Deep High-Resolution Representation Learning for Human Pose Estimation

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git code

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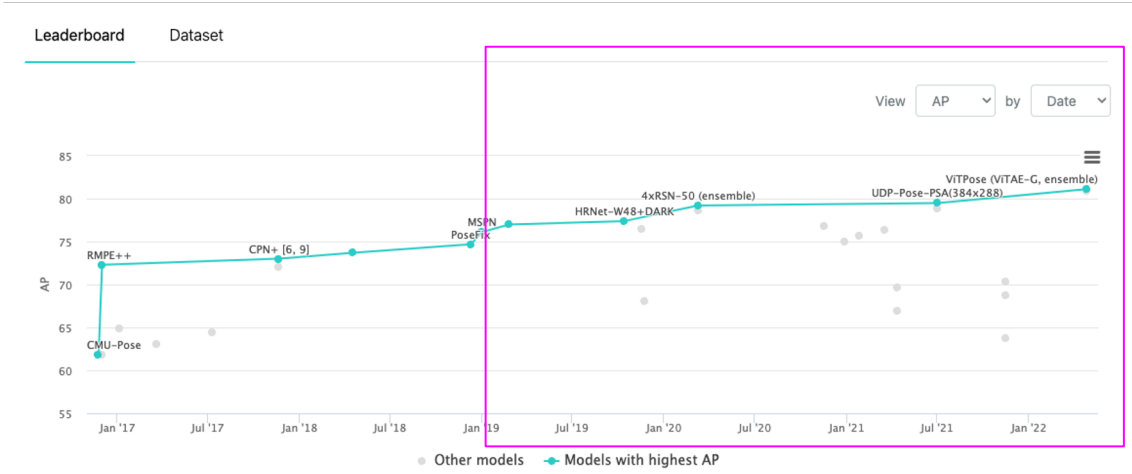
Leader Board : Pose Estimation on COCO test-dev

- 2019년부터 약 2년 간, HR-Net 모델이 SoTA 를 유지
- UDP-Pose-PSA
  - HR-Net 을 Backbone 으로, Polarized Self-attention (PSA) 적용
  - Input size 가 다른 경우 모두 , 기존의 vanilla HR-Net 보다 높은 성능
- DARK : Distribution-Aware coordinate Representation of Keypoint (DARK)
  - Model agnostic 접근. 최종 Heatmap 예측 시, Key-point localization 의 정확성 높이는 효과



Rank	Model	AP ↑	AP50	AP75	APL	APM	AR	Paper	Code	Result	Year
1	**ViTPose** (ViTAE-G, ensemble)	81.1	95.0	88.2	86.0	77.8	85.6	ViTPose: Simple Vision Transformer Baselines for Human Pose Estimation			2022
2	**ViTPose** (ViTAE-G)	80.9	94.8	88.1	85.9	77.5	85.4	ViTPose: Simple Vision Transformer Baselines for Human Pose Estimation			2022
3	**UDP-Pose-PSA** (384x288)	79.5	93.6	85.9	84.3	76.3	81.9	Polarized Self-Attention: Towards High-quality Pixel-wise Regression			2021
4	**4xRSN-50** (ensemble)	79.2	94.4	87.1	76.1	83.8	84.1	Learning Delicate Local Representations for Multi-Person Pose Estimation			2020
5	**UDP-Pose-PSA** (256x192)	78.9	93.6	85.8	83.6	76.1	81.4	Polarized Self-Attention: Towards High-quality Pixel-wise Regression			2021
6	**4xRSN-50**	78.6	94.3	86.6	75.5	83.3	83.8	Learning Delicate Local Representations for Multi-Person Pose Estimation			2020
7	**HRNet-W48+DARK**	77.4	92.6	84.6	83.7	73.6	82.3	Distribution-Aware Coordinate Representation for Human Pose Estimation			2019
8	**HRNet-W48 + extra data**	77	92.7	84.5	83.1	73.4	82	Deep High-Resolution Representation Learning for Human Pose Estimation			2019

Content

- **Human Pose Estimation**
  - Pose Estimation
  - Human Pose Estimation Task
  - Brief History

- **HR-Net**
  - Motivation
  - Model Structure
  - Experiments

Human Pose Estimation

Human Pose Estimation; Pose Estimation

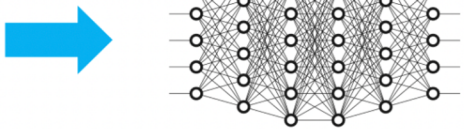
- **Pose Estimation**
  - 주어진 영상 속 Human Object 의 자세 (pose) 를 추정하는 것
  - Pose 추정 = 주요한 관절을 찾는 것
    - 관절 = joints = key points: 사람의 자세를 구성하는 주요 관절 포인트
    - 해당 과제는 아래와 같이 불리기도 함
      - Key-point detection, Pose recognition

  - i.e. 특정 pose 를 만들어내는 Key-points 들을 찾아내는 task (= Key-points Localization)

Human Pose Estimation; Human Pose Estimation Task

- **Overall Process**

Input image



Pose Estimation Network

GT image

- Input image 상 17 개 Key points 의 (x, y) 좌표 값 예측
- Classitiaion task 와는 다르게 up-sampling 을 통해 high-resolution 으로 이미지를 잘 복원하는지가 핵심

- **Overall Process**
  - Data, Annotation (e.g. COCO Dataset)

[Input image]

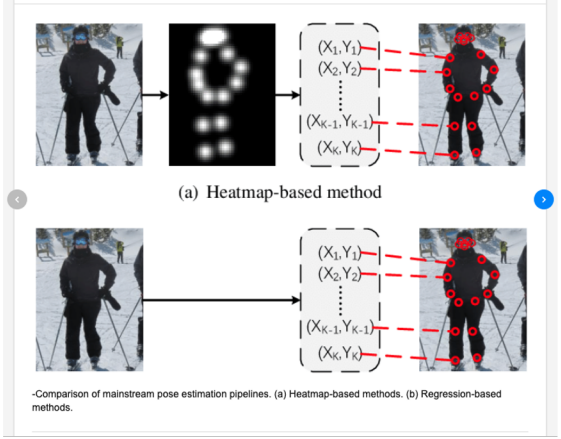
[Annotation] Key points

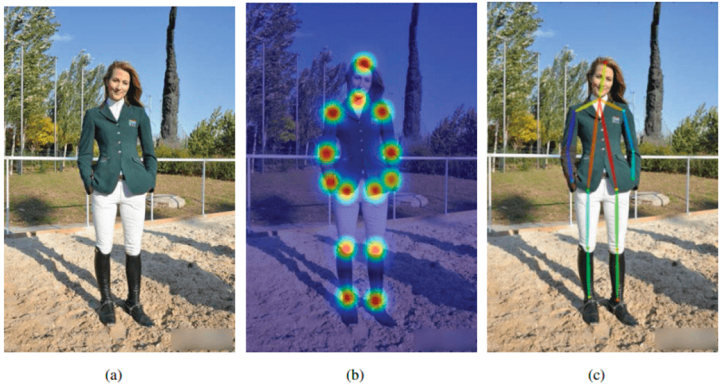
	눈(좌)	코	…	발목 (우)
x	374	367	…	396
y	73	81	…	341
z	2	2	…	2

