Textual Explanations for Self-Driving Vehicles Paper Review

Jinkyu Kim et al. ECCV 2018 07

C.E 18011573 이장후 / Sejong Artificial Intelligence : S team

https://arxiv.org/abs/1807.11546

Topics

1. Attention
2. Abstract, Introduction
3. Related Work
4. Explainable Driving Model
5. BDD-X Dataset
6. Results & Evaluations
7. Conclusion

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Attention

Attention Model Overview

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Key Reference

- http://dmqm.korea.ac.kr/activity/seminar/280
  - Korea University
- https://youtu.be/W2rWgXJBZhU
  - CodeEmporium
- https://youtu.be/Sb3b0ocD8mI?t=2799
  - Stanford university
- https://youtu.be/SysgYptB198
  - Andrew Ng

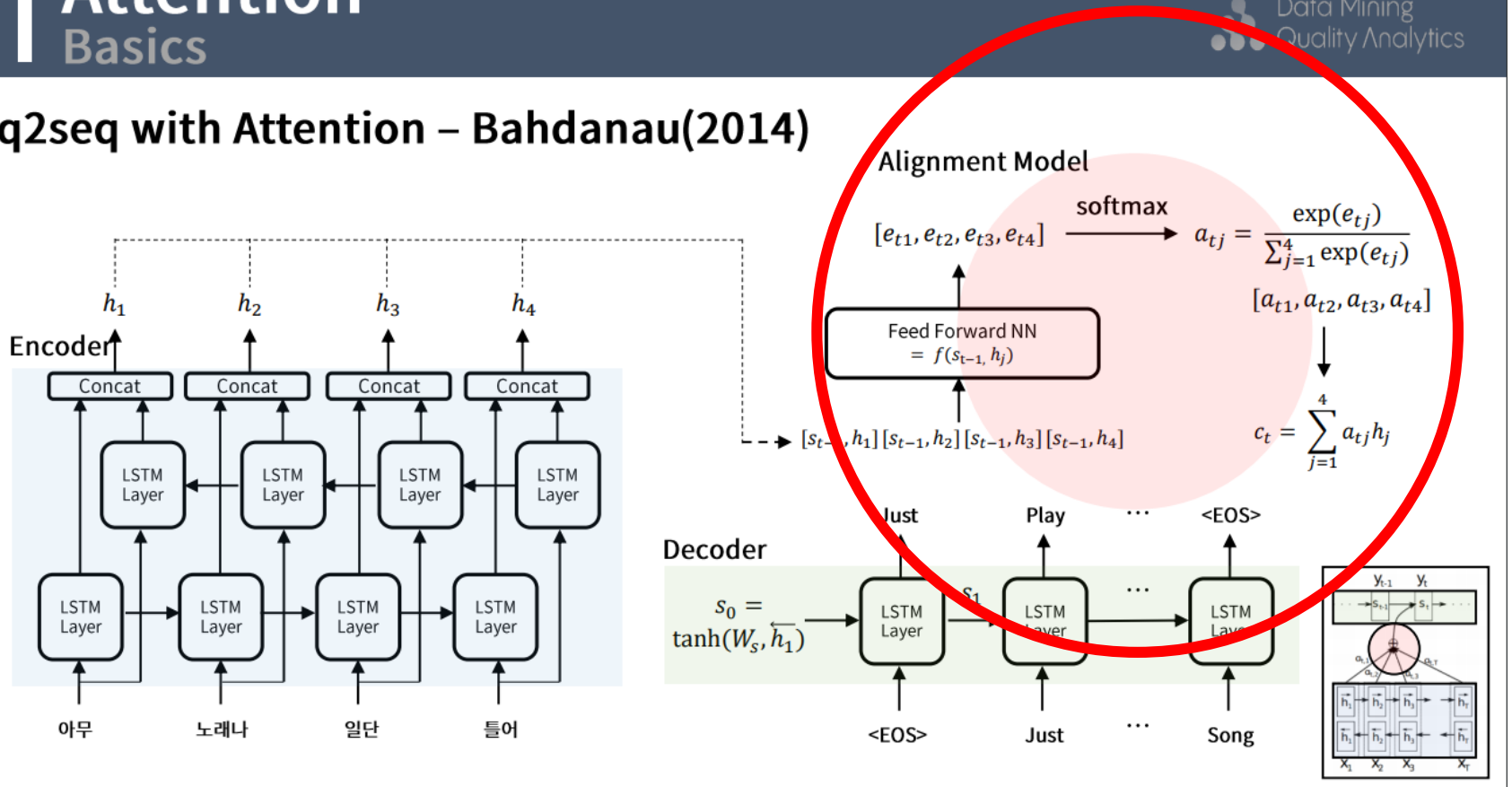
- https://ardino.tistory.com/59
  - https://medium.com/@sunwoopark/show-attend-and-tell-with-pytorch-e45b1600a749

Attention : Machine Translation

02 | Attention Basics

Data Mining Quality Analytics

❖ **Seq2seq with Attention – Bahdanau(2014)**



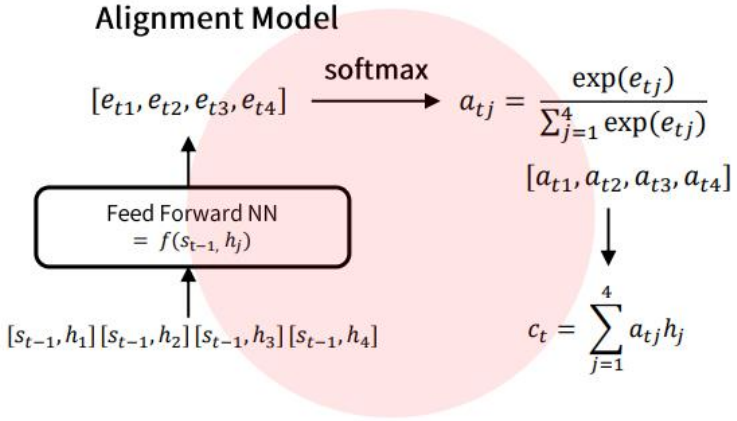
Bahdanau, Dzmitry, Kyunghyun Cho, and Yoshua Bengio. "Neural machine translation by jointly learning to align and translate." *arXiv preprint arXiv:1409.0473* (2014).

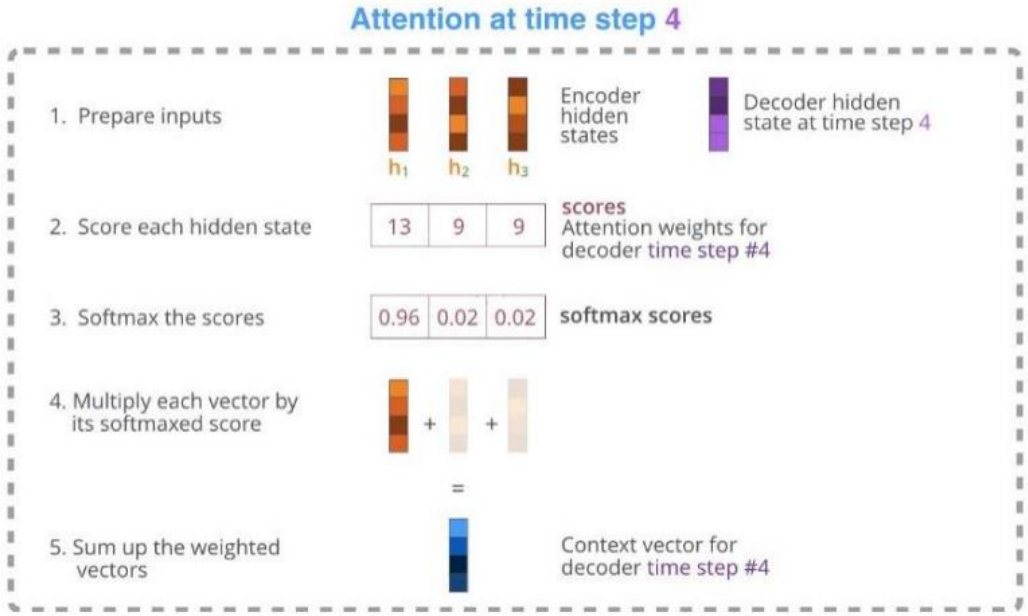
Attention : Machine Translation (2)

02 | Attention Basics

Data Mining Quality Analytics

❖ **Seq2seq with Attention – Bahdanau(2014)**





https://jalammar.github.io/visualizing-neural-machine-translation-mechanics-of-seq2seq-models-with-attention/

Bahdanau, Dzmitry, Kyunghyun Cho, and Yoshua Bengio. "Neural machine translation by jointly learning to align and translate." *arXiv preprint arXiv:1409.0473* (2014).

200214 Open HCAI Seminar – Visual Attention 10/55

Attention : Machine Translation (3)

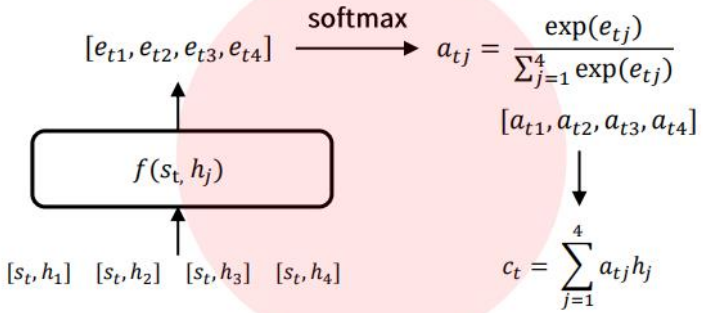
02 | Attention Basics

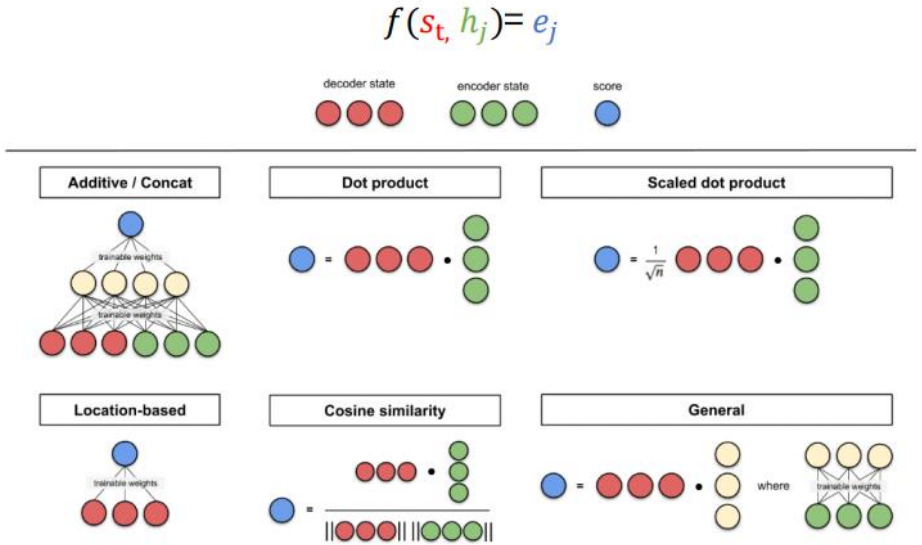
Data Mining Quality Analytics

❖ Seq2seq with Attention – Luong(2015)

- Alignment model의 input으로 s_{t-1}가 아닌 s_t을 사용
- 다양한 similarity function $f(s_t, h_j)$ 제시

Alignment Model



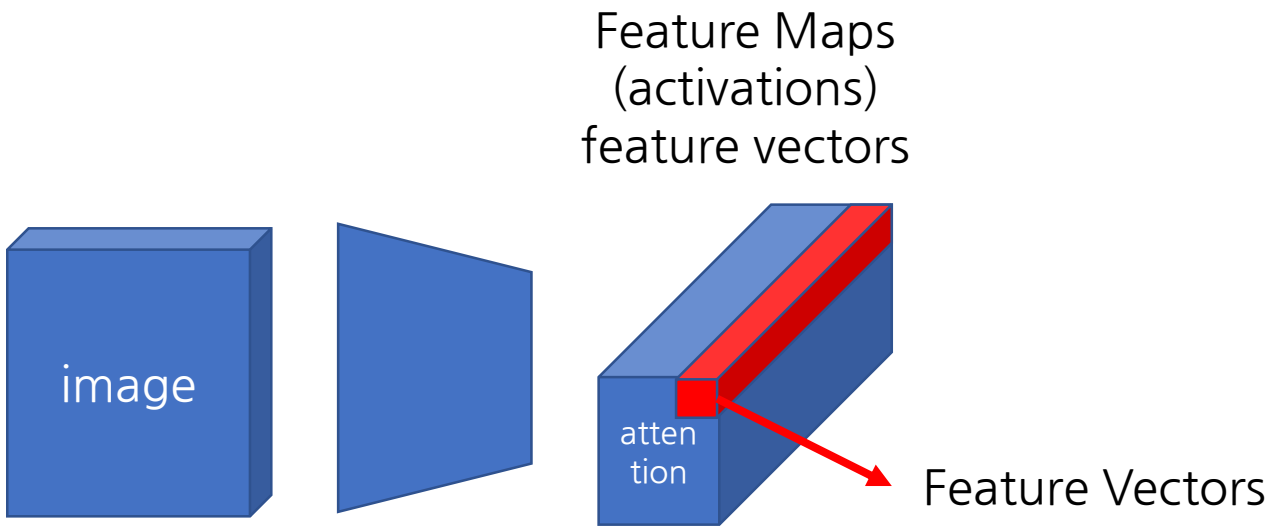


https://towardsdatascience.com/attn-illustrated-attention-5ec4ad276ee3

Luong, Minh-Thang, Hieu Pham, and Christopher D. Manning. "Effective approaches to attention-based neural machine translation." *arXiv preprint arXiv:1508.04025* (2015).

Attention : Computer Vision (Captioning)

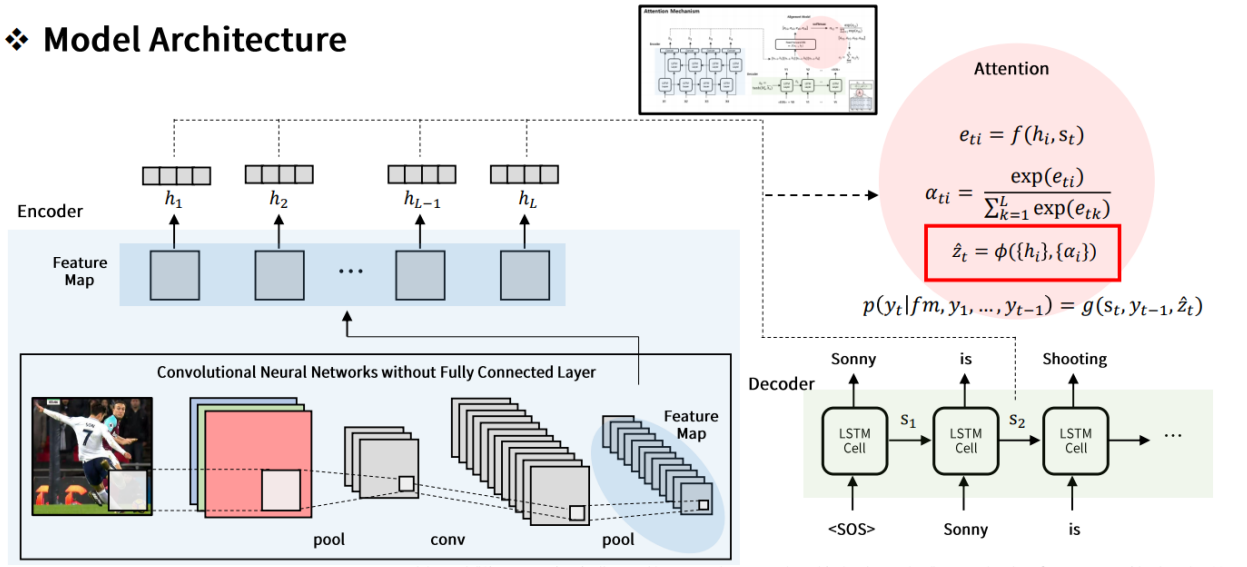
- 아이디어의 태동은 자연어처리 분야의, **Machine Translation**.
  - “Which sequence elements are most important to constructing an accurate output sequence.”
- Vision 쪽에서 attention 의 keynote paper : **“Show, Attend and Tell”**



https://medium.com/@shairozsohail/a-survey-of-visual-attention-mechanisms-in-deep-learning-1043eb25f343

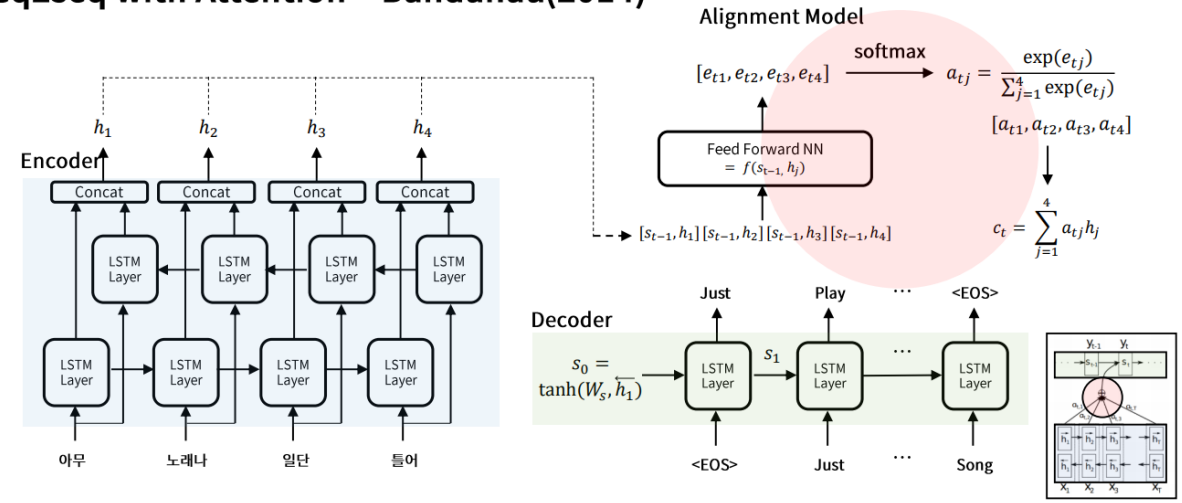
Attention : Computer Vision (Captioning) (1)

❖ **Model Architecture**



Xu, Kelvin, et al. "Show, attend and tell: Neural image caption generation with visual attention." *International conference on machine learning*. 2015.

❖ **Seq2seq with Attention – Bahdanau(2014)**



Bahdanau, Dzmitry, Kyunghyun Cho, and Yoshua Bengio. "Neural machine translation by jointly learning to align and translate." *arXiv preprint arXiv:1409.0473* (2014).

