural Turing Machines (NTM) [Graves et al., 2014]

• Transformer as a controller + memory tokens



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A recurrent neural network, where all its components are implemented with token-based operations.

• RNN with Transformer + TokenLearner





TTM

. . .



TTM



Inputs

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Token Turing Machines - Architecture



Token Turing Machines - Read



TokenLearner



[Ryoo et al., NeurIPS 2021]

Token Turing Machines - Write



Could be interpreted as a recurrent neural network with an explicit memory, where all its components are implemented with token-based operations.

$$Z^{t} = \text{Read}(I^{t}, M^{t})$$
$$O^{t} = \text{Process}(Z^{t})$$
$$M^{t+1} = \text{Write}(M^{t}, O^{t}, I^{t})$$
$$Y^{t} = \text{Output}(O^{t})$$

Temporal activity detection

Comparison against SOTA

| Method | Setting | modality | mAP |
|--|---------|--------------|-------|
| I3D + super-events (Piergiovanni & Ryoo, 2018) | offline | RGB + Flow | 19.41 |
| I3D + super-events + TGM (Piergiovanni & Ryoo, 2019) | offline | RGB + Flow | 22.30 |
| I3D + STGCN (Ghosh et al., 2020) | offline | RGB + Flow | 19.09 |
| I3D + biGRU + VS-ST-MPNN (Mavroudi et al., 2020) | offline | RGB + Object | 23.7 |
| Coarse-Fine (w/ X3D) (Kahatapitiya & Ryoo, 2021) | offline | RGB | 25.1 |
| I3D + CTRN (Dai et al., 2021a) | offline | RGB | 25.3 |
| I3D + MS-TCT (Dai et al., 2022) | offline | RGB | 25.4 |
| I3D + PDAN (Dai et al., 2021b) | offline | RGB + Flow | 26.5 |
| I3D + CTRN (Dai et al., 2021a) | offline | RGB + Flow | 27.8 |
| I3D (Carreira & Zisserman, 2017) | online | RGB + Flow | 17.22 |
| X3D (Feichtenhofer, 2020) | online | RGB | 18.87 |
| ViViT-B (Arnab et al., 2021) | online | RGB | 23.18 |
| ViViT-B + TTM (ours) | online | RGB | 26.34 |
| ViViT-L (Arnab et al., 2021) | online | RGB | 26.01 |
| ViViT-L + TTM (ours) | online | RGB | 28.79 |

Charades dataset



Temporal activity detection

Comparison against regular Transformers

| Method | mAP | GFLOPS |
|--|-------|---------|
| ViViT only | 23.18 | - |
| Alternative temporal models | | |
| Temporal MLPMixer (tokens=96) | 24.41 | 0.382 |
| Causal Transformer (tokens=96) | 25.85 | 0.523 |
| Temporal Transformer (tokens=96) | 25.61 | 1.269 |
| Temporal MLPMixer (tokens=3360) | 24.26 | 13.317 |
| Causal Transformer (tokens=3360) | 25.88 | 29.695 |
| Temporal Transformer (tokens=3360) | 25.53 | 112.836 |
| Alternative recurrent networks | | |
| LSTM | 23.96 | 0.107 |
| Recurrent Transformer (tokens=16+16) | 25.97 | 0.410 |
| Recurrent Transformer (tokens=3136+16) | 25.97 | 17.10 |
| Token Turing Machines | | |
| TTM-Mixer ($n = 16$) | 25.83 | 0.089 |
| TTM-Transformer ($n = 16$) | 26.24 | 0.228 |
| TTM-Mixer ($n = 3136$) | 26.14 | 0.704 |
| TTM-Transformer ($n = 3136$) | 26.34 | 0.842 |

Charades dataset



Time complexity is much lower: O(T) vs. O(1).

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Charades dataset



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Spatio-temporal activity detection

Comparison against MeMViT, which is a memory + MViT.

| Model | mAP | +GFLOPS |
|------------------------------|-------------|---------|
| MViT | 26.2 | - |
| + memory (i.e., MeMViT [66]) | 28.5 (+2.3) | 1.3 |
| ViViT-B | 25.2 | - |
| + TTM per video | 27.9 (+2.7) | 0.8 |
| + TTM per box (# layers=1) | 31.3 (+6.1) | 1.0 |
| + TTM per box (# layers=4) | 31.5 (+6.3) | 2.0 |

On AVA v2.2, with K400 pre-training

AVA v2.2 dataset



Left: Sit, Talk to, Watch; Right: Crouch/Kneel, Listen to, Watch



Left: Sit, Ride, Talk to; Right: Sit, Drive, Listen to



Left: Stand, Carry/Hold, Listen to; Middle: Stan Carry/Hold, Talk to; Right: Sit, Write



Left: Stand, Watch; Middle: Stand, Play instrument; Right: Sit, Play instrument

Robot action policy learning



Data used in Google's Robotics Transformer-1 (RT-1)

Data: 130k episodes of over 700+ tasks, collected using 13 robots over 17 months

Goal: robot control

[RT-1, RSS 2023]

Robot action policy learning





Data used in Google's Robotics Transformer-1 (RT-1)

[Robotics Transformer-1, RSS 2023]

Summary

Token Turing Machines

• Represent and process a sequence of many tokens

It is a generic framework - a recurrent Transformer with token-based memory

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https://github.com/google-research/scenic/tree/main/scenic/projects/token_turing