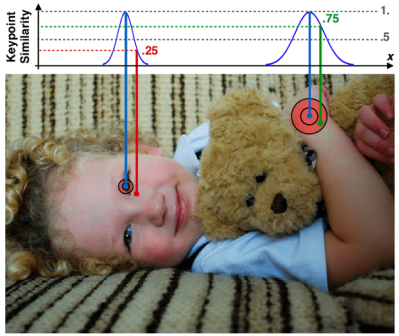
- 3개 tuple (x, y, z)
- x, y: (x, y), 2D image 좌표
- z: visibility flag
  - 0 : 이미지 내 존재하지 않는 키 포인트 (not labeled)
  - 1 : 이미지 내 존재하지만, 겉으론 보이지 않는 키 포인트
  - 2 : 이미지 내 존재하고, 겉으로도 보이는키 포인트

- **Regression vs Heatmap**
  - Regression 접근 (x, y)
    - (2013) DeepPose : Human Pose Estimation via Deep Neural Networks (Toshev, CVPR)
    - 최초의 딥러닝 기반 2D Human pose estimation model
    - CNN regressor 를 통해 key-points 의 좌표 값 (x, y) 를 직접 추정
    - 기존 방법론 대비 큰 성능 향상을 이루진 못함

  - Heatmap 접근 [loc = (x,y)]
    - (2015) Efficient Object Localization Using Convolutional Networks (Jonathan Tompson, CVPR)
    - Output 을 (x, y) 좌표 대신, Heatmap 을 통해 상대적인 빈도, 확률값으로 가져가도록 함
    - Input image 의 여러 pose 로 인해 생기는 다양성을 잘 포용하고, 보다 Robust 한 모델을 가능하게 함
    - 좌표 기반 방법론보다 2배 이상 높은 성능







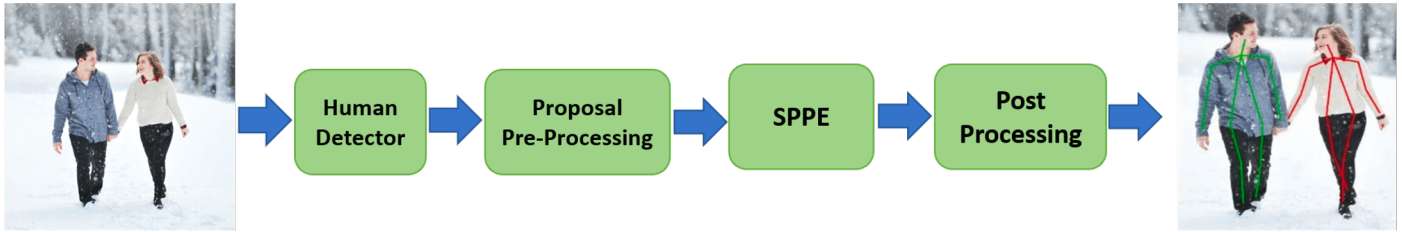
Human Pose Estimation; Human Pose Estimation Task

- **Single vs Multi**
  - Single-Person Pose Estimation (SPPE)
  - Multi-Person Pose Estimation
    - Top-Down Approaches
    - Bottom-Up Approaches

Figure 5: Single-Person Vs. Multi-Person Pose Estimation

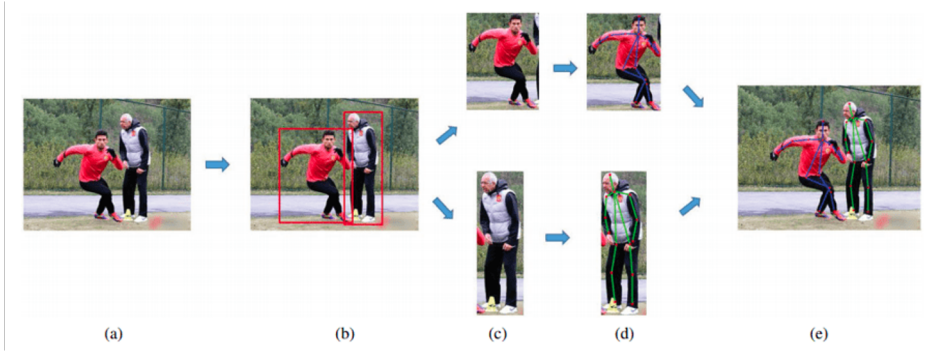
Human Pose Estimation; Human Pose Estimation Task

- **Single vs Multi**
  - Single-Person Pose Estimation (SPPE)
  - **Multi-Person Pose Estimation**
    - **Top-Down Approaches ⇒ HR-Net**
    - Bottom-Up Approaches



Original Image

Result



- 사실상 Single Pose Estimation Task
  1. Object (사람) Detection
  2. Key Points Detection (매 사람마다)

- 속도 느림, 정확도 높음

Human Pose Estimation; Human Pose Estimation Task

- **Single vs Multi**
  - Single-Person Pose Estimation (SPPE)
  - **Multi-Person Pose Estimation**
    - Top-Down Approaches
    - **Bottom-Up Approaches**

Original Image

Result

1. Key Points Detection (모든 사람)
2. 각 Key Points 의 연결

- 속도 빠름, 정확도 낮음

Human Pose Estimation; Brief History

- ML (1970~)
  - Pictorial Structure Model
- **AlexNet (2012)**
- **DeepPose (2013)**
  - **Deep Learning Network 최초 접목**
- ResNet (2015)
- Deconvolution Network (2015)
- Efficient Object Localization Using Convolutional Networks (2015)
  - **Heatmap based approach**
- Convolutional Pose Machines (2016)
  - Receptive field 확대, Global Context 학습
- Stacked hourglass networks for human pose estimation (2016)
  - Global + Local Context 학습
- Deeper Cut (2016)
- Cascaded Pyramid Network for Multi-Person Pose Estimation (2018)
  - Global Net + Refine Net
- Simple Baselines for Human Pose Estimation and Tracking (2018)
  - + Deconvolution
- **HR-Net (2019)**
  - **Parallel Multi-Resolution Feature structure**
- Polarized Self-Attention (2021)