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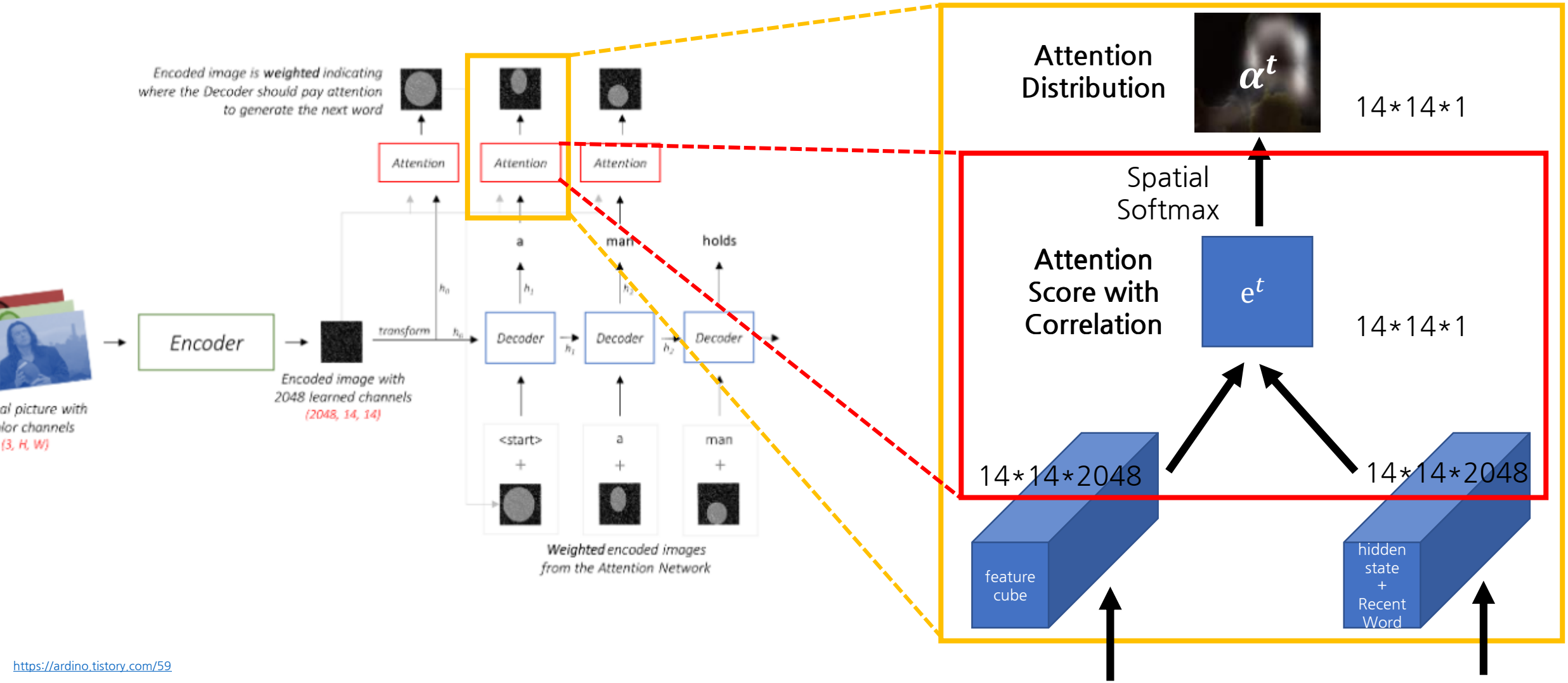
Attention : Computer Vision (Captioning) (2)



https://ardino.tistory.com/59

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Attention? Localization?

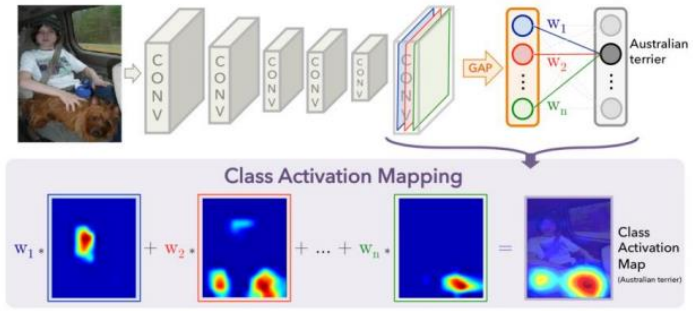
- Attention : Interpretability (Localization) + Performance
  - ref : DMQA Lab (Korea University)

02 | Attention Conclusion

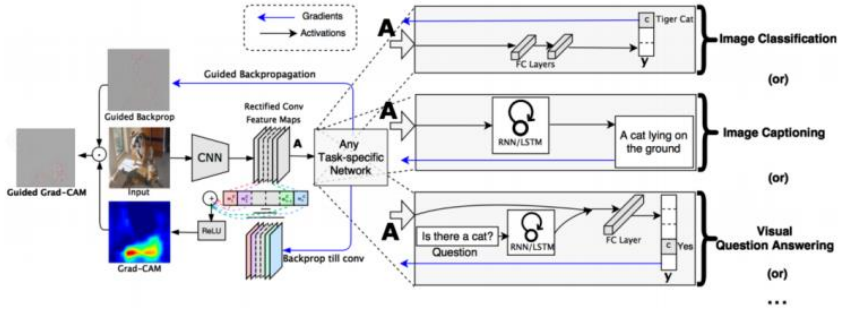
Data Mining Quality Analytics

❖ **Localization vs Attention**

- Localization: Interpretability
- Attention: Interpretability + Model performance



Class Activation Map(CAM)



Grad_CAM

Zhou, Bolei, et al. "Learning deep features for discriminative localization." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2016.

Selvaraju, Ramprasaath R., et al. "Grad-cam: Visual explanations from deep networks via gradient-based localization." *Proceedings of the IEEE international conference on computer vision*. 2017.

http://dmqm.korea.ac.kr/activity/seminar/280

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+ Naming

- 그… 그만하라굿!

arxiv.org › cs ▾ 이 페이지 번역하기

Show and Tell: A Neural Image Caption Generator

2014. 11. 17. - In this **paper**, we present a generative model based on a deep recurrent architecture that combines recent advances in computer vision and ...

O Vinyals 저술 - 2014 - 3713회 인용 - 관련 학술자료

arxiv.org › cs ▾ 이 페이지 번역하기

Show, Attend and Tell: Neural Image Caption Generation with ...

2015. 2. 10. - Title:**Show**, **Attend and Tell**: Neural Image Caption Generation with Visual Attention ... We also show through visualization how the model is able to automatically learn to fix its ... Which authors of this **paper** are endorsers?

K Xu 저술 - 2015 - 5445회 인용 - 관련 학술자료

2014, Image Captioning

2015, Image Captioning

2015, Speech Recognition

2017

2015

arxiv.org › cs ▾ 이 페이지 번역하기

Show, Ask, Attend, and Answer: A Strong Baseline For Visual ...

2017. 4. 11. - Abstract: This **paper** presents a new baseline for visual question **answering** task. Given an image and a question in natural language, our ...

V Kazemi 저술 - 2017 - 85회 인용 - 관련 학술자료

arxiv.org › cs ▾ 이 페이지 번역하기

Listen, Attend and Spell

2015. 8. 20. - Abstract: We present **Listen**, **Attend and Spell** (LAS), a neural network that learns to transcribe ... Which authors of this **paper** are endorsers?

W Chan 저술 - 2015 - 288회 인용 - 관련 학술자료

arxiv.org › cs ▾ 이 페이지 번역하기

Ask, Attend and Answer: Exploring Question-Guided Spatial ...

2015. 11. 17. - Title:**Ask**, **Attend and Answer**: Exploring Question-Guided Spatial Attention for Visual Question **Answering** ... We evaluate our model on two published visual question **answering** ... Which authors of this **paper** are endorsers?

H Xu 저술 - 2015 - 513회 인용 - 관련 학술자료

Abstract, Introduction

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Abstract, Introduction

DNN 자율주행차를 이용자가 받아들이기 위해서는 당연히 높은 신뢰가 요구.

- 동작에 대한 설명이 필요.
- 왜 이런 동작을 했는지를 이해할 필요.
- 더 효율적으로 소통할 필요.

그렇다면 어떤 정보를 소통해야 하나?

- rationalization : 악셀을 밟거나 제동을 하거나 등 이러한 뉴럴넷 동작의 결정을 주고 동작에 대한 설명 (post-hoc manner)
- introspective explanation : 악셀을 밟거나 제동을 하거나 등의 결정이 처리되는 그 이유. 그 동작에 대한 운전자 입장에서의 설명

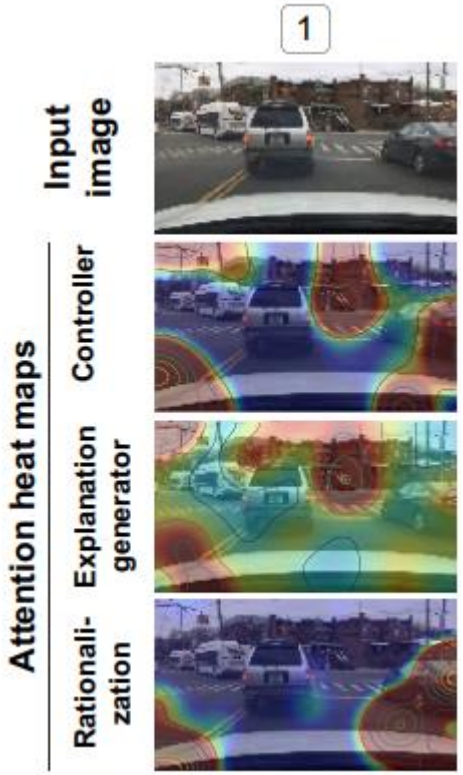
Abstract, Introduction

- 기존에는 Activation map, Visual Attention 을 통해서 자율주행 분야에서 설명가능성을 얻고자 했음.
- 그런데 그러한 방법들은, 뉴럴넷의 동작과 바로 연결이 안 됨. 또한 이용자가 그걸 일일이 생각하면서 다시 돌려보아야 함. 예를 들어, “신호등이 빨간색이므로 차의 브레이크를 밟습니다.” 에 비해 정면을 촬영한 이미지에 신호등이 Activation 된 것은 번거로울 수 있음.
- 따라서 이용자에게 generating textual description 을 통해 rationalization 과 introspective explanation 을 제공하는 것에 집중함.

Abstract, Introduction

3 Contributions

- **Contribution 1**. textual description 을 통한 rationalization 과 introspective explanation 을 제공하는 방법 제안
- **Contribution 2**. 다른 정보를 주지 않고 vehicle controller 의 동작 결과와 이미지만을 잘 연결해서 textual explanation 을 생성해낸 것 (rationalization) 과, vehicle controller 의 attention context 와 이미지를 연결해서 textual explanation 을 생성해낸 것 (introspective explanation) 을 비교하고, 어떠한 결과보다 어떤 결과를 도출하는 네트워크의 상태 (state) 를 활용해서 학습하는 것이 더 좋다는 것을 밝힘.
- **Contribution 3**. 77시간어치 Berkeley Deep Drive 데이터셋에 eXplanation (BDD-X) Dataset 을 추가함. (Human-Annotated)



Human: The car steadily driving + now that the cars are moving.

Ours (WAA): The car is driving forward + because traffic is moving freely.

Ours (SAA): The car heads down the road + because traffic is moving at a steady pace.

Rationalization: The car slows down + because it's getting ready to a stop sign.

Textual Explanations for Self-Driving Vehicles

사람이 평가한 결과입니다.

Type	Model	Control inputs	λ_a	λ_c	Correctness rate	
					Explanations	Descriptions
Rationalization	Ours (no constraints)	Y	0	0	64.0%	92.8%
Introspective explanation	Ours (with SAA)	Y	-	100	62.4%	90.8%
	Ours (with WAA)	Y	10	100	**66.0%**	**93.5%**

Related Work

1. End to End Learning for AV
2. Visual and Textual Explanations

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Related Work - End to End Learning for AV

자율주행차 controller 을 만드는 방법은 크게 두 가지로 나뉨.

이 논문은 end-to-end 방법론. (최근 이쪽 연구는 대부분 end-to-end 로 진행)

- 여러가지를 인지한 결과를 조립해서 만드는 방법 (mediated)
  - 신호등 인식 모델, 보행자 인식 모델, 차선 인식 모델을 모두 활용해서 컨트롤러 생성
- 그냥 사진이나 영상을 주고 통째로 학습시켜버리는 방법 (end-to-end)
  - input : 최근 몇 타임동안의 영상, 조향, 악셀 … etc, output : 조향, 악셀 … etc

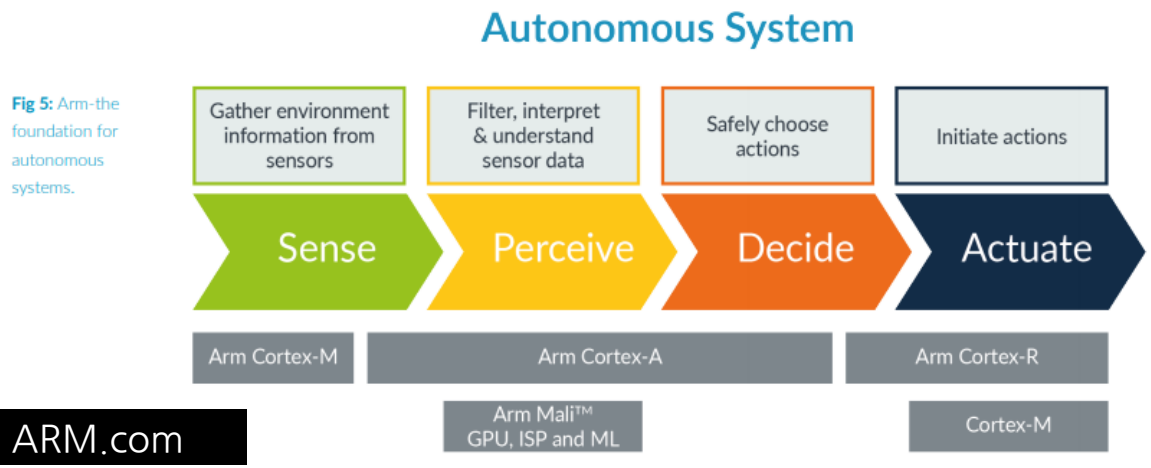
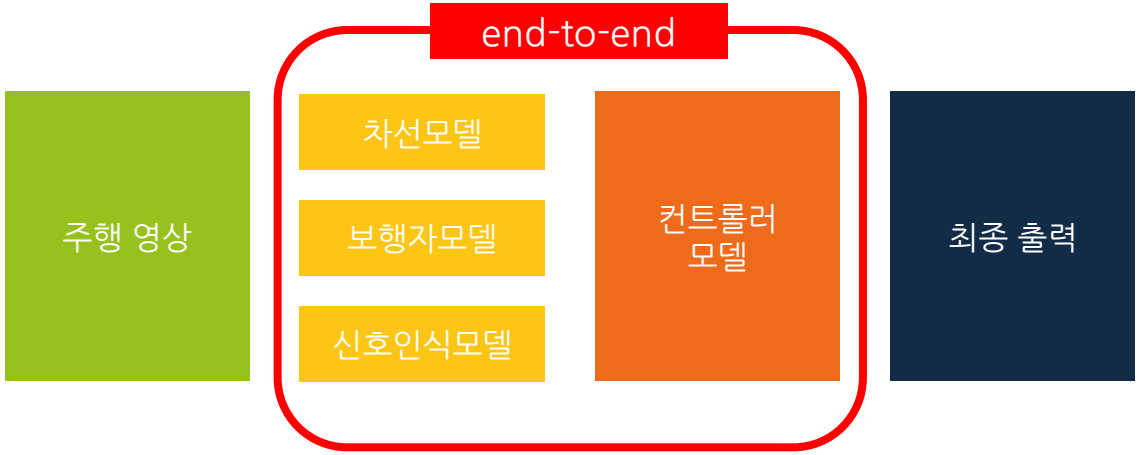


Fig 5: Arm-the foundation for autonomous systems.

ARM.com



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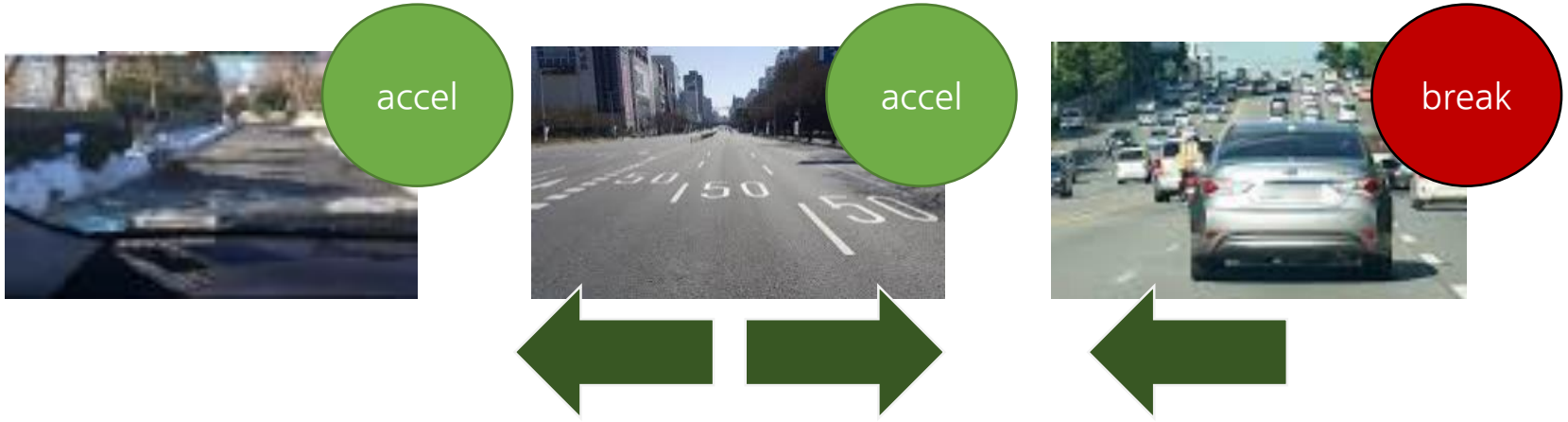
Related Work - End to End Learning for AV

기존의 end to end 시도들, (그리고 한계 지적 : 설명력 부족)

- (1) : dashcam image -> control
- (2) : 이전차량상태 + raw image pixel -> control

end to end 방법론 자율주행데이터셋 만드는 방법

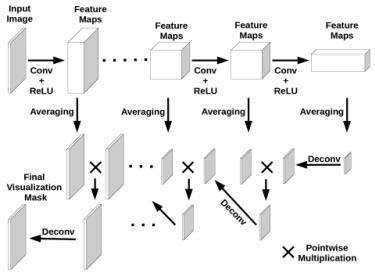
- Behavior cloning : 사람 실주행으로부터 조향, 엑셀, 브레이크 로그와 영상 페어 데이터를 만들고, 지도학습.