- Deep Learning network (CNN) 접목
- Heatmap based Approach 시도 등장

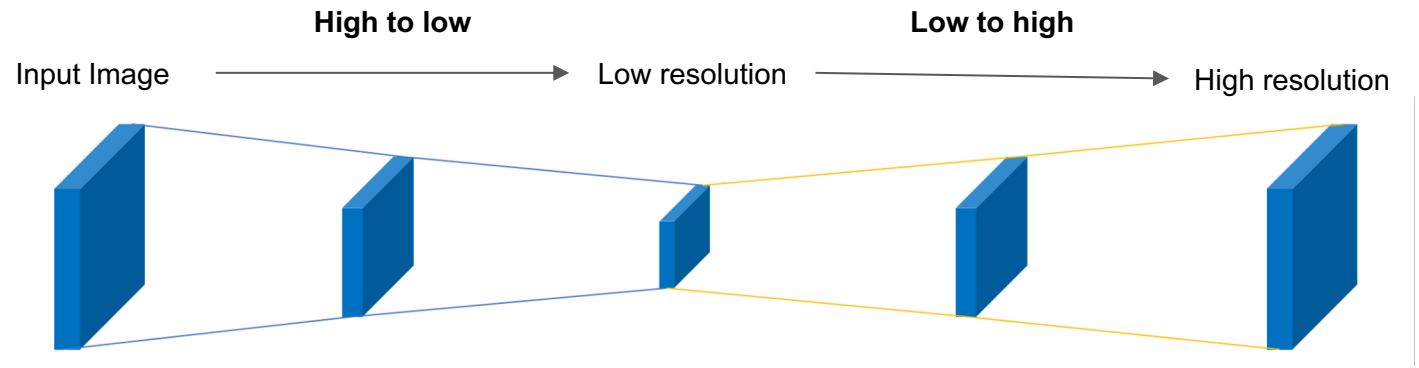
- Global + Local Feature 학습
- High-Resolution 복원

HR-Net

HR-Net; Motivation

- **기존의 접근**
  - **High-to-low**
  - **Low-to-high**

$$\mathcal{N}_{11} \rightarrow \mathcal{N}_{22} \rightarrow \mathcal{N}_{33} \rightarrow \mathcal{N}_{44}.$$



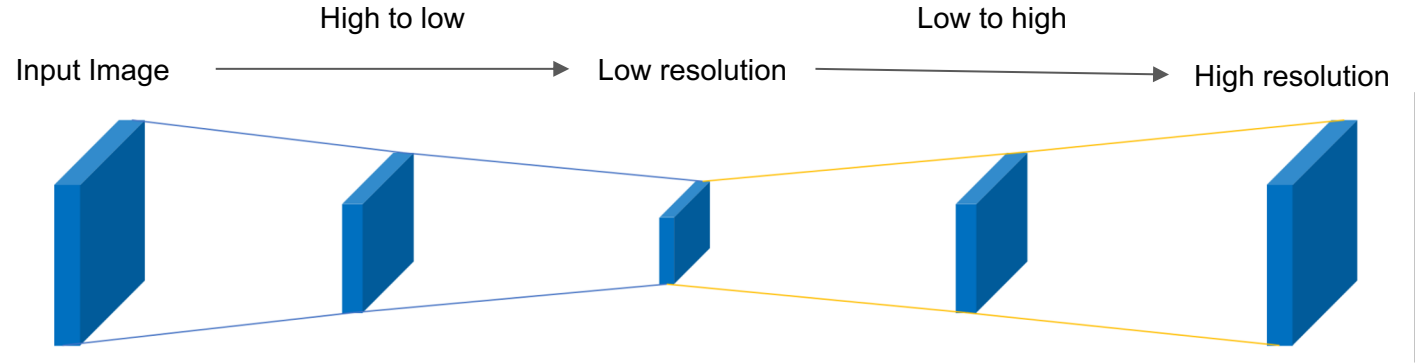
- Classification 수행 시, image feature extraction
  - Strided Convolution
  - Pooling
- Small Object 혹은 Detail 한 spatial information 의 손실

Pixel-wise prediction 에 부정적 영향

- Image 복원
  - Upsampling
  - Transposed convolution

HR-Net; Motivation

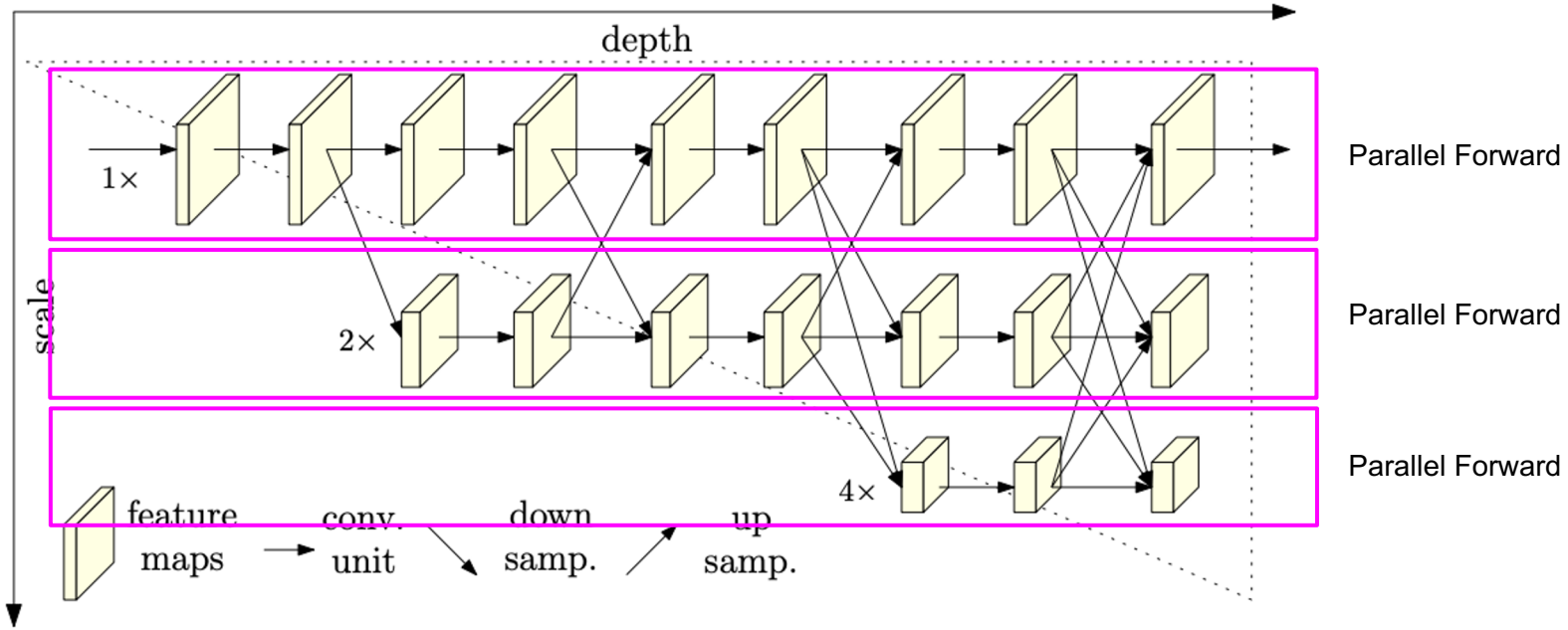
- **기존의 접근**
  - High-to-low
  - Low-to-high



- **Network 직렬화**
  - **Local, Global 특징 추출과 학습의 과정이 직렬화되어 있어, 최종적으로 Up-sampling 에 모든 process 가 과도한 의존**
    - 직렬 구조를 벗어나면 receptive field 를 확장하면서도 local information 손실이 크지 않을 것.

HR-Net; Model Structure

- **HR-Net**
  - 병렬화 (parallel)
  - 병렬적인 하위 네트워크들로 Multi-scale Resolution 을 그대로 유지하며 다양한 scale 의 spatial 정보 학습
  - 병렬적인 하위 네트워크 간 학습 정보를 공유하게 해, Multi-scale 의 spatial 정보를 더욱 풍부하게 학습할 수 있음



HR-Net; Model Structure

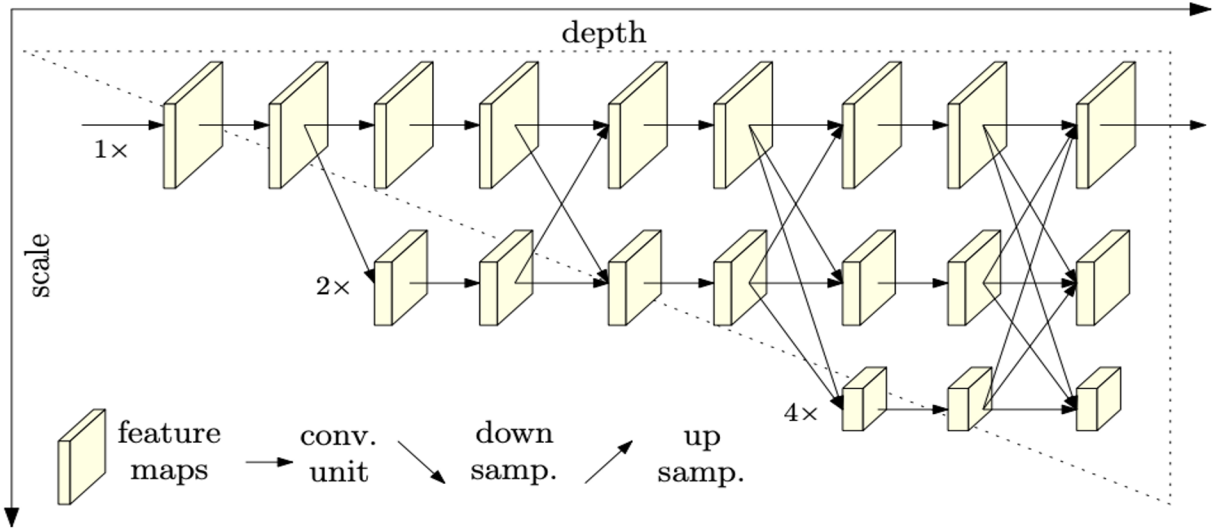
- **HR-Net**
  - 하나의 row 안에서 resolution 이 모두 동일하게 구성
  - Row 가 밑으로 내려갈수록 high-to-low resolution 네트워크를 통해 down-sampling
  - Resolution scale 은 동일하면서, scale 별로 resolution 유지
  - 다양한 scale 정보 학습 가능
  - 각 row 의 high network 는 수평, 병렬적으로 forward 진행

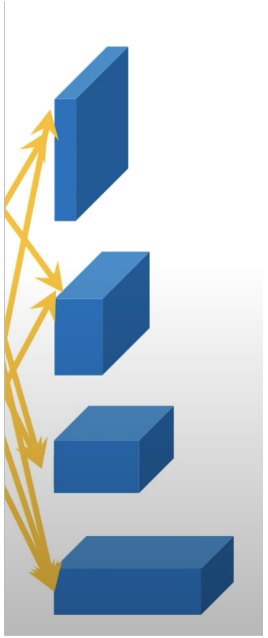
$$
\begin{array}{ccccccc}
\mathcal{N}_{11} & \rightarrow & \mathcal{N}_{21} & \rightarrow & \mathcal{N}_{31} & \rightarrow & \mathcal{N}_{41} \\
 & \searrow & \mathcal{N}_{22} & \rightarrow & \mathcal{N}_{32} & \rightarrow & \mathcal{N}_{42} \\
 & & & \searrow & \mathcal{N}_{33} & \rightarrow & \mathcal{N}_{43} \\
 & & & & & \searrow & \mathcal{N}_{44}.
\end{array}
$$

- N_{sr}에서 앞자리는 stage, r은 downsample된 단계를 의미한다. \
- N_{sr}은 첫번째 subnetwork(N_{11})의 해상도의 $\frac{1}{2^{r-1}}$
- high-resolution subnetwork을 처음 stage로 시작한다.
- high-to-low resolution subnetworks을 하나씩 추가한다.

HR-Net; Model Structure

- **HR-Net**
  - Forward 만 진행하면 다양한 scale 정보가 따로 놀게 됨.
    - 따라서 forward 과정과 더불어 scale 정보를 fusion 될 수 있도록 함.
  - 이러한 과정을 통해서 마지막 stage 에서는 각 resolution 별로 중요한 global, local 정보들이 풍부하게 담길 수 있음.