Related Work - Visual and Textual Explanations

기존의 rationalization 과 introspective explanation 을 제공하는 방법들

- (1) : CNN Deconvolution
- (2) : Image Captioning, CNN Justification with LSTM
- (3) : Deconvolution Based Pixelwise Activation Map
  - VisualBackProp: visualizing CNNs for autonomous driving, 2016
- **(4) : Attention Based Explanations with Causal filtering**
  - 의의 : 동작에 영향을 미치는 부분을 콕 집어서 표시하는 방법을 제안함.
  - Interpretable Learning for Self-Driving Cars by Visualizing Causal Attention 2017
    - https://openaccess.thecvf.com/content_ICCV_2017/papers/Kim_Interpretable_Learning_for_ICCV_2017_paper.pdf



이러한 설명들을 가장 빨리 평가(justify)

하는 방법은 textual justification 이라고 주장.

http://www.columbia.edu/~aec2163/NonFlash/Papers/VisualBackProp.pdf

Explainable Driving Model

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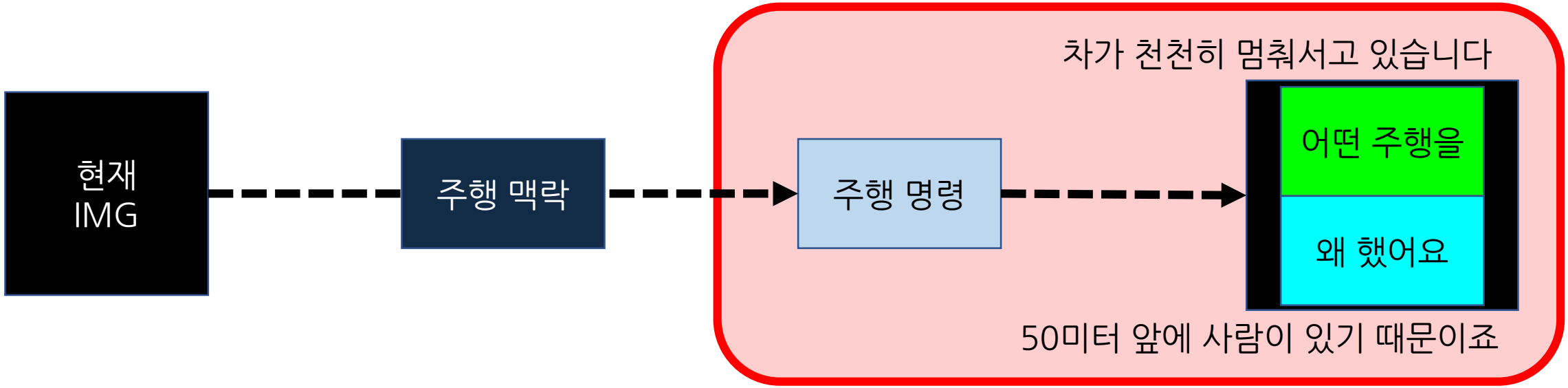
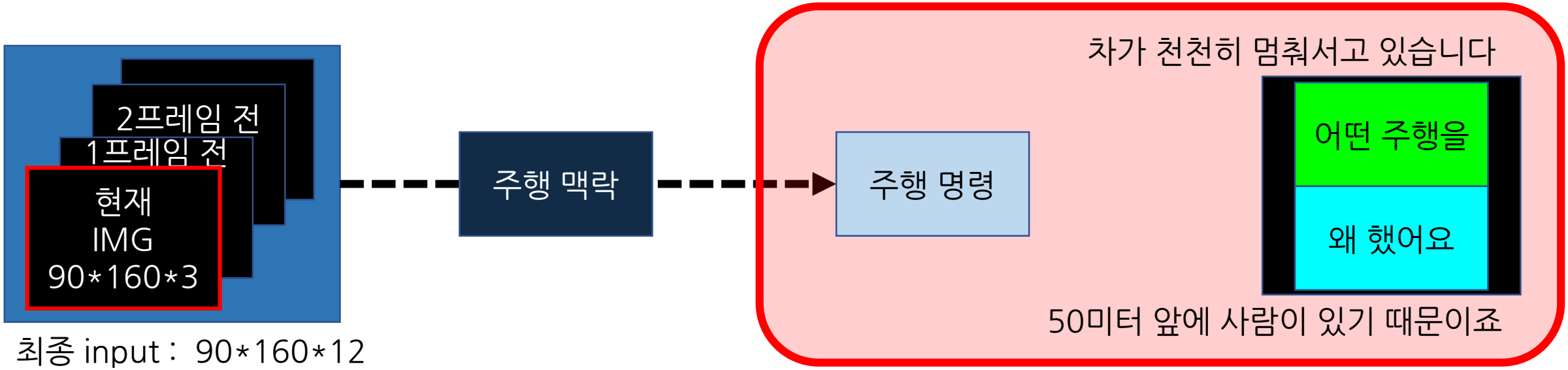
Purposed Model

- 이미지를 바탕으로, 아래와 같은 output 을 내는 end-to-end 모델을 구상
- Vehicle Controller
- Vehicle Controller description
- justification (explanation)



Purposed Model

- input 으로 IMG 를 넣어줄 때, 최근 4 frame 의 input 들을 쌓아서 넣어줌.
  - resize : nearest neighbor 로 downsampling
  - normalize : resize 된 각 이미지 frame 마다 (x-m)/std 정규화



최종 input : 90*160*12

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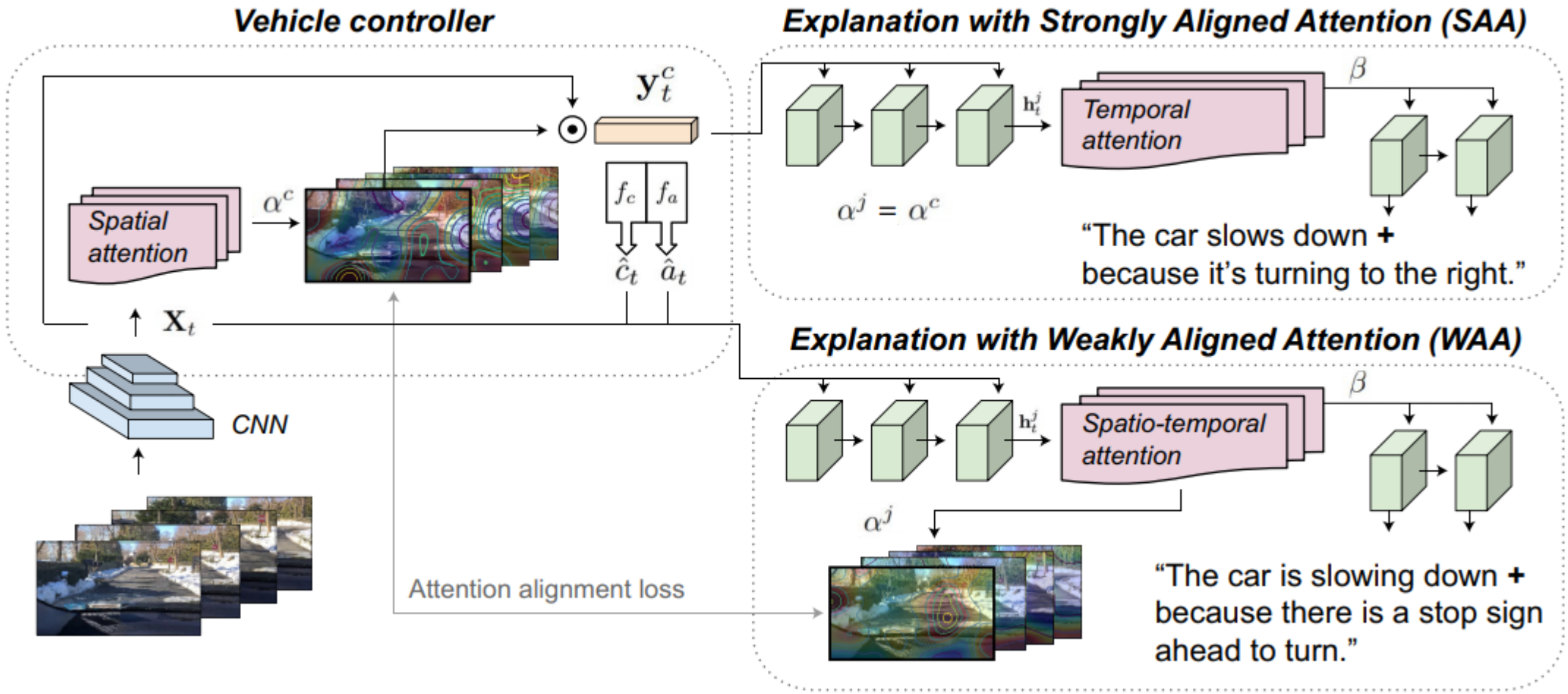
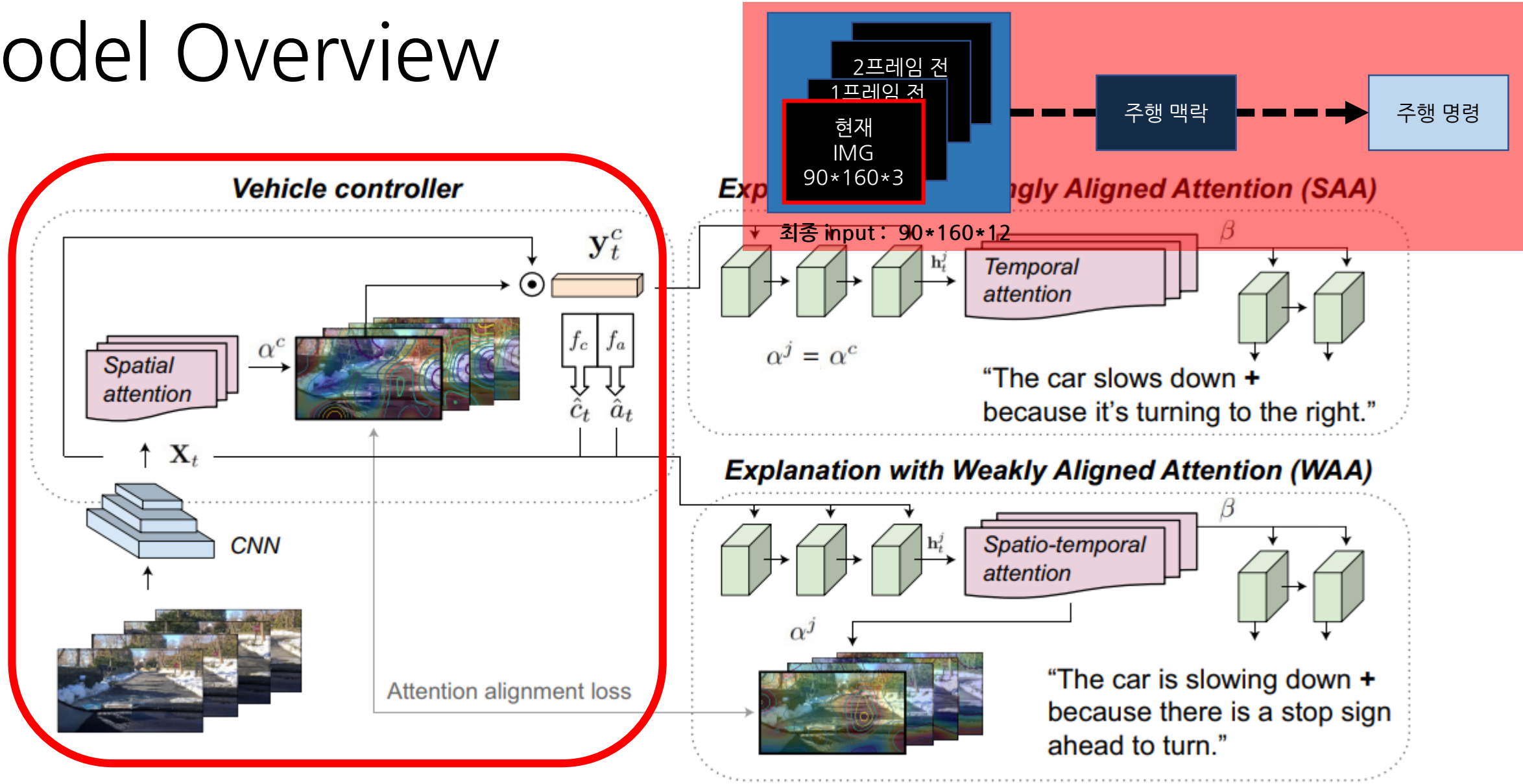
Model Overview



Model Overview



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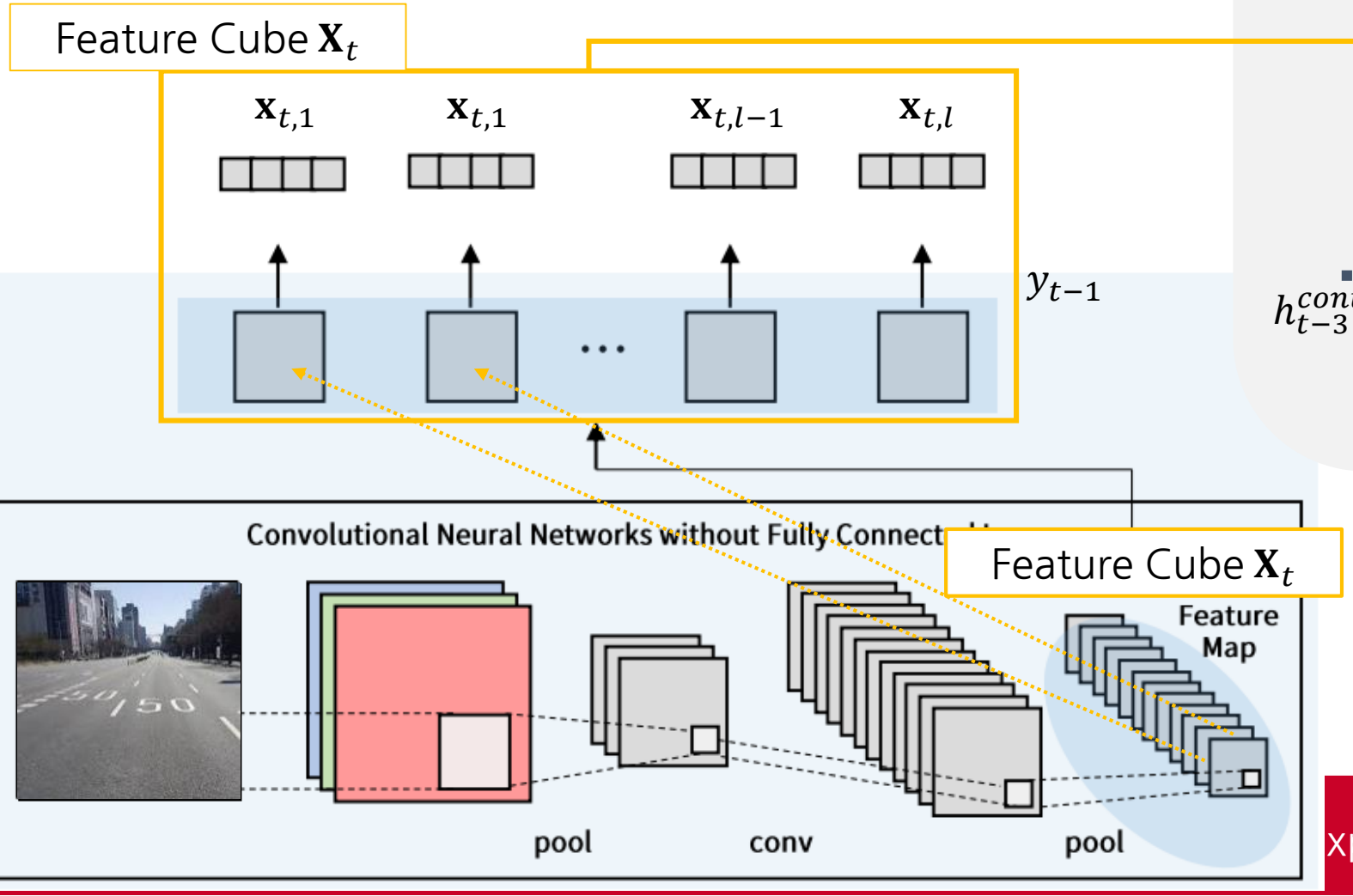
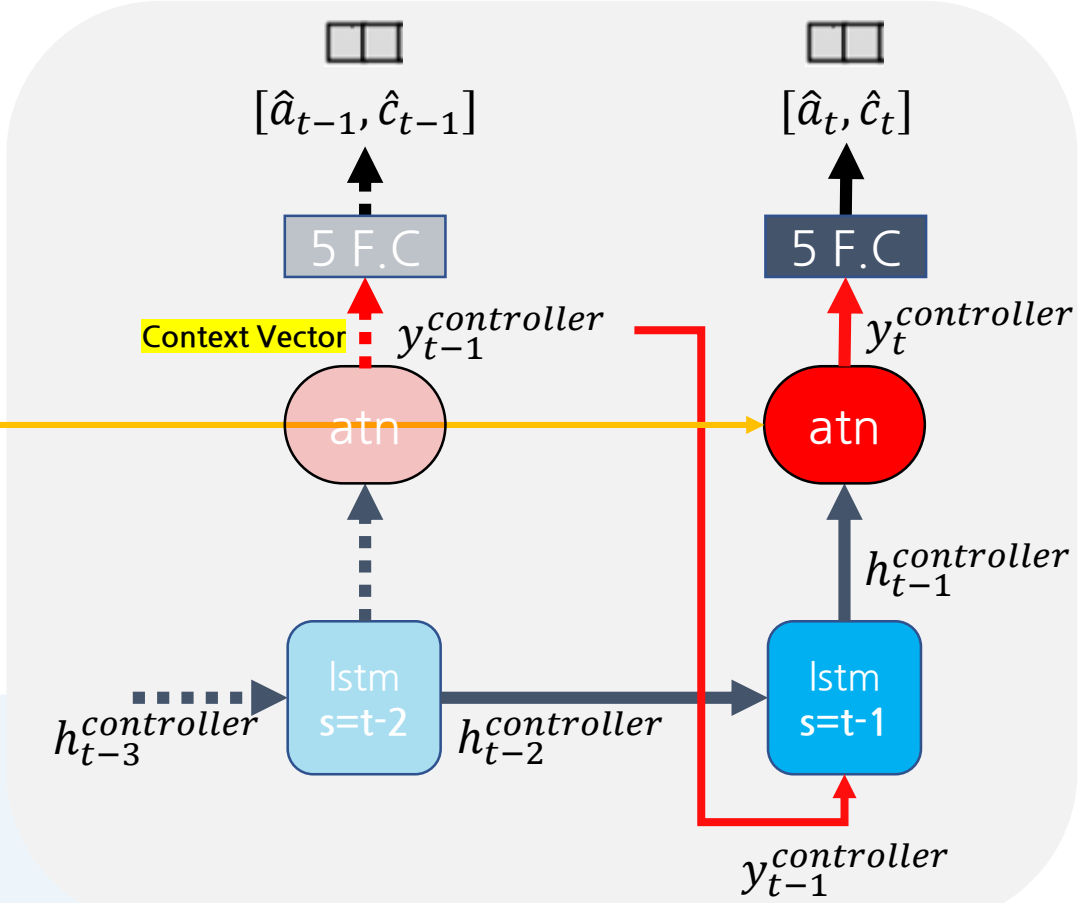
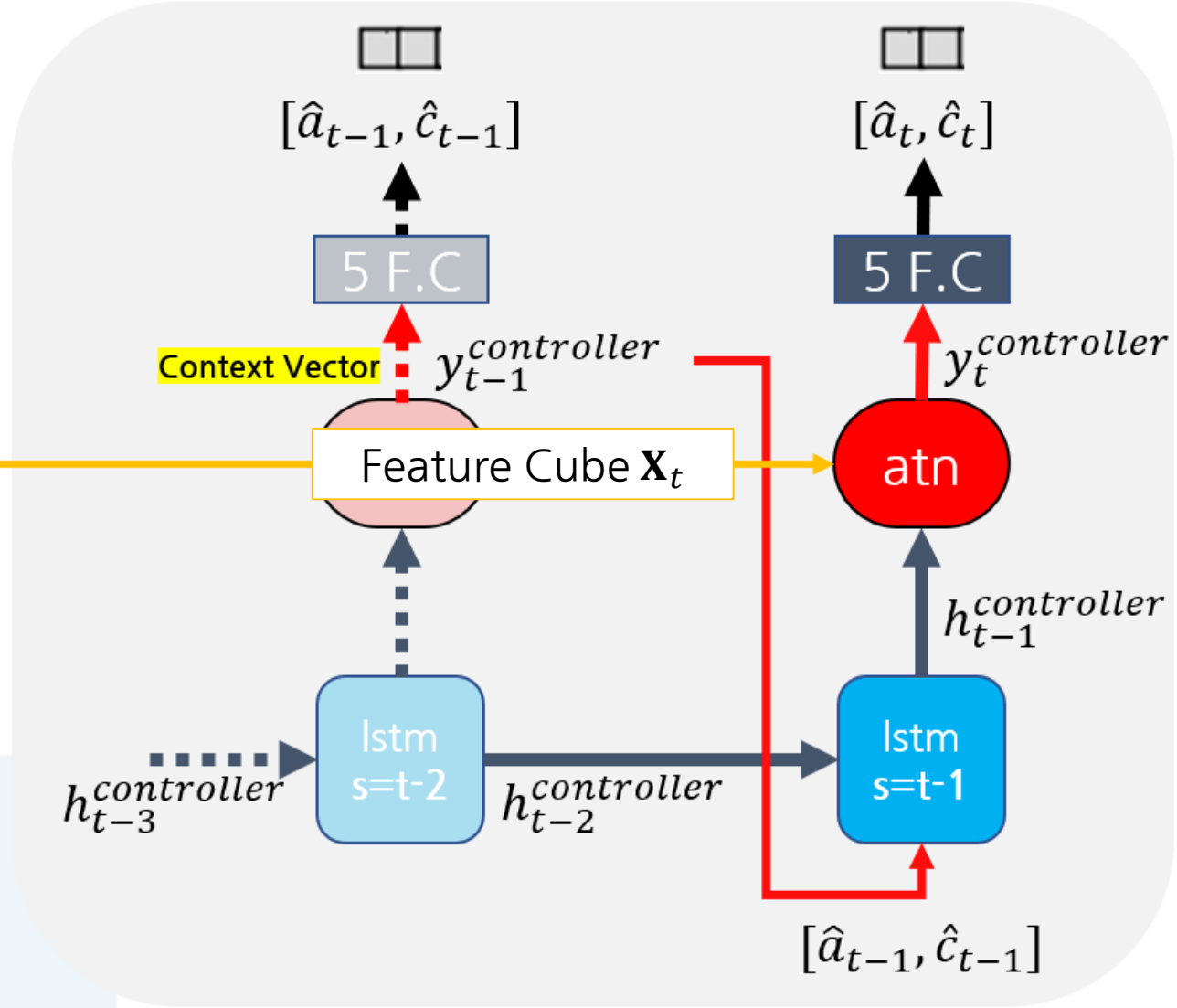
Model - Controller