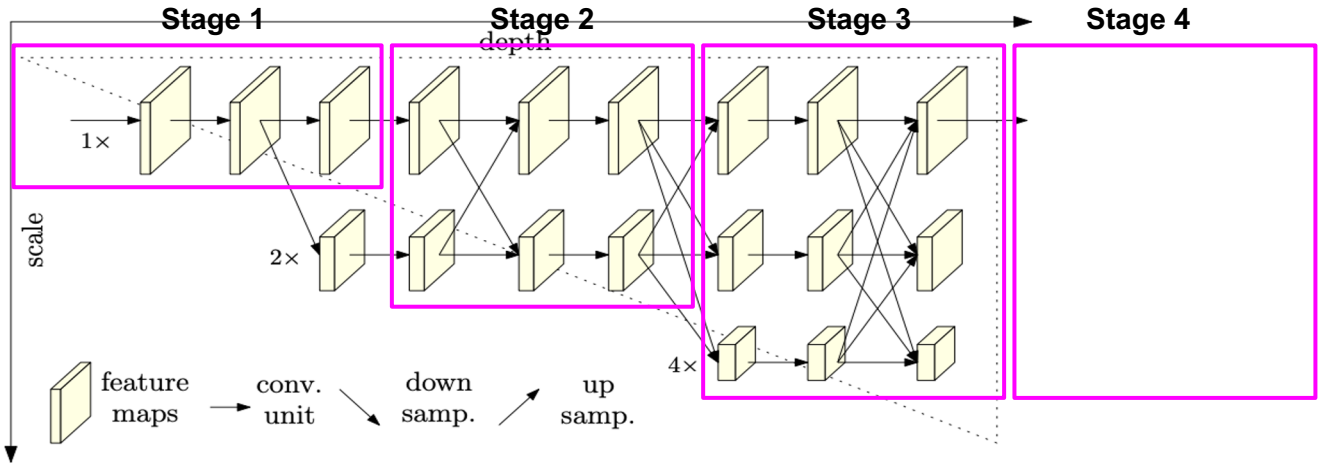




HR-Net; Model Structure

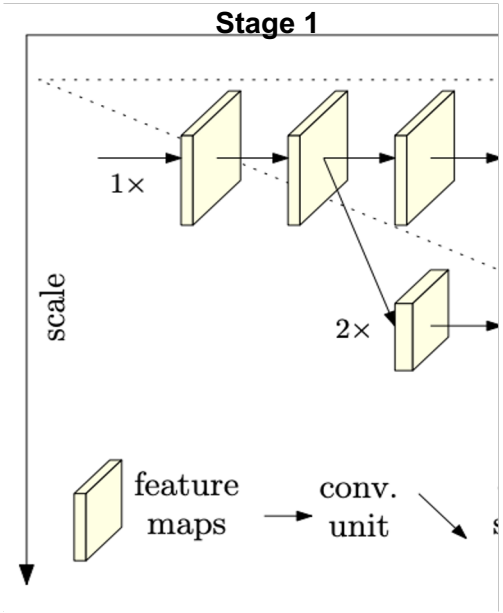
- **HR-Net**
  - 병렬적으로 구성된 Sub-네트워크 간 Fusion 을 통해, 상단의 High Resolution 을 유지하며 Global, Local 정보 학습
    - Low resolution : 넓은 receptive field 로 상대적으로 풍부한 semantic information 을 가짐
    - High resolution : positional information 이 많이 살아 detail 한 정보를 가짐

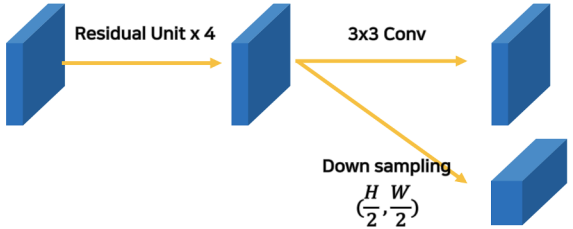
  - HR-Net 은 4개의 stage 로 구성되어 있으며, 이를 서로 병렬적으로 fusion



HR-Net; Model Structure

- **HR-Net**
  - Stage 1
    - 하나의 resolution 유지
  - 병렬적으로 구성된 Sub-네트워크 간 Fusion 을 통해, 상단의 High Resolution 을 유지하며 Global, Local 정보 학습

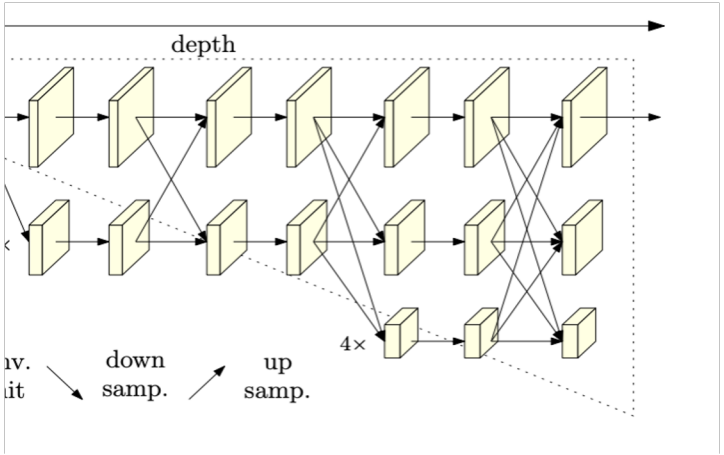




HR-Net; Model Structure

- **HR-Net**
  - Stage 2~4
    - 본격적으로 fusion 과 transition 진행
  - 병렬적으로 구성된 Sub-네트워크 간 Fusion 을 통해, 상단의 High Resolution 을 유지하며 Global, Local 정보 학습

Stage 2 ~ 4



1. Multi-resolution 간 **Fusion**
   a. **Exchange Unit**
      i. Down-sampling (halve) 3*3 Conv (Stride=2, Padding=1)
      ii. Up-sampling (double) Nearest-neighbor Up-sampling (* 2)