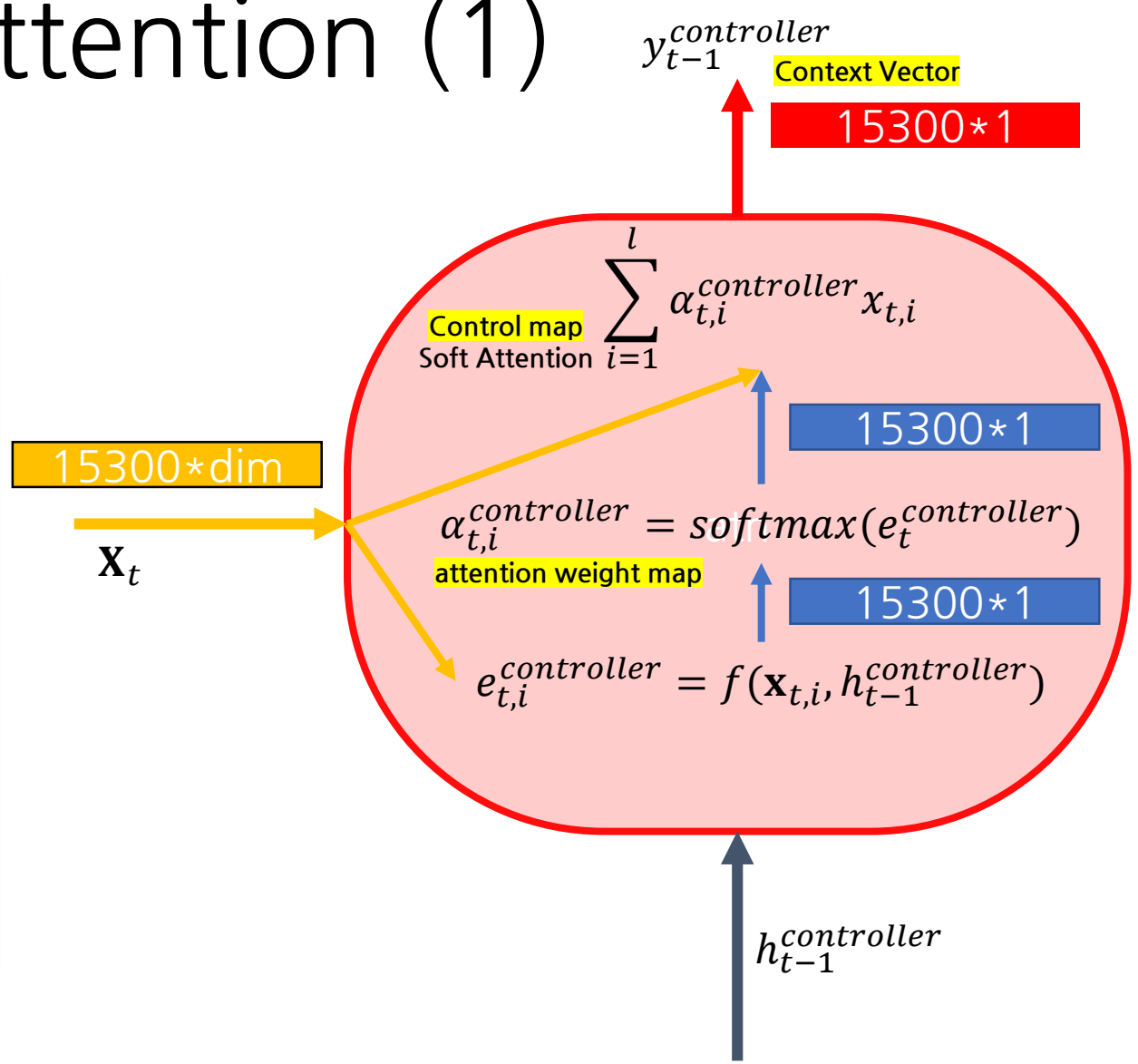
- $\hat{a}_{t-1}$: 이번엔 엑셀(=브레이크) 를 얼마나 밟을까?
- $\hat{c}_{t-1}$: 이번엔 차선을 어떻게 바꿀까?





Model - Controller - Attention (1)





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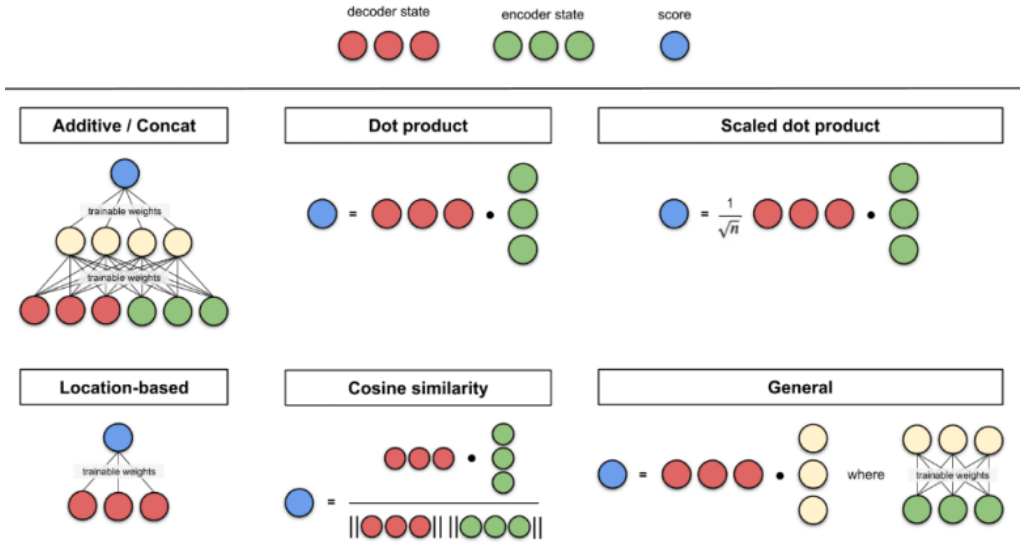
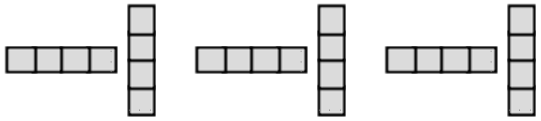
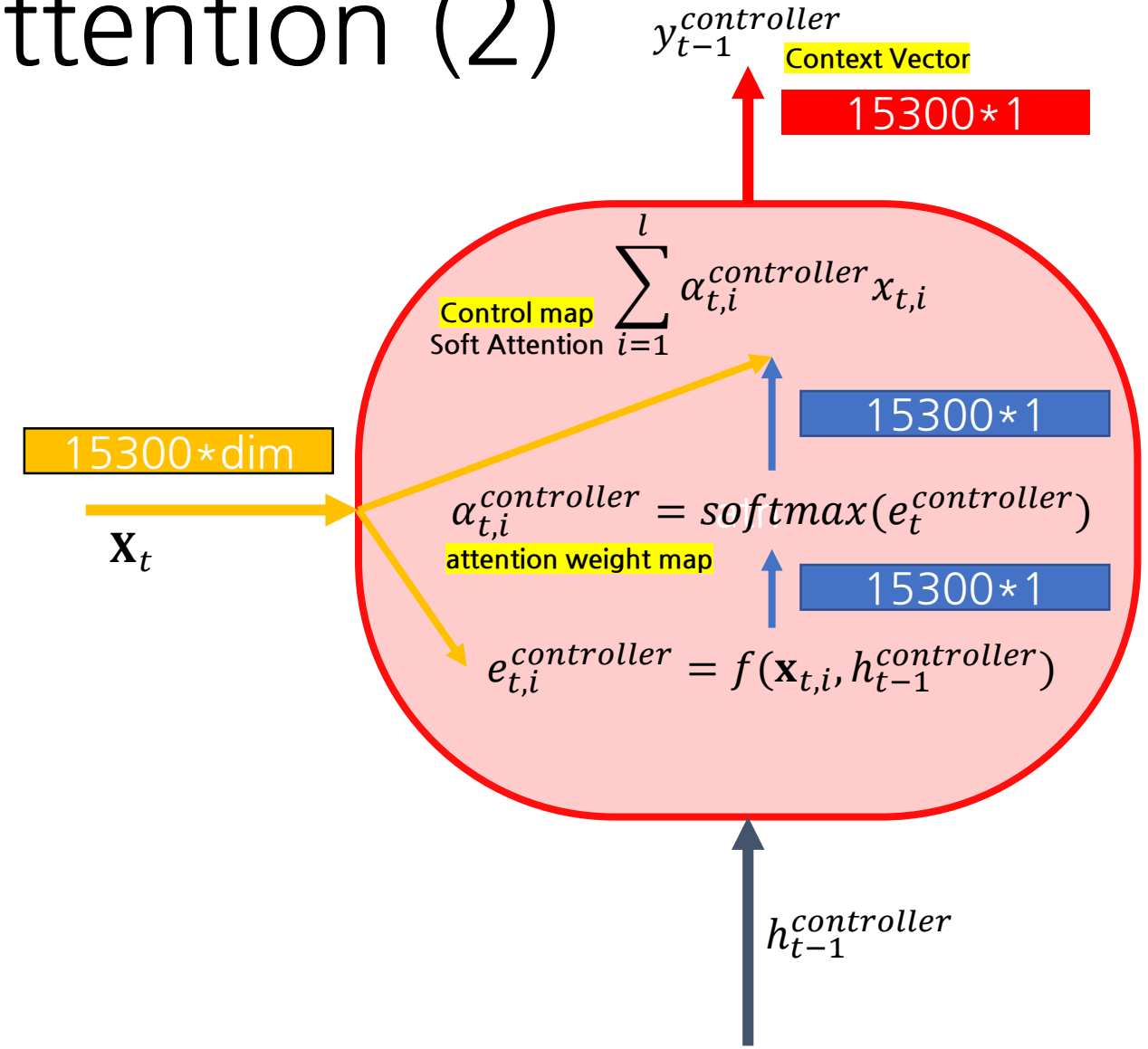
Model - Controller - Attention (2)

$f(s_t, h_j) = e_j$



$$e_{t,i}^{controller} = f(\mathbf{x}_{t,i}, h_{t-1}^{controller}) = Corr(\mathbf{x}_{t,i}, h_{t-1}^{controller})$$





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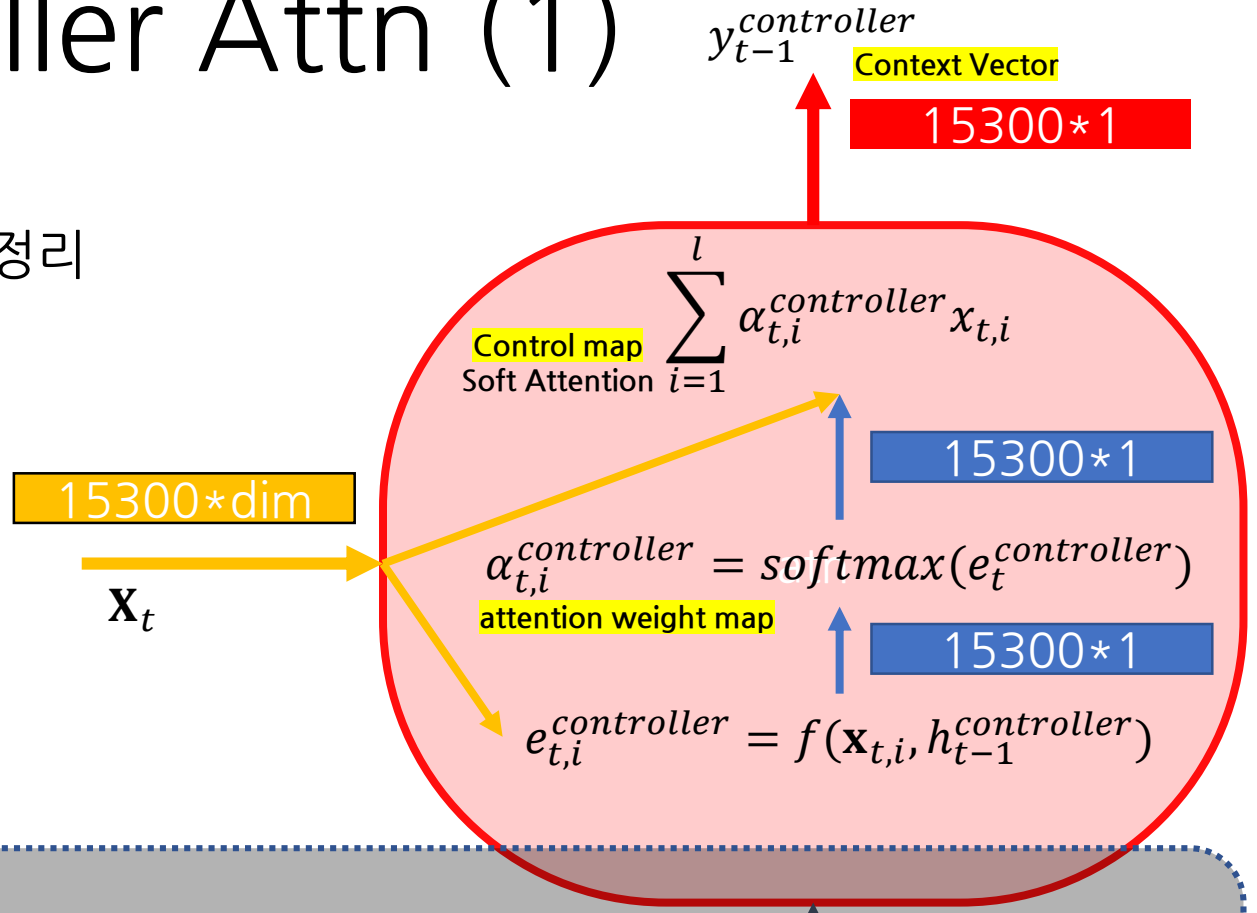
Understanding Controller Attn (1)

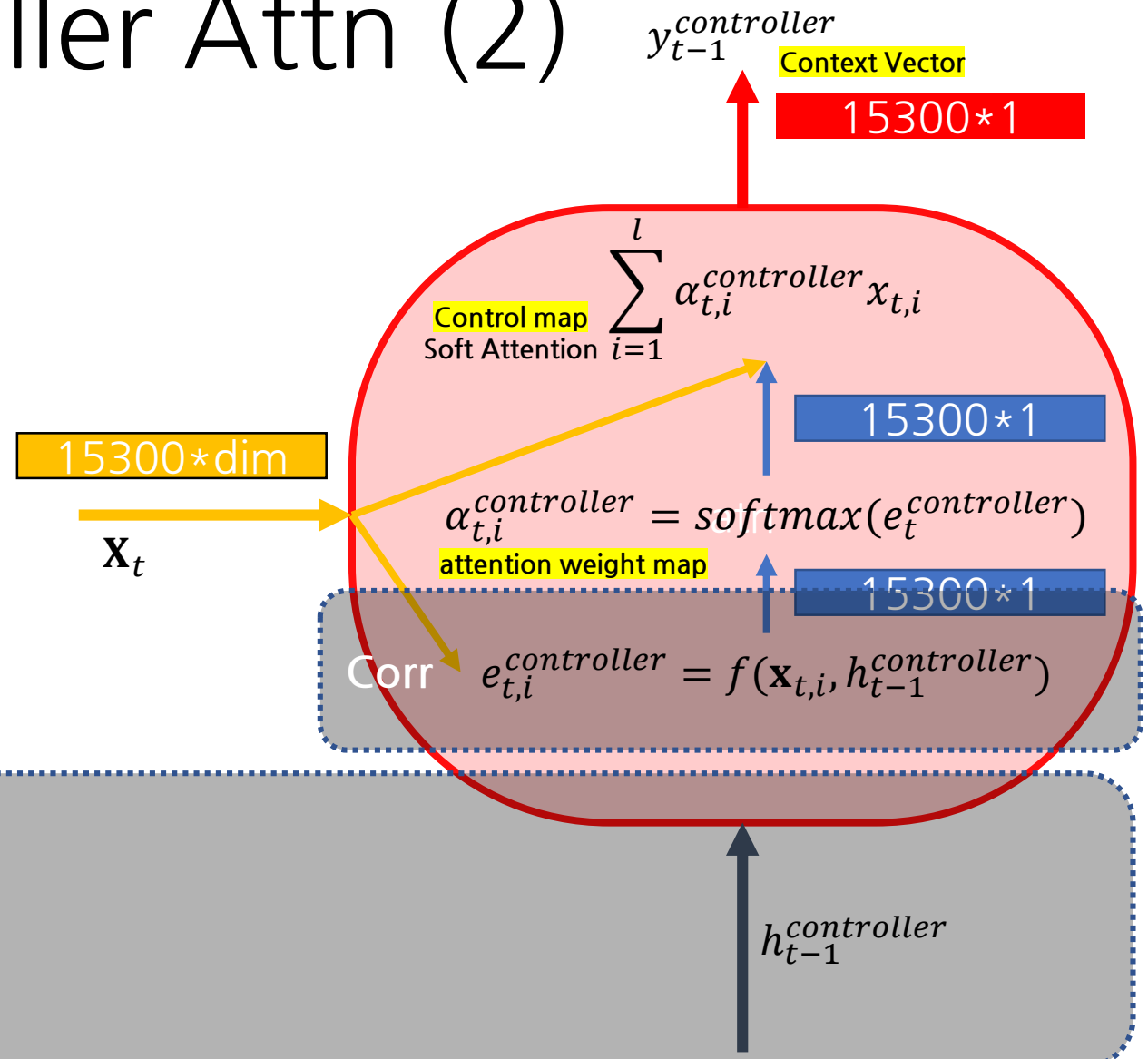
나같이 Spatial Attention 을 처음 접해서

직관적 이해가 안 되는 사람을 돕기 위해 한 번만 다시 정리



이전 attention 의 context 와
이전 상태에 대한 정보를 받음.

Understanding Controller Attn (2)



방금 받은 정보와, 4개 frame 으로부터 조합한 image $\mathbf{x}_t$ 의 correlation 을 구함.

이전 attention 의 context 와
이전 상태에 대한 정보를 받음.

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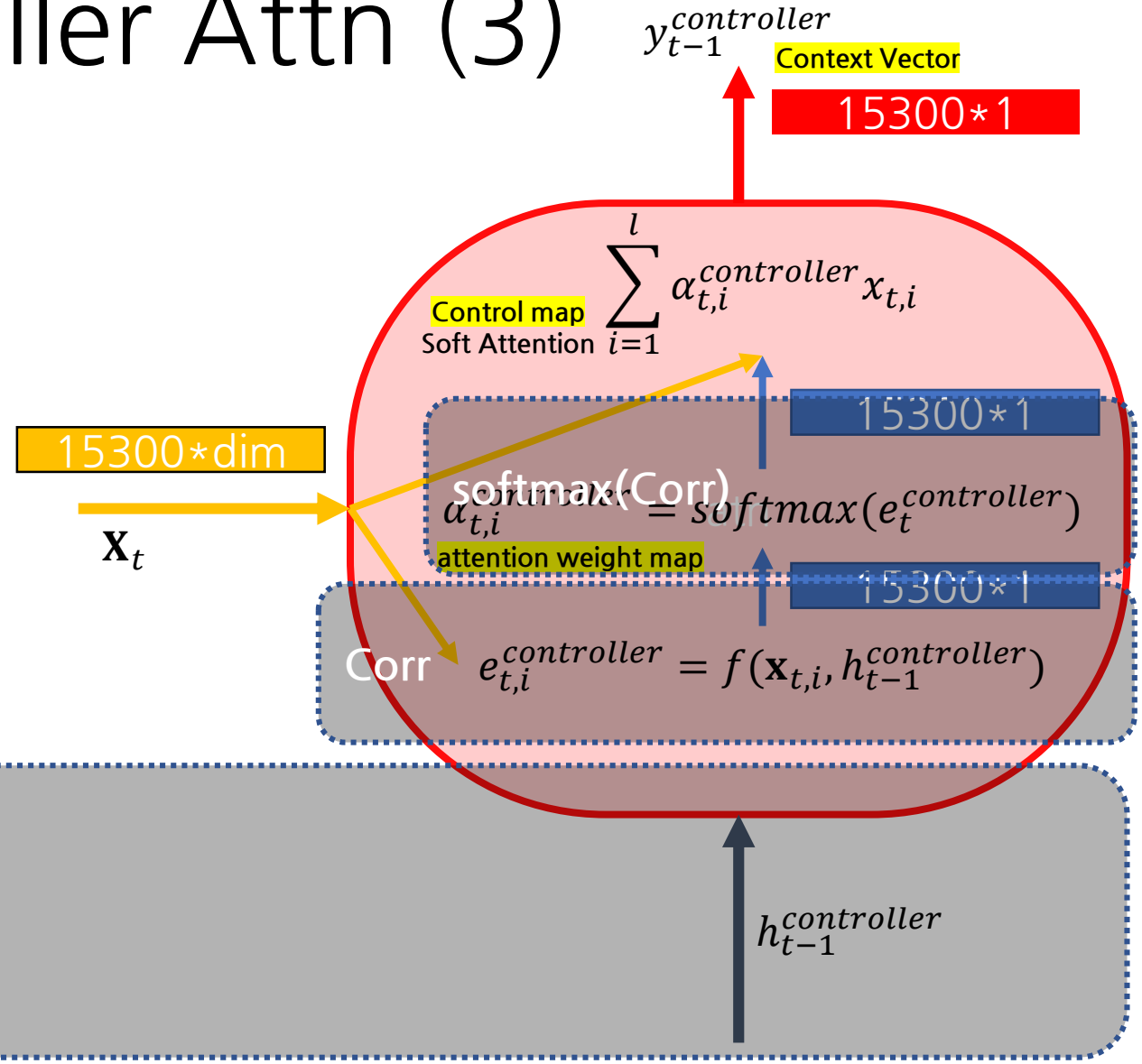
Understanding Controller Attn (3)



Attention Weight Map : 각 Correlation 값을 Softmax 에 넣음. 즉 상관 관계 값을, 이미지상에서 현재 집중할 위치와의 상관관계 확률 값으로 바꾸어 줌.

방금 받은 정보와, 4개 frame 으로부터 조합한 image $\mathbf{x}_t$ 의 correlation 을 구함.

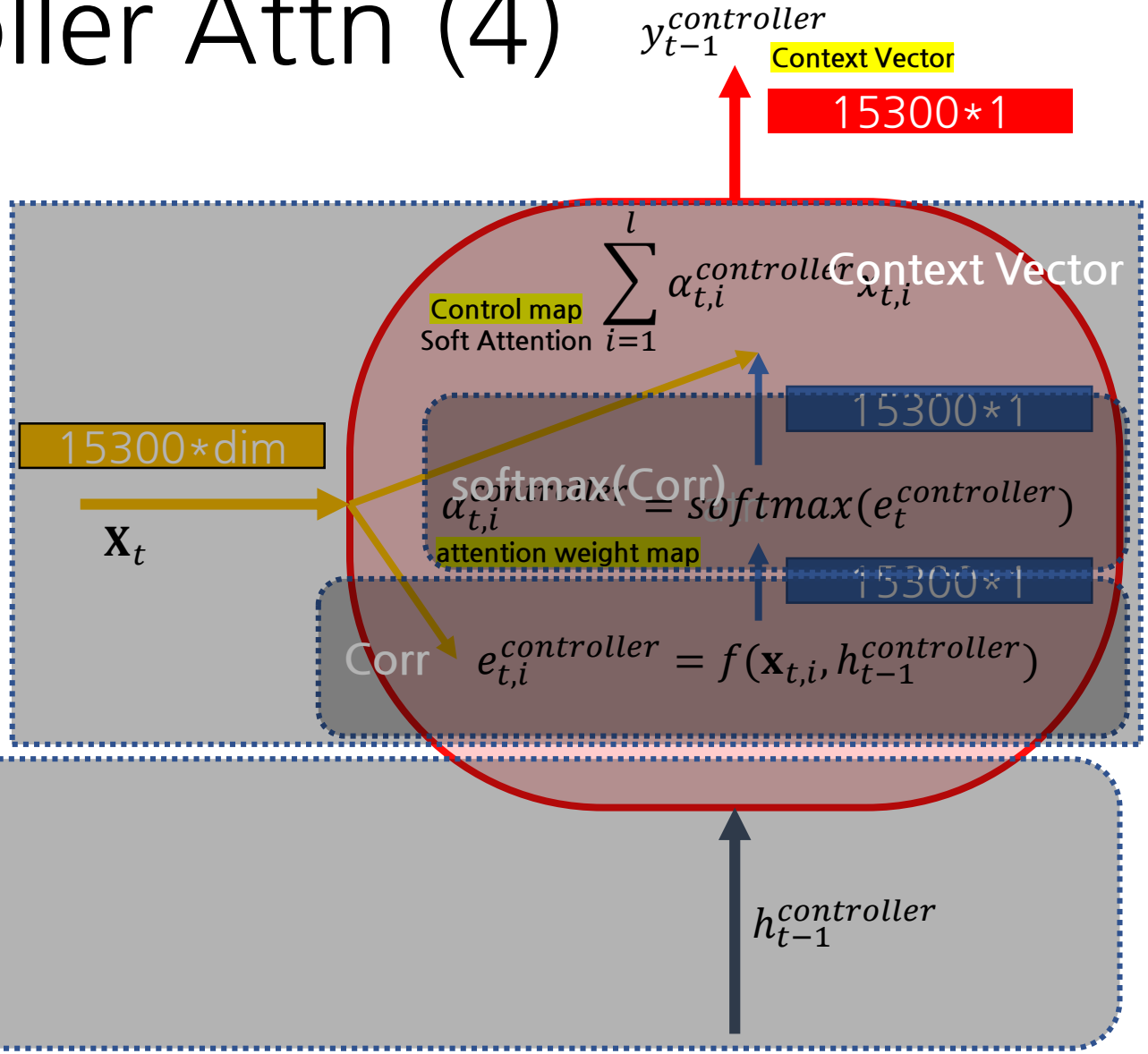
이전 attention 의 context 와
이전 상태에 대한 정보를 받음.

Understanding Controller Attn (4)

Context Vector : 방금 Attention Weight Map 을 실제 특징을 담은 공간적 cube $\mathbf{X}_t$ 에 가중치처럼 곱해서 공간적 특징에 중요도를 매겨서 다시 만든 피처값

Attention Weight Map : 각 Correlation 값을 Softmax 에 넣음. 즉 상관 관계 값을, 이미지상에서 현재 집중할 위치와의 상관관계 확률 값으로 바꾸어 줌.

방금 받은 정보와, 4개 frame 으로부터 조합한 image $\mathbf{X}_t$ 의 correlation 을 구함.



이전 attention 의 context 와
이전 상태에 대한 정보를 받음.

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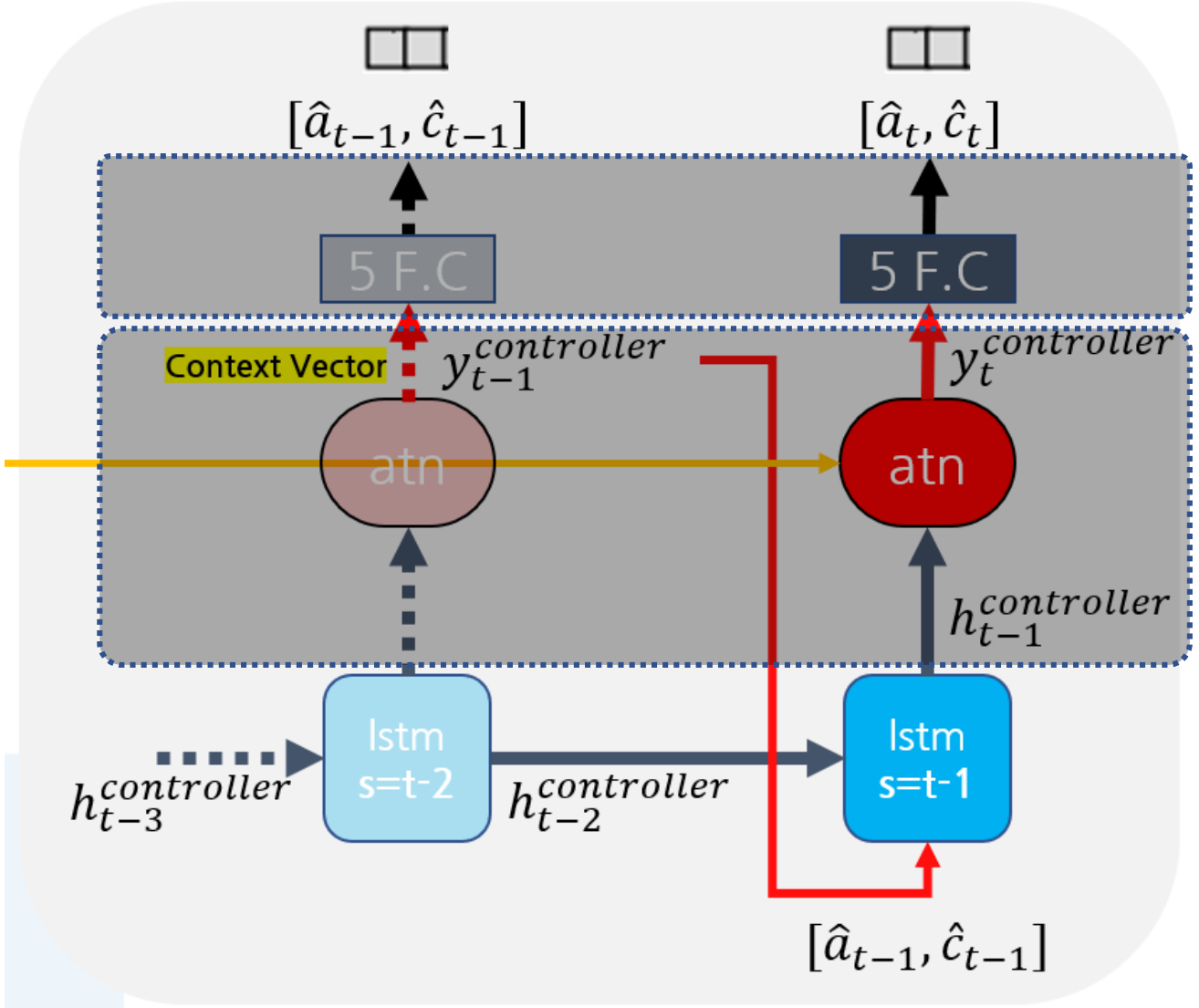
Understanding Controller Attn (5)

이를 FC Layer (논문에서는 5 개의 FC Layer) 을 거치며 Context Vector 가 가속/감속, 차선 전환 값으로 변환

Context Vector : 방금 Attention Weight Map 을 실제 특징을 담은 공간적 cube $\mathbf{x}_t$ 에 가중치처럼 곱해서 공간적 특징에 중요도를 매겨서 다시 만든 피처값



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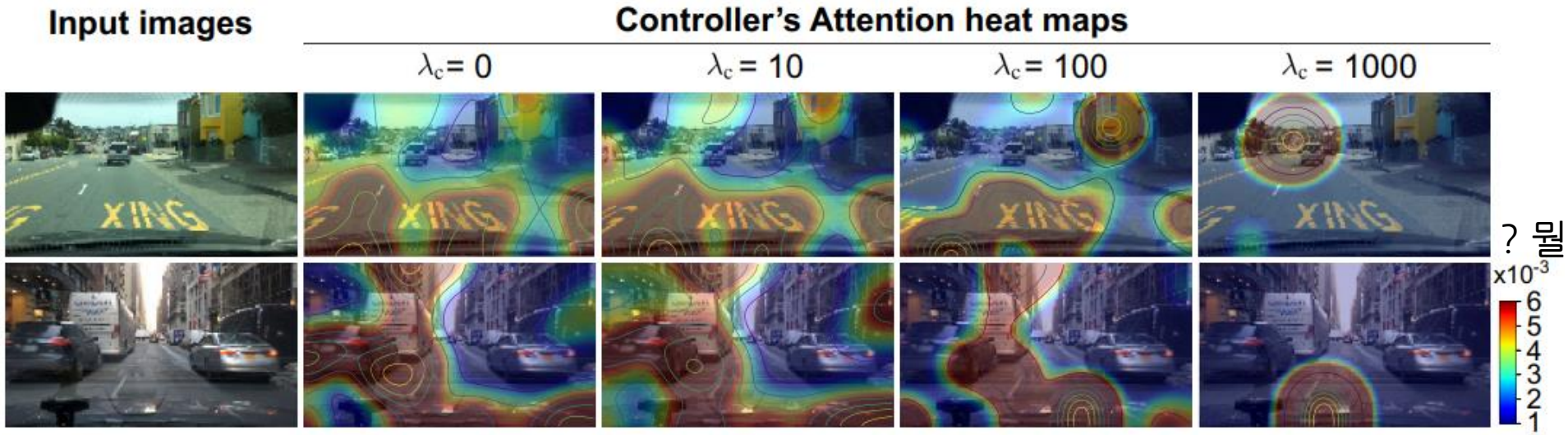
Controller Loss

가속/감속 차선전환 정보량이 많으면 패널티 (entropy)