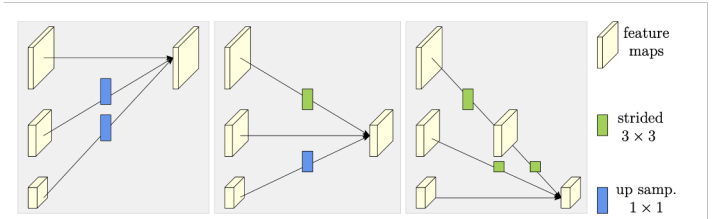
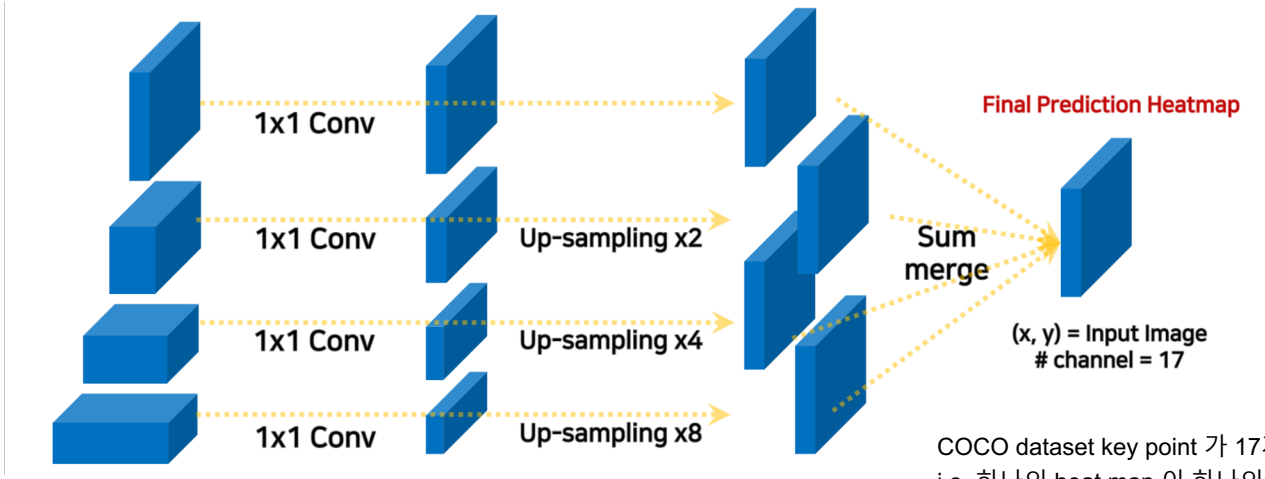


Figure 3. Illustrating how the exchange unit aggregates the information for high, medium and low resolutions from the left to the right, respectively. Right legend: strided 3×3 = strided 3×3 convolution, up samp. 1×1 = nearest neighbor up-sampling following a 1×1 convolution.

1. Resolution scale 확장하는 **Transition**
   a. Down-sampling : 가로, 세로 절반의 resolution

HR-Net; Model Structure

- **HR-Net**
  - Stage 4
    - 원본 이미지 shape 에 맞게 upsampling
    - 최종 resolution 에 맞춰준 후에, merge 하여 final prediction heatmap 생성
    - 최종 heatmap 은 (x, y, 17) dimension
    - 마지막 exchange unit 으로부터 나온 high-resolution representations output 으로 regress
  - Loss function 은 MSE (평균 제곱 오차)
  - GT heatmap 은 각 keypoint 에 2D 가우시안 분포를 적용해서 구함



COCO dataset key point 가 17개
i.e. 하나의 heat map 이 하나의 key point 관절에 대한 예측 값

HR-Net; Experiments

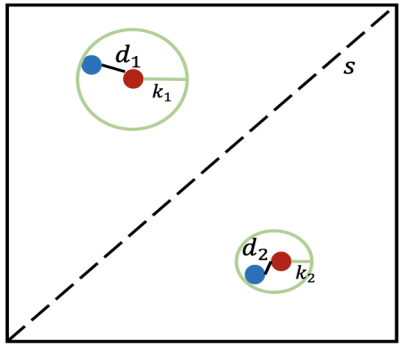
- **데이터 셋**
  - **COCO Keypoint Detection**
    - 학습 데이터 : 57,000 images (person instances: 150k)
    - Evaluation : 5,000 Images (val), 20,000 Images (test-dev)
    - # Key-points : 17

- **평가 지표**
  - 유사성 측정 지표 : OKS (=Object Keypoint Similarity)
    - 키 포인트 유사성 측정을 위함
  - 평가 Metric : AP (=Average Precision)

- **평가 지표**
  - 유사성 측정 지표 : OKS (=Object Keypoint Similarity)
    - 키 포인트 유사성 측정을 위함
    - 0 (Worst) ~ 1 (Best) 사이의 값

$$\frac{\sum_i \exp\left(-d_i^2/2s^2k_i^2\right)\delta(v_i > 0)}{\sum_i \delta(v_i > 0)}$$

d_i	Euclidean 거리(Ground-Truth 관절(key-point), 예측 관절)
v_i	Visibility flag ($v_i > 0$: 이미지 내 존재하는 모든 키 포인트)
s	객체 Bounding box 대각선 길이
k_i	관절 종류마다 사전 설정되어 있는 상수



- $s^2k_i^2$ 역할 : 각 Image, 관절 마다 일종의 '정규화'

  - Average Precision
    - OKS Threshold 에 따른 Precision, Recall 값
    - Precision-Recall curve

HR-Net; Experiments

- **Results**

Table 1. Comparisons on the COCO validation set. Pretrain = pretrain the backbone on the ImageNet classification task. OHKM = online hard keypoints mining [11].

Method	Backbone	Pretrain	Input size	#Params	GFLOPs	AP	AP^{50}	AP^{75}	AP^{M}	AP^{L}	AR
8-stage Hourglass [40]	8-stage Hourglass	N	256 × 192	25.1M	14.3	66.9	–	–	–	–	–
CPN [11]	ResNet-50	Y	256 × 192	27.0M	6.20	68.6	–	–	–	–	–
CPN + OHKM [11]	ResNet-50	Y	256 × 192	27.0M	6.20	69.4	–	–	–	–	–
SimpleBaseline [72]	ResNet-50	Y	256 × 192	34.0M	8.90	70.4	88.6	78.3	67.1	77.2	76.3
SimpleBaseline [72]	ResNet-101	Y	256 × 192	53.0M	12.4	71.4	89.3	79.3	68.1	78.1	77.1
SimpleBaseline [72]	ResNet-152	Y	256 × 192	68.6M	15.7	72.0	89.3	79.8	68.7	78.9	77.8
HRNet-W32	HRNet-W32	N	256 × 192	28.5M	7.10	73.4	89.5	80.7	70.2	80.1	78.9
HRNet-W32	HRNet-W32	Y	256 × 192	28.5M	7.10	74.4	90.5	81.9	70.8	81.0	79.8
HRNet-W48	HRNet-W48	Y	256 × 192	63.6M	14.6	75.1	90.6	82.2	71.5	81.8	80.4
SimpleBaseline [72]	ResNet-152	Y	384 × 288	68.6M	35.6	74.3	89.6	81.1	70.5	79.7	79.7
HRNet-W32	HRNet-W32	Y	384 × 288	28.5M	16.0	75.8	90.6	82.7	71.9	82.8	81.0
HRNet-W48	HRNet-W48	Y	384 × 288	63.6M	32.9	**76.3**	**90.8**	**82.9**	**72.3**	**83.4**	**81.2**