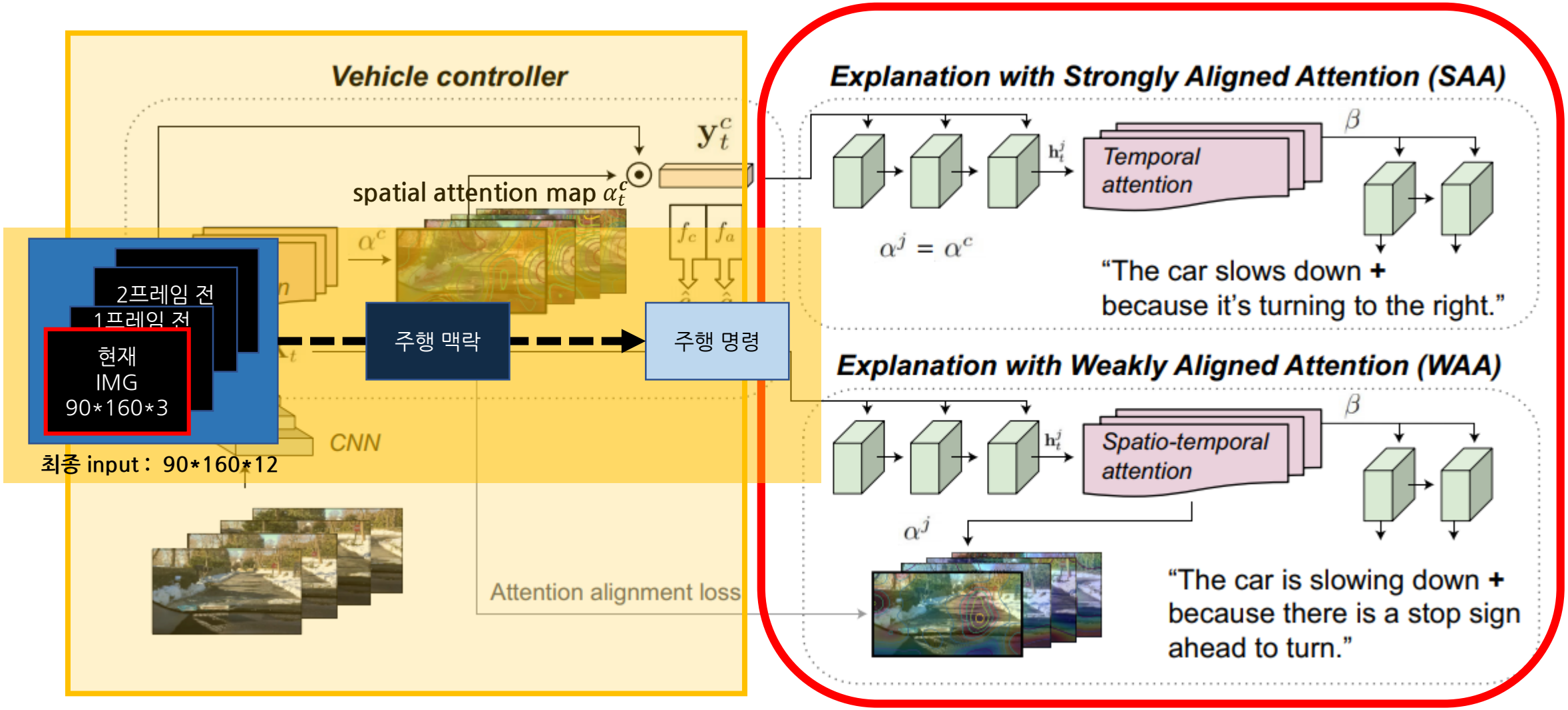
$$\mathcal{L}_c = \sum_t \left((a_t - \hat{a}_t)^2 + (c_t - \hat{c}_t)^2 + \lambda_c H(\alpha_t^c) \right) \quad (2)$$

The entropy is computed on the attention map as though it were a probability distribution. Minimizing loss corresponds to minimizing entropy. Low entropy attention maps are sparse and emphasize relatively few regions. We use a hyperparameter λ_c to control the strength of the entropy regularization term.



? 뭘 보고있누?

Model Overview



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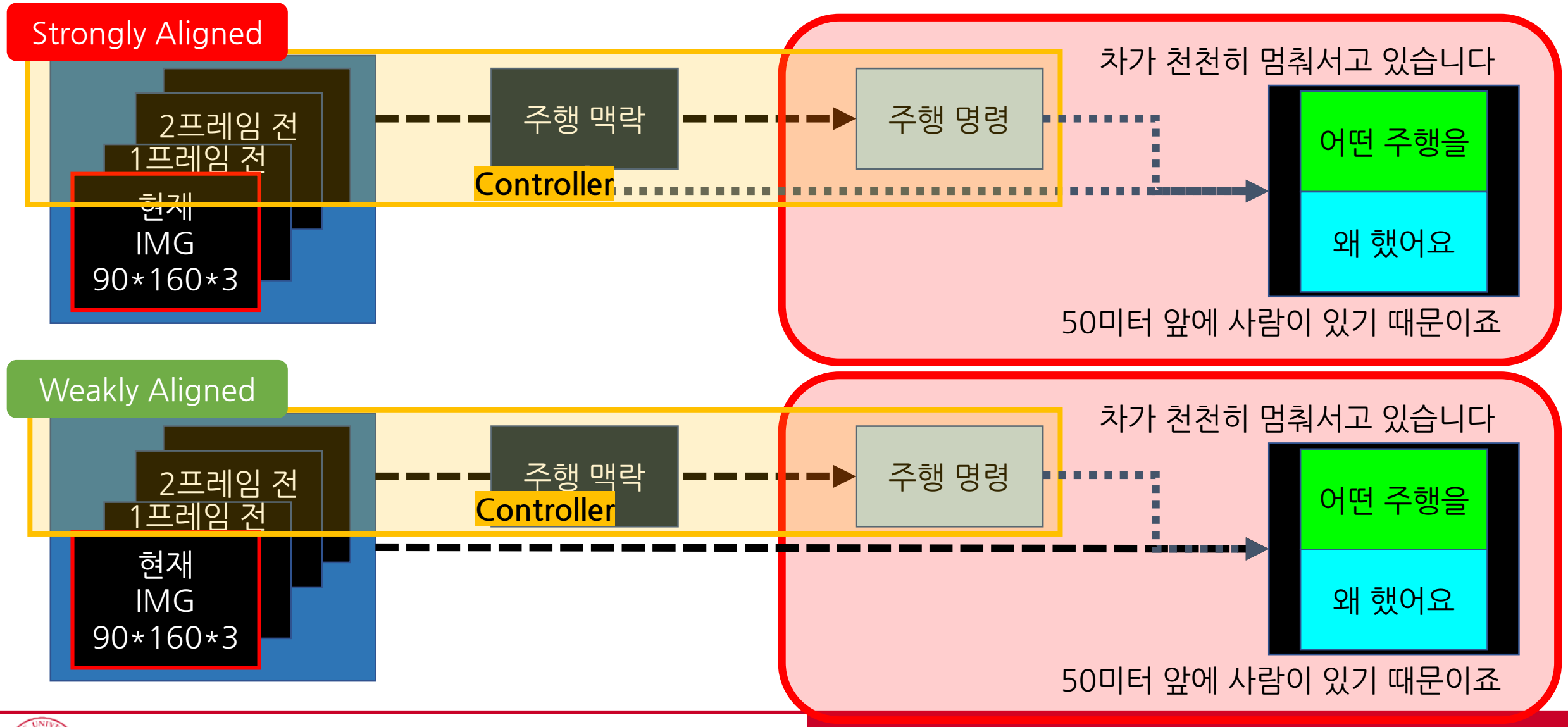
Attention Alignment



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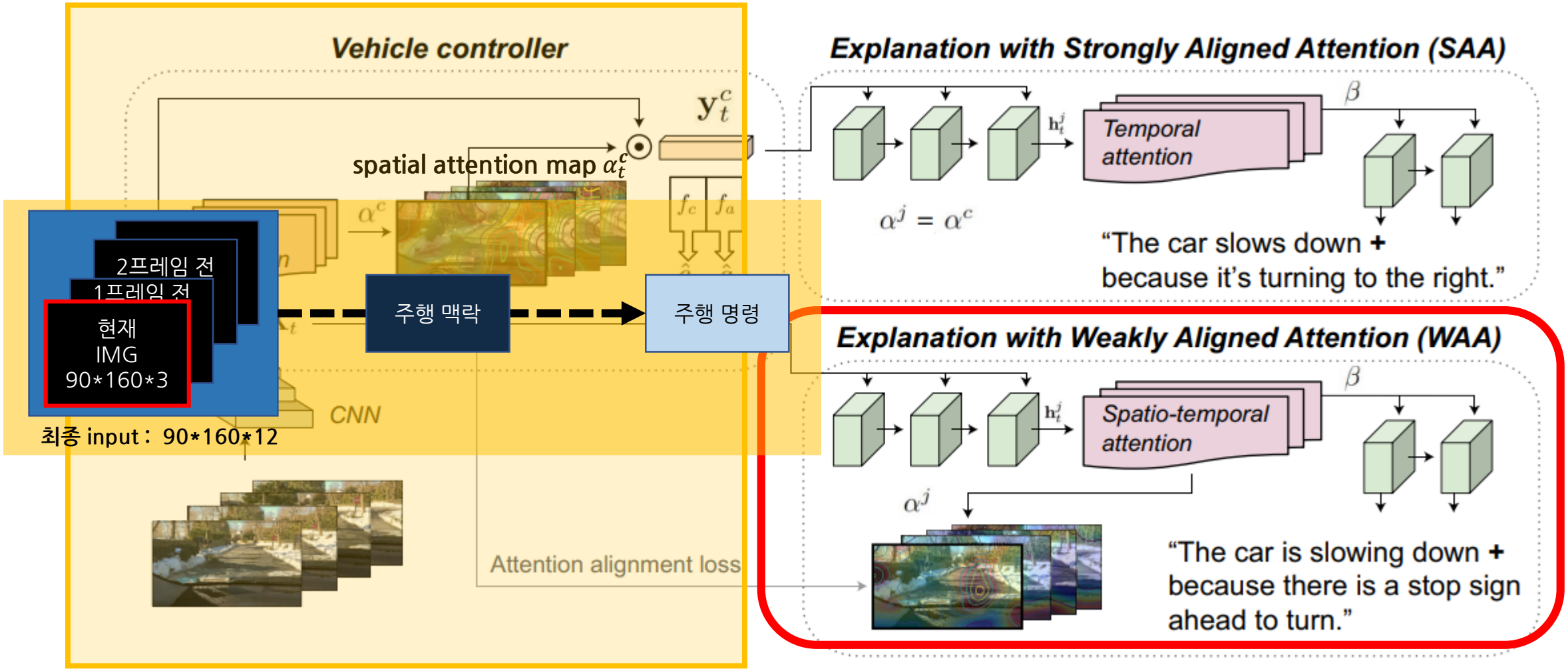
Model Overview



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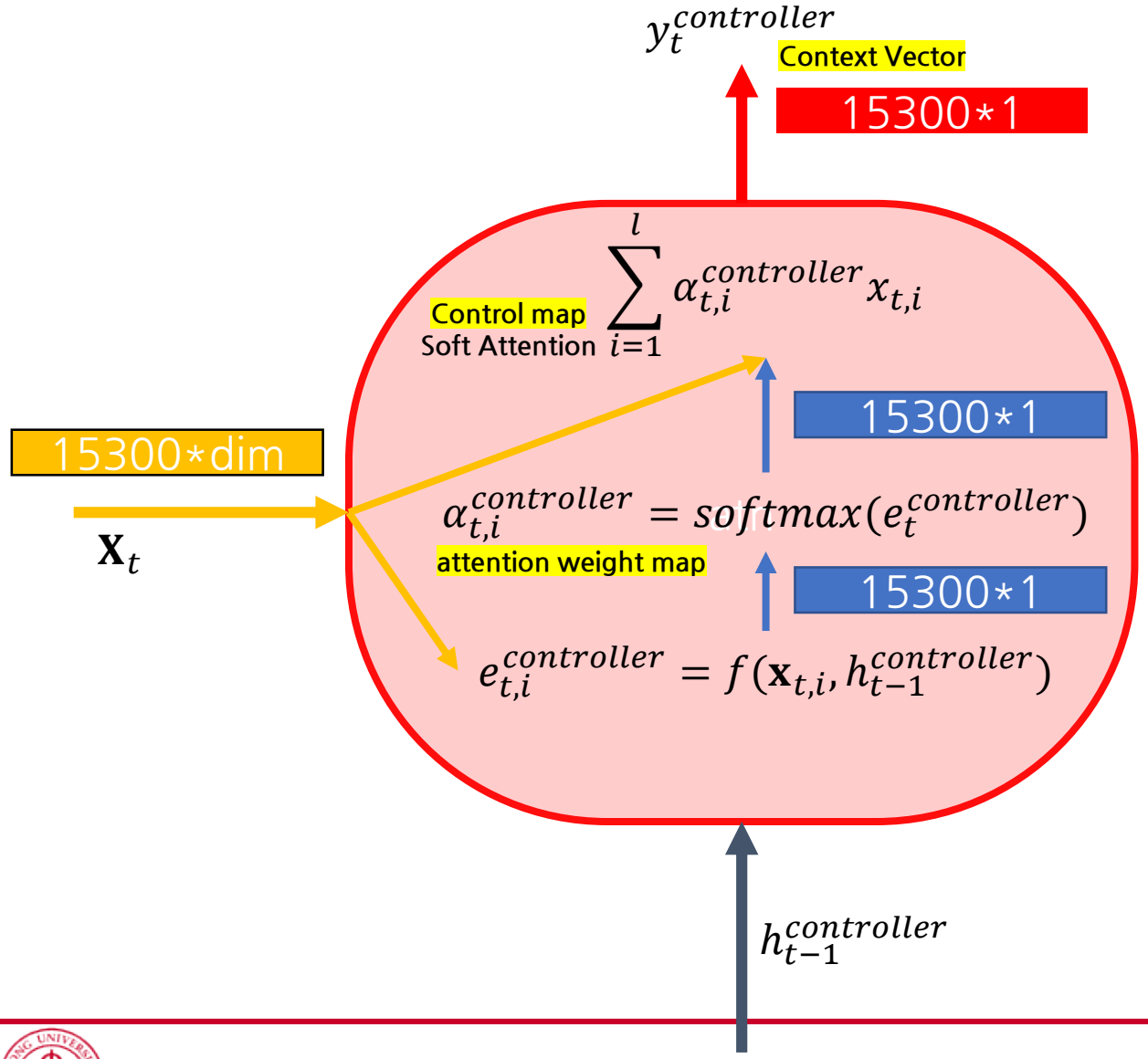
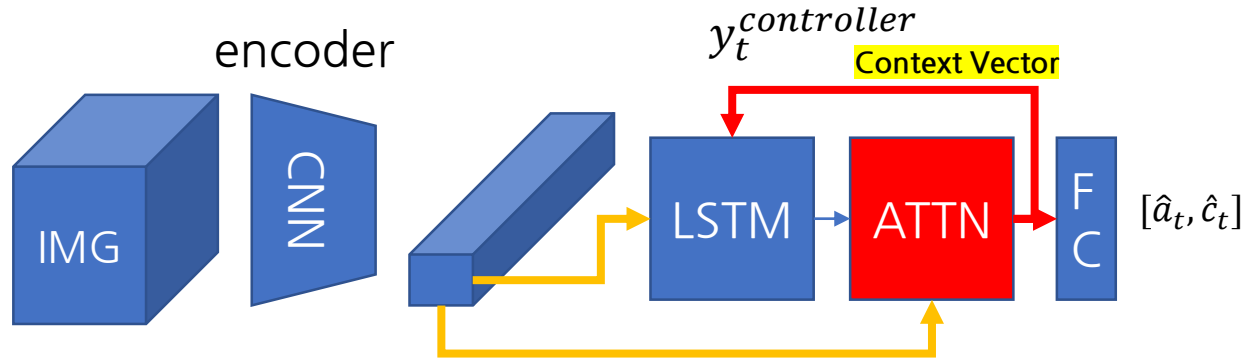
Controller





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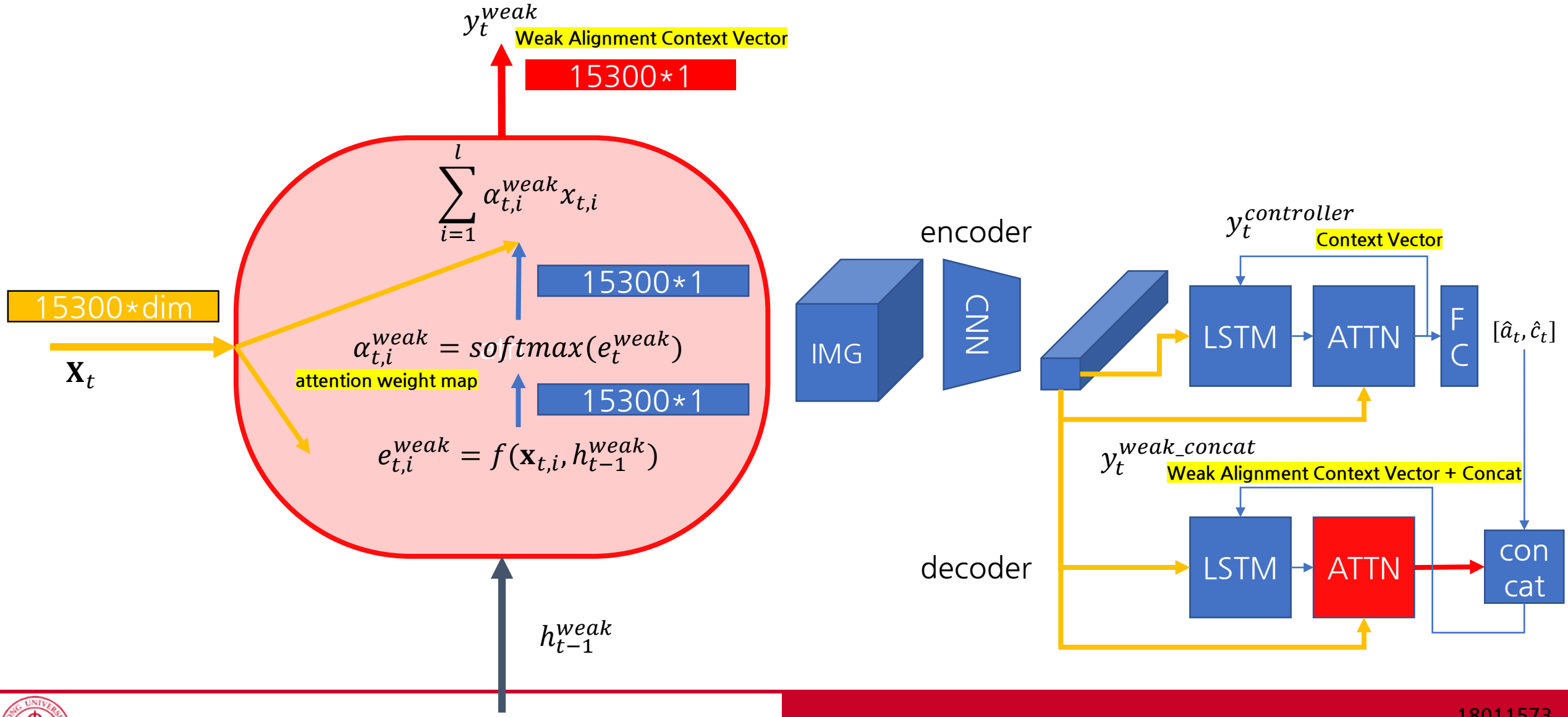
Weakly Aligned Attention Explanation