- Simple Baseline 대비 더 가볍고, 연산량이 적지만, 높은 모델의 성능 (Small HR-Net, HRNet-W32)
- CPN 계열 모델 대비, 각각 AP 4.6, 4.0 포인트 성능 향상, 다만 HR-Net 의 복잡도 크기는 다소 증가
- 이전 SOTA 인 Simple Baseline 의 small, large 모델 대비 모두 적은 parameter 와 연산량으로 더 높은 성능 달성
- Pre-train 모델 사용할 경우, 모델의 AP 1 point 상승
- HR-Net 의 사이즈 증가 시, AP 1 point 를 비롯해 전반적으로 다소 성능 지표 상승

HR-Net; Experiments

- **Results**

Table 2. Comparisons on the COCO test-dev set. #Params and FLOPs are calculated for the pose estimation network, and those for human detection and keypoint grouping are not included.

Method	Backbone	Input size	#Params	GFLOPs	AP	AP^{50}	AP^{75}	AP^{M}	AP^{L}	AR
Bottom-up: keypoint detection and grouping										
OpenPose [6]	–	–	–	–	61.8	84.9	67.5	57.1	68.2	66.5
Associative Embedding [39]	–	–	–	–	65.5	86.8	72.3	60.6	72.6	70.2
PersonLab [46]	–	–	–	–	68.7	89.0	75.4	64.1	75.5	75.4
MultiPoseNet [33]	–	–	–	–	69.6	86.3	76.6	65.0	76.3	73.5
Top-down: human detection and single-person keypoint detection										
Mask-RCNN [21]	ResNet-50-FPN	–	–	–	63.1	87.3	68.7	57.8	71.4	–
G-RMI [47]	ResNet-101	353 × 257	42.6M	57.0	64.9	85.5	71.3	62.3	70.0	69.7
Integral Pose Regression [60]	ResNet-101	256 × 256	45.0M	11.0	67.8	88.2	74.8	63.9	74.0	–
G-RMI + extra data [47]	ResNet-101	353 × 257	42.6M	57.0	68.5	87.1	75.5	65.8	73.3	73.3
CPN [11]	ResNet-Inception	384 × 288	–	–	72.1	91.4	80.0	68.7	77.2	78.5
RMPE [17]	PyraNet [77]	320 × 256	28.1M	26.7	72.3	89.2	79.1	68.0	78.6	–
CFN [25]	–	–	–	–	72.6	86.1	69.7	78.3	64.1	–
CPN (ensemble) [11]	ResNet-Inception	384 × 288	–	–	73.0	91.7	80.9	69.5	78.1	79.0
SimpleBaseline [72]	ResNet-152	384 × 288	68.6M	35.6	73.7	91.9	81.1	70.3	80.0	79.0
HRNet-W32	HRNet-W32	384 × 288	28.5M	16.0	74.9	92.5	82.8	71.3	80.9	80.1
HRNet-W48	HRNet-W48	384 × 288	63.6M	32.9	**75.5**	**92.5**	**83.3**	**71.9**	**81.5**	**80.5**
HRNet-W48 + extra data	HRNet-W48	384 × 288	63.6M	32.9	**77.0**	**92.7**	**84.5**	**73.4**	**83.1**	**82.0**

  - Bottom-up Approach 보다 높은 정확도 (AP)
  - SimpleBaseline 대비 더 작은 모델 사이즈와 적은 연산 복잡도로 더 높은 성능 달성
  - 추가 데이터 (AI Challenger) 훈련 시, 가장 높은 AP (77.0) 달성

- **Qualitative results**

Figure 4. Qualitative results of some example images in the MPII (top) and COCO (bottom) datasets: containing viewpoint and appearance change, occlusion, multiple persons, and common imaging artifacts.

HR-Net; Experiments

- **Ablation Study**
  - Repeated multi-scale fusion
    - Fusion 의 정도가 증가할수록, 정확도 (AP) 높아짐 (비례)
    - Fusion 의 정도
      - Model C > Model B > Model A

Table 6. Ablation study of exchange units that are used in repeated multi-scale fusion. Int. exchange across = intermediate exchange across stages, Int. exchange within = intermediate exchange within stages.

Method	Final exchange	Int. exchange across	Int. exchange within	AP
(a)	✓			70.8
(b)	✓	✓		71.9
(c)	✓	✓	✓	73.4

- **Ablation Study**
  - 다양한 resolution 의 heatmap 각각의 성능 관찰
    - 여러 resolution 별로 heatmap 성능 확인
    - Resolution 이 커질수록 성능이 비례해서 증가
    - 가장 작은 resolution 성능은 AP 가 10 이하이기 때문에 표기하지 않음.
    - **Resolution impact the key-point prediction quality**

  - Input size 에 따른 모델의 성능 향상 관찰
    - 이미지 size 별로 baseline, HR-Net 성능 비교
    - Image size 가 작을수록 성능 향상 폭이 큼. 지속적인 성능 향상을 보임.
    - **High resolution 을 유지하는 것이 중요함.**

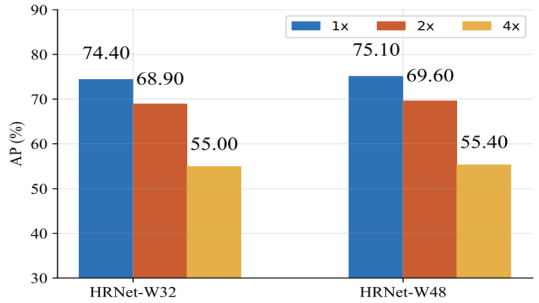


Figure 5. Ablation study of high and low representations. 1×, 2×, 4× correspond to the representations of the high, medium, low resolutions, respectively.