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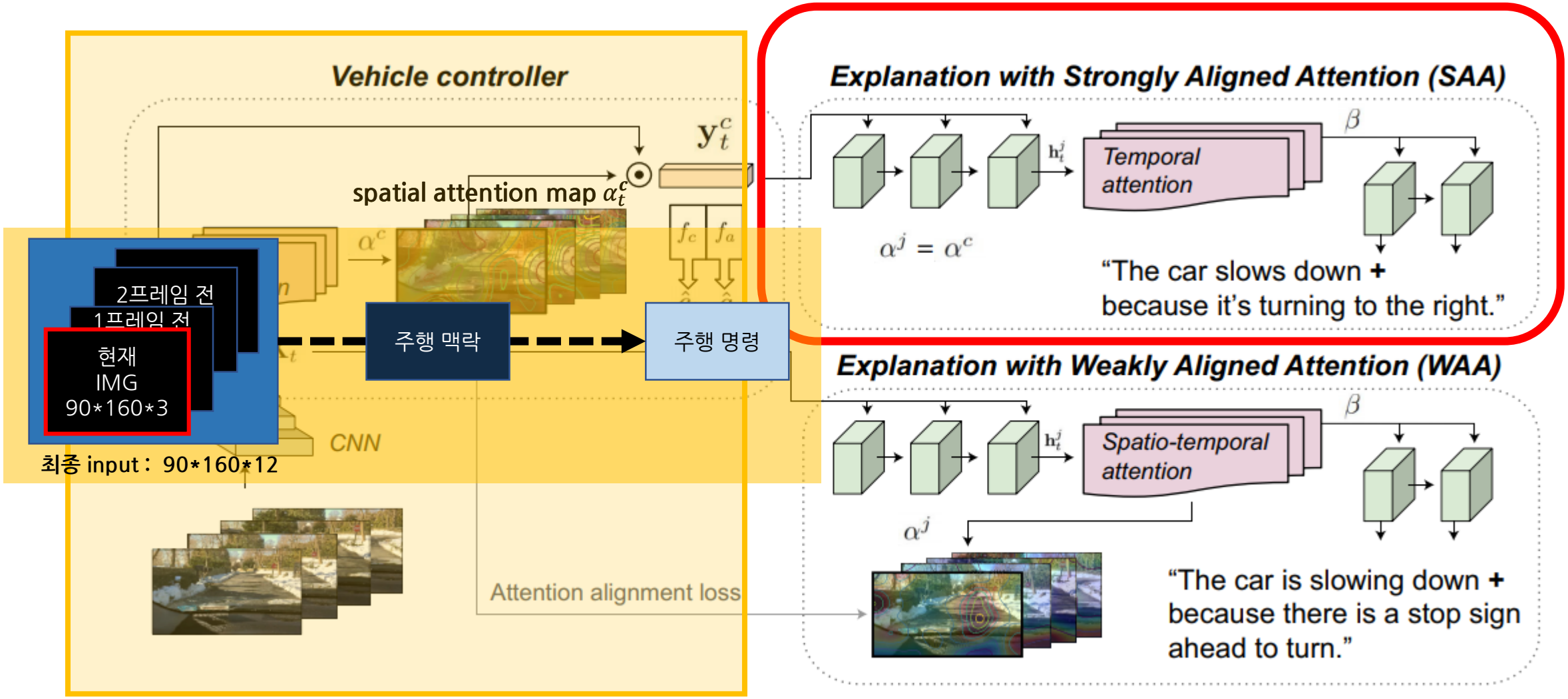
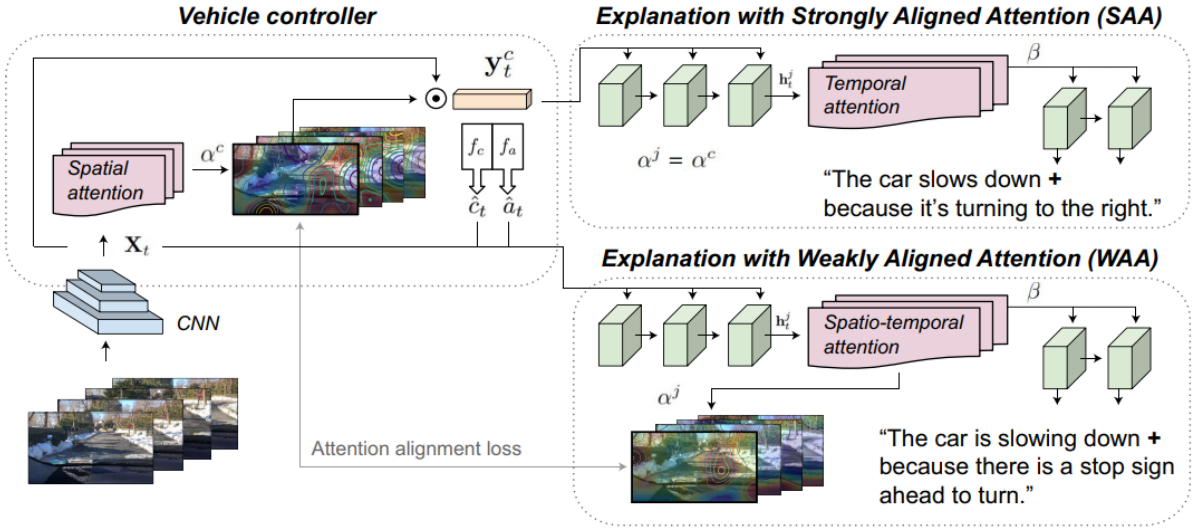
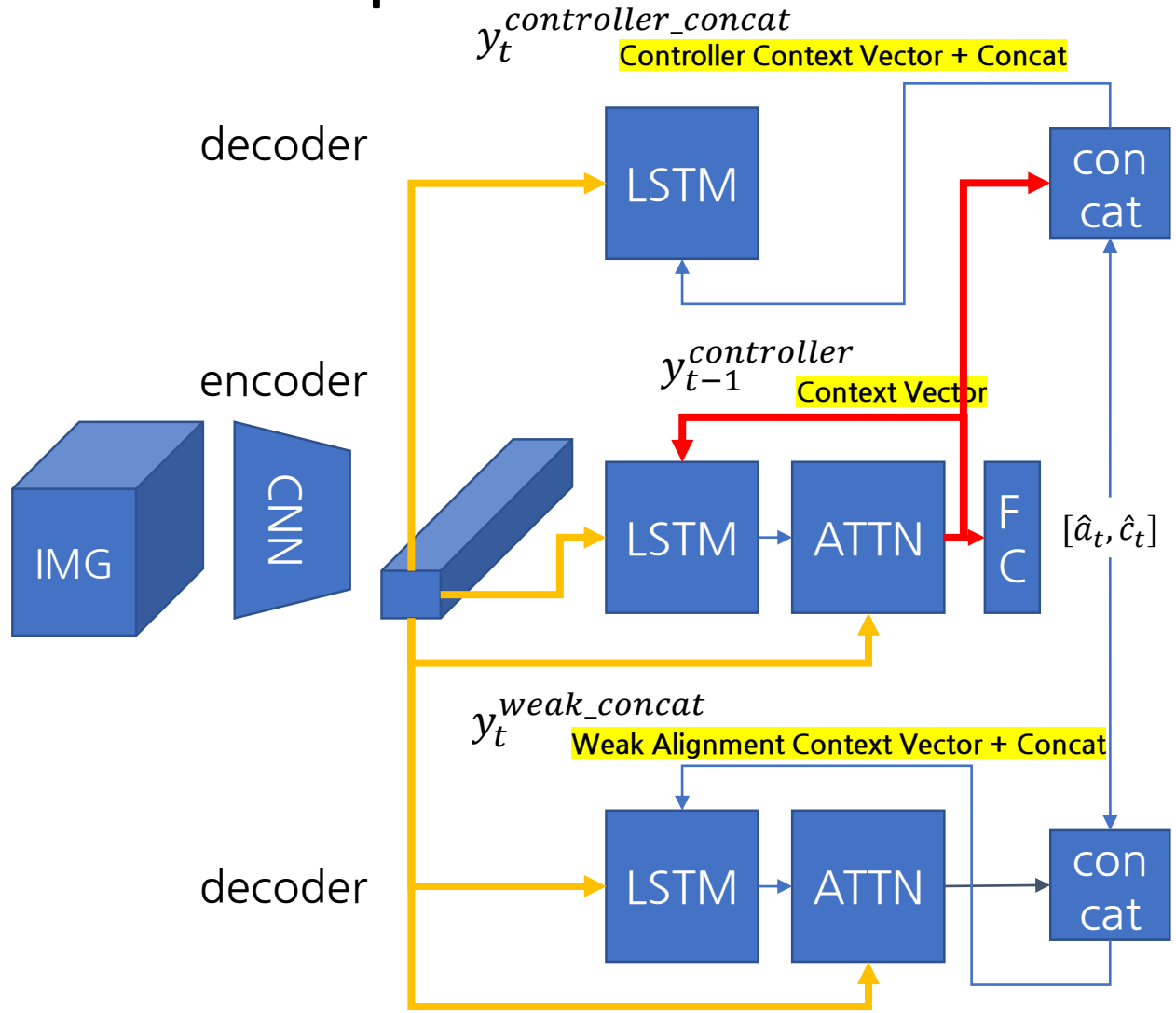
Model Overview



Strongly Aligned Attention Explanation





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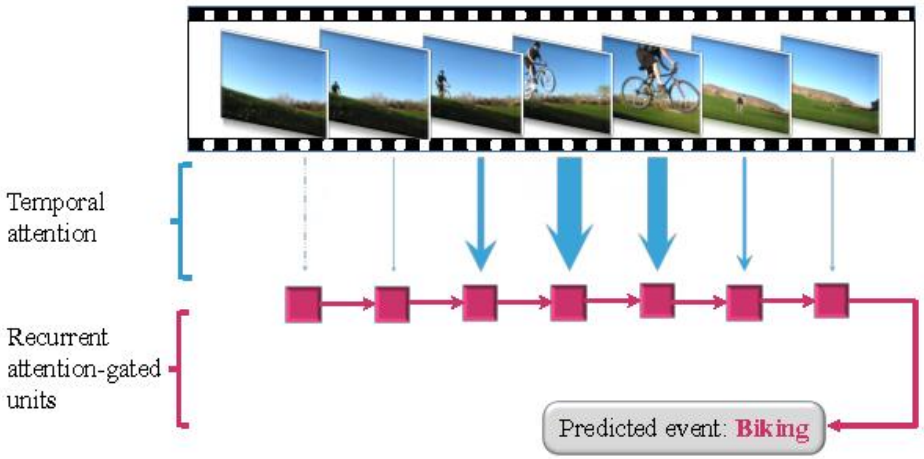
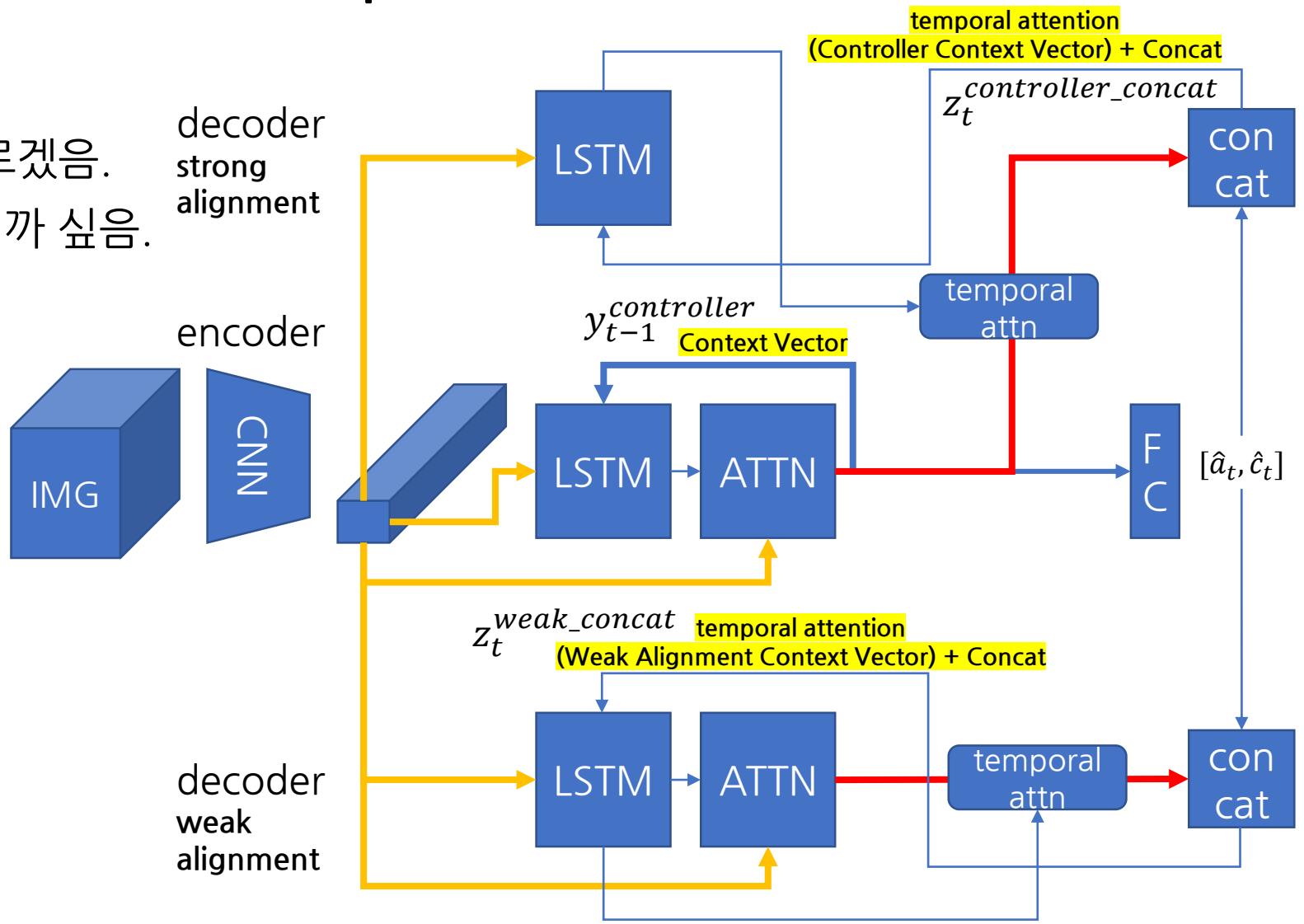
Aligned Attention + Temporal Attention

Temporal Attention

- 이쯤 되니 어떻게 동작하는지는 잘 모르겠음.
- 그냥 일반적인 기계번역 어텐션이 아닐까 싶음.





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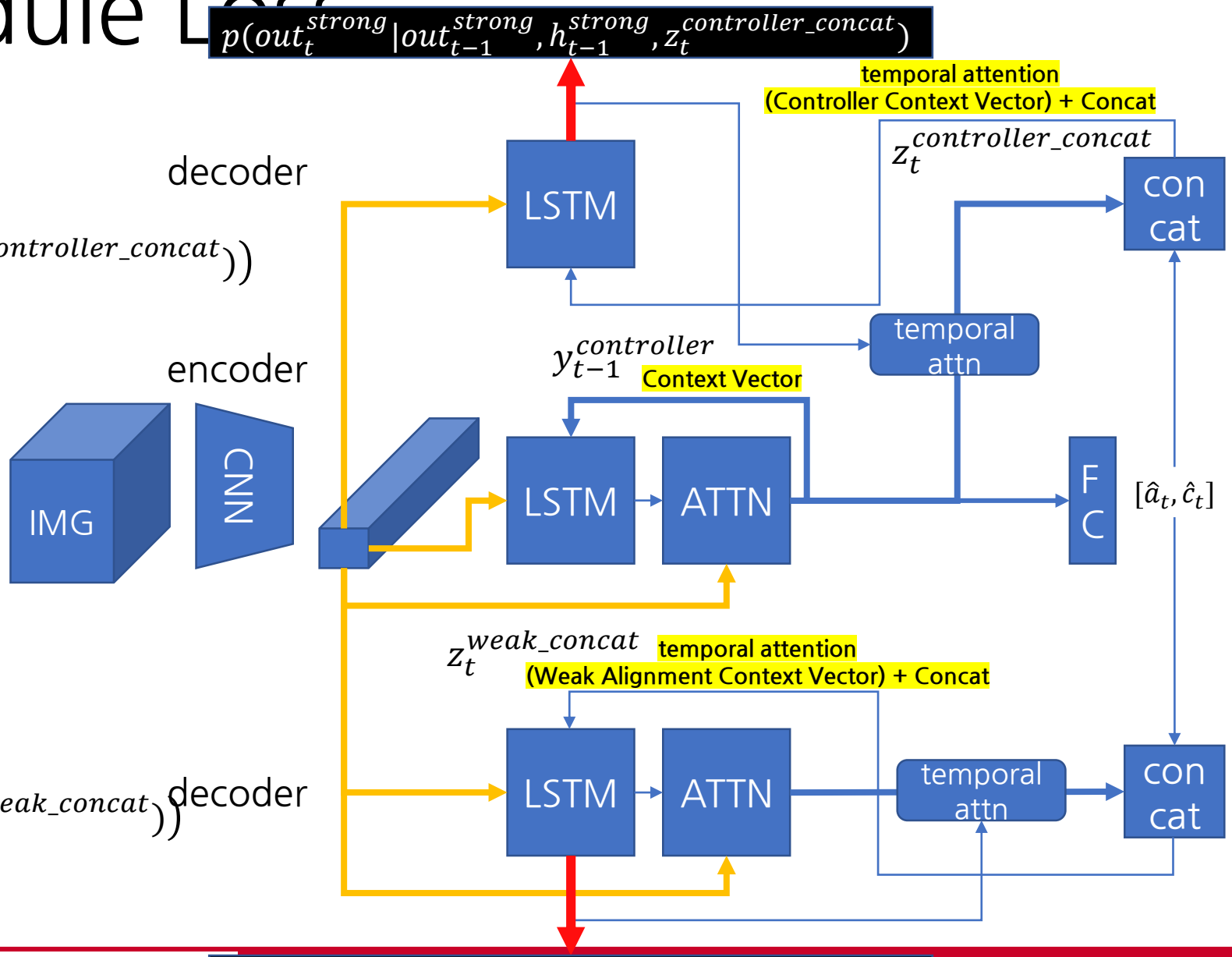
Explanation Module Loss

$$L_{weak\_explanation} = \sum_t log\left(p(out_t^{strong} | out_t^{strong}, h_{t-1}^{strong}, z_t^{controller\_concat})\right)$$

$$L_{strong\_explanation} = \sum_t log\left(p(out_t^{weak} | out_{t-1}^{weak}, h_{t-1}^{weak}, z_t^{weak\_concat})\right)$$



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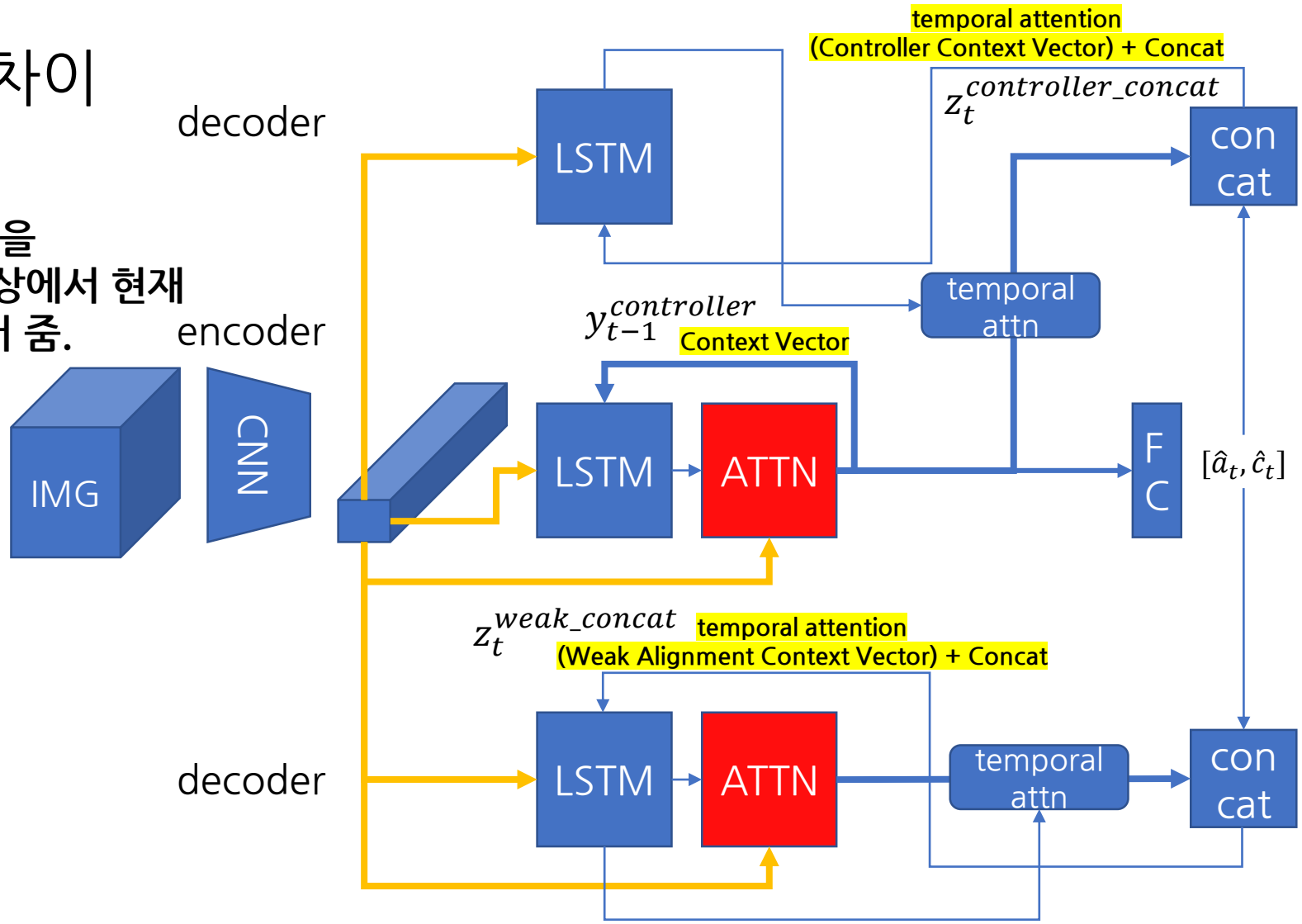
Attention Model Loss

- 두 attention map 사이의 차이
- $\alpha_t^{controller} || \alpha_t^{weak}$

Attention Weight Map : 각 Correlation 값을 Softmax 에 넣음. 즉 상관 관계 값을, 이미지상에서 현재 집중할 위치와의 상관관계 확률 값으로 바꾸어 줌.

$$L_{attn} = \lambda_{attn} \sum_t D_{KL}\left(\alpha_t^{controller} || \alpha_t^{weak}\right)$$



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Total Loss

$$\mathcal{L}_c = \sum_t \left((a_t - \hat{a}_t)^2 + (c_t - \hat{c}_t)^2 + \lambda_c H(\alpha_t^c) \right) \quad (2)$$

여기서 c 는 controller

$$L_{weak\_explanation} = \sum_t log\left(p(out_t^{strong} | out_t^{strong}, h_{t-1}^{strong}, z_t^{controller\_concat})\right)$$

$$L_{strong\_explanation} = \sum_t log\left(p(out_t^{weak} | out_{t-1}^{weak}, h_{t-1}^{weak}, z_t^{weak\_concat})\right)$$

$$L_{attn} = \lambda_{attn} \sum_t D_{KL}\left(\alpha_t^{controller} || \alpha_t^{weak}\right)$$

$$L = L_{controller} + L_{attn} + L_{weak\_explanation} + L_{strong\_explanation}$$

이게 도대체 왜되는걸까.

About Dataset : BDD-X

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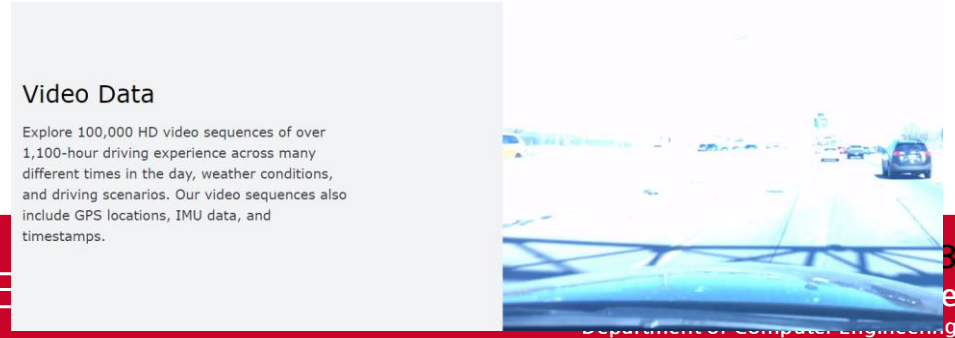
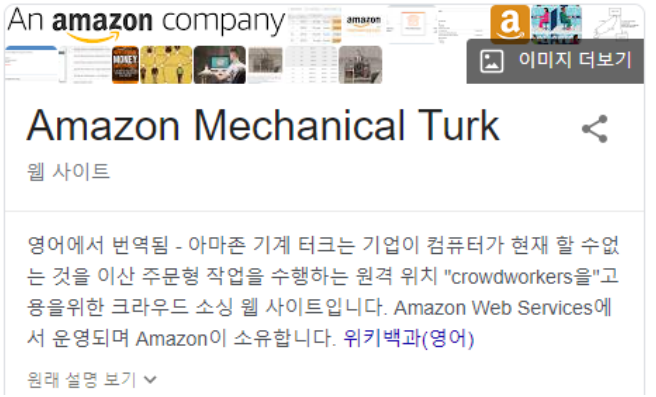
Dataset : BBD-X?

- 논문의 네 번째 단락은 BBD-X : Berkeley DeepDrive eXplanation 이야기.
- 전부 만든 것은 아니고 이미 Berkeley DeepDrive 데이터셋은 존재했음.
  - 차량에 장착된 카메라로 촬영된 영상의 집합
  - 40초정도 길이
  - 도시에서 촬영된 영상들로 구성
  - 다양한 기후에서 녹화됨, 낮과 밤에 모두 녹화됨.
  - lane marking 이 없는 도로에서도 녹화됨.
- 이 논문에서 textual explanation model 을 학습시키기 위해 Berkeley DeepDrive 데이터셋 영상에, 주행영상에 대한 설명을 추가한 것.
- 이걸 BBD-X 라고 이름붙인듯.

https://bdd-data.berkeley.edu/



Dataset : Annotation



- 라벨링 크라우드소싱을 함. *와 뭐 저런게 다있냐*
- 믿을만한 라벨링 결과를 얻기 위해, 다양한 노력을 함
  - 미국 도로에 익숙한 사람들만 선발함.
  - 한번 시험을 봐서 양질의 라벨링 인력을 뽑았음. (“qualified workers”, pass a test)
  - annotation 하는 방법을 미리 강의함.
- 라벨링한 것들은 다음과 같음
  - description : “운전자 입장에서” 운전자가 무엇을 하는지
  - justification (explanation) : “운전자 입장에서” 운전자가 왜 그러한 동작을 하는지
  - time stamp : 이러한 동작들의 시작점, 끝점.
  - 라벨링할 때 세심한 배려 : description 칸과 justification 칸이 따로 있어서, 안 헷갈리도록 함. 하지만 데이터를 실제로 모델에 활용할 때는 두 칸에 입력이 들어온 내용을 합쳐서 하나의 문장으로 학습시킴.

Dataset : Statics

- 데이터 특성
  - 40초짜리 영상에서 동작 3개정도를 입력함.
  - 데이터셋의 총 description/justification (explanation) 2600개
  - description/justification (explanation) 포함되는 동영상 프레임 8.4Million 개

- 당연하게도, 흔한 단어들과 흔한 추론들이 자주 등장하는 경향.
  - description : “앞으로 가고있음.” “멈춰있음.” “가속 중임” …
  - justification (explanation) : “신호등이 ~~해서..” “차가 ~~해서..” “횡단보도 ~~”

Dataset : Inter-Human Agreement

- 데이터 수집과정에서 특히 재밌는 부분
  - 사람들끼리 데이터셋 일부를 두고 교차검증을 함 (inter-human agreement)
  - 총 6948 개의 영상 중, 998 개의 영상에 대해서 2명이 라벨링하고 비교함.
    - 전체 영상에 대해서 두 번씩 시킬 수는 없으니까.

- 수집한 데이터 타당성 평가
  - 라벨링된 부분의 개수는 비슷한가?
  - 라벨링된 부분은 시간적으로 얼마나 겹치는가? (temporal IoU)
  - 이미지 설명이 얼마나 합당한지를 보는 정량적 지표에 따른 점수는 충분히 높은가? (CIDEr Socre)

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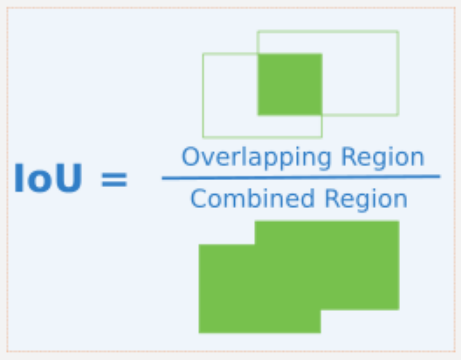
Dataset : Inter-Human Agreement - Result

- 라벨링된 부분의 개수는 비슷한가?
  - 총 998 개의 영상 중 72% 의 영상은 두 명의 라벨링 개수 차이가 3개 이내였다.
  - 예를 들어 48초짜리 영상에서 A는 4개, B는 1개 라벨을 달았다면 차이는 3개.



- 라벨링된 부분은 시간적으로 얼마나 겹치는가? (temporal IoU)
  - 하나의 영상을 평가한 두 명은 평균적으로 63% 동일한 구간에 라벨링했다.
  - 예를 들어 A가 1초~3초 에 라벨링, B가 1초~2초에 라벨링하면 IoU 50%

- 이미지 설명이 얼마나 합당한지를 보는 정량적 지표에 따른 점수는 충분히 높은가? (CIDEr Socre)
  - 이게 어떻게 돌아가는 것인지는 모르겠음.

www.cv-foundation.org › papers ▾ PDF 이 페이지 번역하기

CIDEr: Consensus-Based Image Description Evaluation - The ...

We propose a new automatic consensus metric of image description quality – **CIDEr** (Consensus-based Image De- scription Evaluation). Our metric measures the similarity of a generated sentence against a set of ground truth sentences written by humans. Our metric shows high agreement with consensus as assessed by humans.

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Results & Evaluation

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Training Details (1)

encoder

- CNN 5 layer
- CNN 을 거치며 추출된 Feature cube 의 shape 는 12x20x64

controller

- FC 5 layer

training

- 우선 vehicle controller 을 training 시킴.
- 그리고 controller 을 얼리고 explanation generator 을 학습시킴.

Training Details (2)

- Adam, dropout 0.5, Xavier init.
- 8:1:1 dataset split
- Titan X 로 1일 이내 학습.

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Evaluation Details - Controller

- Controller 평가
  - 이 논문에서 제안하는 Controller 의 경우, 브레이크와 엑셀에 연속적인 변화가 존재하는 output 임. 이미지마다 독립적인 output 을 가지는 방식보다, 논문에서 제안한 네트워크가, “시간적인 정보들을 기억” 하고 있기 때문에 (사람도 그러긴 하니까.) 특히 도시환경에서 더 정확할 수 있다고 주장함.
  - 독립적인 output 만을 사용하는 다른 컨트롤러와 차이가 있어서 유의미한 평가를 하기 위해 독립적 output 을 가지는 controller 모델을 올렸음. 단, CNN 은 동일한 것을 사용함.
    - 그런데, CNN 도 이 논문에서 제안한 controller 에 맞게 from scratch 로 학습됐는데 CNN 이 동일해도 되나 싶음.

Model	λ_c	Mean of absolute error (MAE)		Mean of distance correlation	
		Acceleration (m/s^2)	Course (degree)	Acceleration (m/s^2)	Course (degree)
CNN+FC [3]†	-	6.92 [7.50]	12.1 [19.7]	0.17 [0.15]	0.16 [0.14]
CNN+FC [3]+P	-	6.09 [7.73]	6.74 [14.9]	0.21 [0.18]	0.39 [0.33]
CNN+LSTM+Attention [11]†	-	6.87 [7.44]	10.2 [18.4]	0.19 [0.16]	0.22 [0.18]
CNN+LSTM+Attention+P (Ours)	1000	5.02 [6.32]	6.94 [15.4]	0.65 [0.25]	0.43 [0.33]
CNN+LSTM+Attention+P (Ours)	100	2.68 [3.73]	6.17 [14.7]	0.78 [0.28]	0.43 [0.34]
CNN+LSTM+Attention+P (Ours)	10	2.33 [3.38]	6.10 [14.7]	0.81 [0.27]	0.46 [0.35]
CNN+LSTM+Attention+P (Ours)	0	**2.29 [3.33]**	**6.06 [14.7]**	**0.82 [0.26]**	**0.47 [0.35]**

Evaluation Details - Explanation (1)

- description/justification (explanation) 평가 지표로는
  - METEOR
  - CIDEr-D
  - BLEU

- 객관적인 비교를 위해 SOTA S2V2 를 논문의 5 Layer CNN 을 활용하여 구현하고, 논문에서 제안하는 모델들을 비교.

Evaluation Details - Explanation (1)

- S2VT 모델보다 Attention 이 결합된 Alignment 모델이 현재 우리가 하고자 하는 task 에서 더 좋은 모습을 보인다.

Type	Model	Control inputs	λ_a	λ_c	Explanations (*e.g., "because the light is red"*)			Descriptions (*e.g., "the car stops"*)		
					BLEU-4	METEOR	CIDEr-D	BLEU-4	METEOR	CIDEr-D
	S2VT [25]	N	-	-	6.332	11.19	53.35	30.21	27.53	179.8
	S2VT [25]+SA	N	-	-	5.668	10.96	51.37	28.94	26.91	171.3
	S2VT [25]+SA+TA	N	-	-	5.847	10.91	52.74	27.11	26.41	157.0
Rationalization	Ours (no constraints)	Y	0	0	6.515	12.04	61.99	31.01	28.64	205.0
Introspective explanation	Ours (with SAA)	Y	-	0	6.998	12.08	62.24	**32.44**	29.13	213.6
	Ours (with SAA)	Y	-	10	6.760	12.23	63.36	29.99	28.26	203.6
	Ours (with SAA)	Y	-	100	7.074	12.23	66.09	31.84	29.11	214.8
	Ours (with WAA)	Y	10	0	6.967	12.14	64.19	32.24	29.00	**219.7**
	Ours (with WAA)	Y	10	10	6.951	**12.34**	68.56	30.40	28.57	206.6
	Ours (with WAA)	Y	10	100	**7.281**	12.24	**69.52**	32.34	**29.22**	215.8

Evaluation Details - Explanation (1)

- 250개를 무작위로 뽑아서 사람이 직접 네트워크의 output 을 평가
- 완벽, 맞음, 약간 오류, 치명적 오류 4지 선다.
- 성공 기준 : 적어도 2명 이상이 완벽, 맞음에 투표해야 True

Type	Model	Control inputs	λ_a	λ_c	Correctness rate	
					Explanations	Descriptions
Rationalization	Ours (no constraints)	Y	0	0	64.0%	92.8%
Introspective explanation	Ours (with SAA)	Y	-	100	62.4%	90.8%
	Ours (with WAA)	Y	10	100	**66.0%**	**93.5%**

Conclusion

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Conclusion

- Controller 로 먼저 학습시켜서 뽑은 CNN Feature, 게다가 attention 으로 인해 더욱 제한된 피처들만으로도 충분히 성공적으로 Explanation 을 만들어낼 수 있다.
  - 이 Feature 은, image 에서 유의미한 정보들을 사람이 제시한 것이 아니고, 단지 image 로부터 브레이크와 엑셀 결과를 뽑아내면서 자동적으로 학습한 제한된 (grounded) Feature 임. 이런 것으로부터
  - Attention 을 결합하면 더 좋은 성능을 낸다.
  - 논문에서 제안한 두 가지 attention 배열 모두 준수한 성능을 보여준다.

Suggestion

- Causal Filtering (?) 을 이용하면 detection 에서 더 좋은 성능을 낼 수 있지 않을까 하고 툭 던짐.
- 운전자의 시선과 협력하는 모델을 만들면 어텐션을 더 재밌게 만들 수 있지 않을까 하고 제안함.

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thank you!

- 스터디가 필요한 곳
  - Causal Filtering?
  - Temporal Attention?
  - CIDEr-D score?
  - Attention Back-Prop, How it works?
  - KL divergence / Cross Entropy Detail

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