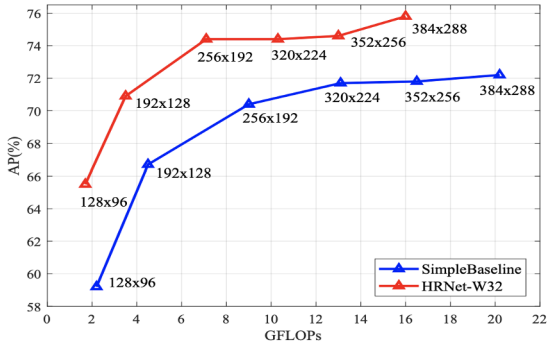
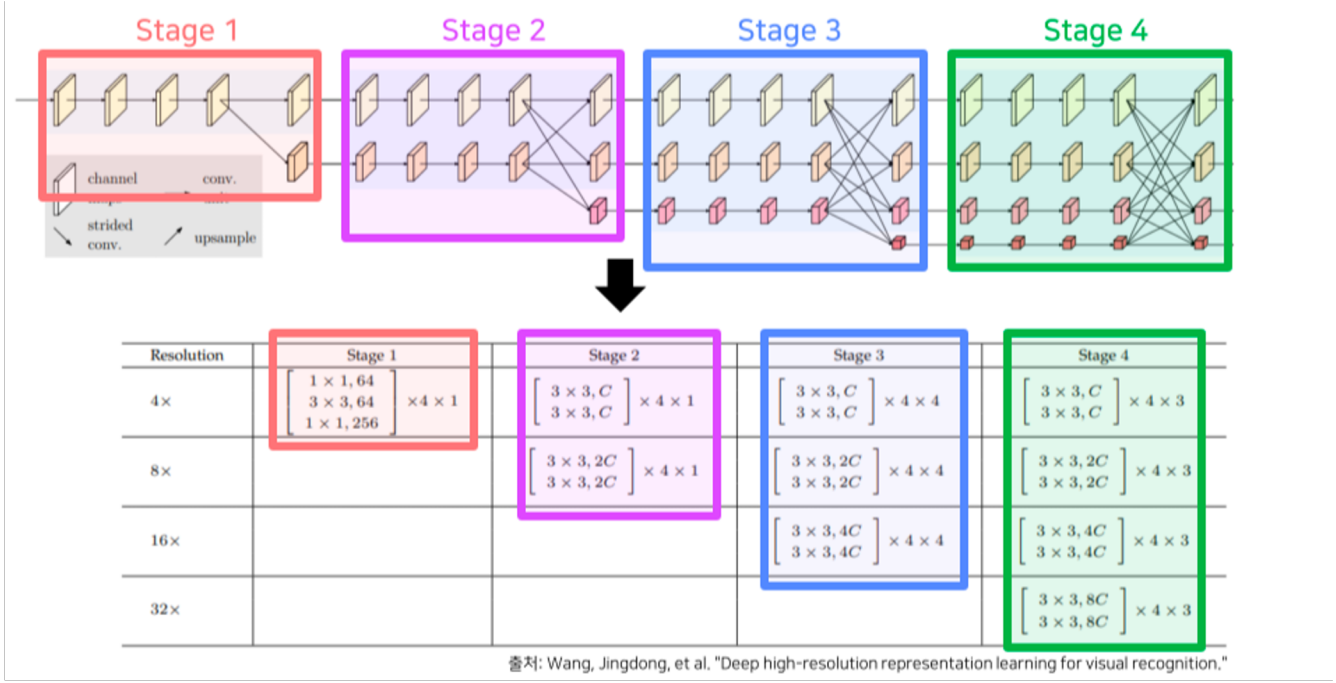


Figure 6. Illustrating how the performances of our HRNet and SimpleBaseline [72] are affected by the input size.

HR-Net; Summary



Resolution	Stage 1	Stage 2	Stage 3	Stage 4
4×	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix} \times 4 \times 1$	$\begin{bmatrix} 3\times3, C \\ 3\times3, C \end{bmatrix} \times 4 \times 1$	$\begin{bmatrix} 3\times3, C \\ 3\times3, C \end{bmatrix} \times 4 \times 4$	$\begin{bmatrix} 3\times3, C \\ 3\times3, C \end{bmatrix} \times 4 \times 3$
8×		$\begin{bmatrix} 3\times3, 2C \\ 3\times3, 2C \end{bmatrix} \times 4 \times 1$	$\begin{bmatrix} 3\times3, 2C \\ 3\times3, 2C \end{bmatrix} \times 4 \times 4$	$\begin{bmatrix} 3\times3, 2C \\ 3\times3, 2C \end{bmatrix} \times 4 \times 3$
16×			$\begin{bmatrix} 3\times3, 4C \\ 3\times3, 4C \end{bmatrix} \times 4 \times 4$	$\begin{bmatrix} 3\times3, 4C \\ 3\times3, 4C \end{bmatrix} \times 4 \times 3$
32×				$\begin{bmatrix} 3\times3, 8C \\ 3\times3, 8C \end{bmatrix} \times 4 \times 3$

출처: Wang, Jingdong, et al. "Deep high-resolution representation learning for visual recognition."

- **복원 (Low resolution -> High resolution) 없이, 모든 과정에서 High resolution 유지**
- **Multi-resolution 표상을 반복적으로 fusion 하여, 보다 신뢰할만한 High Resolution Representation 생성**

Research Trends

Research Trends

- **Confluence**
  - https://hutomdev.atlassian.net/wiki/spaces/COM/pages/2564620328/2022+Research+Trends

- Arxiv Sanity: 가장 최신의 논문을 볼수 있는 최대 저장소
- SCI-HUB: DOI입력시 유료논문 공짜열람
- Arxiv : 논문보자!! 여기서 Artificial Interlligence, Computer Vision and Pattern Recogntion 두가지 관심분야 보자!
- Paper With code: 논문뿐만아니라 코드도 한번에 볼수 있는 곳
- labml.ai: 아카이브 대체 trends 사이트? pytorch Implmentation ⇒ 수식으로 변환 하는사이트도 있는 듯?
- semantic sanity: paper recomendation
- benty-fields: research pool ? paper, 세미나, 저널클럽 등 ?
- shortscience.org: paper 요약 사이트
- deepmonitoring.org: 트위터 기반 paper trends. keyword 기반 검색 가능

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