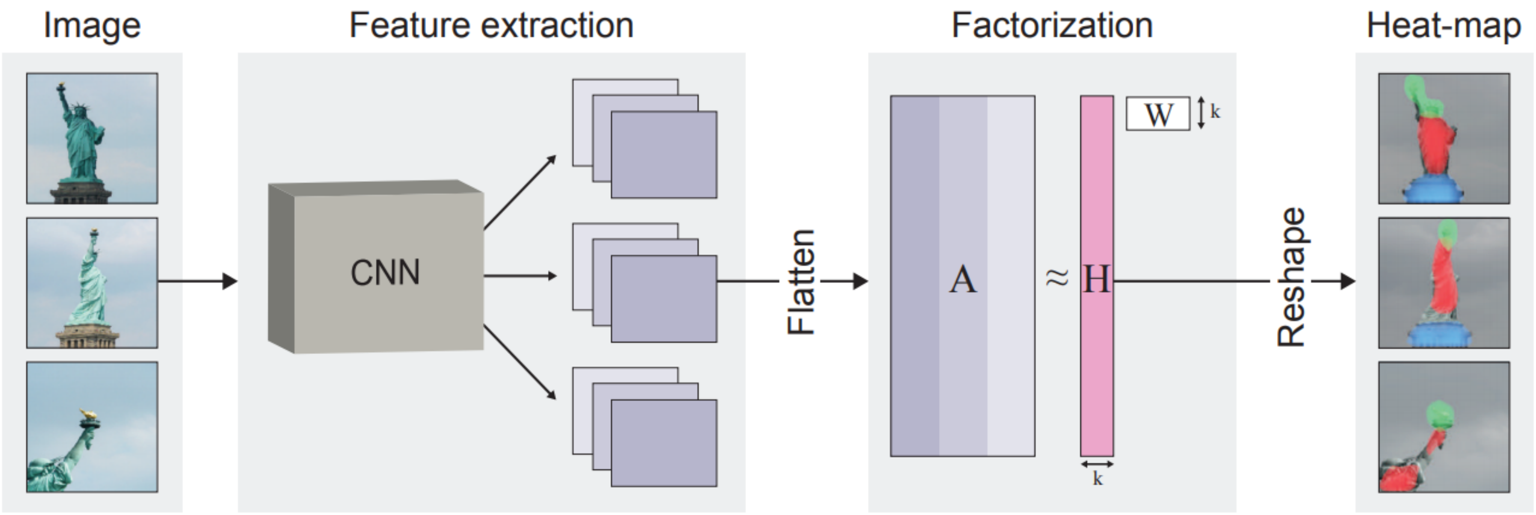
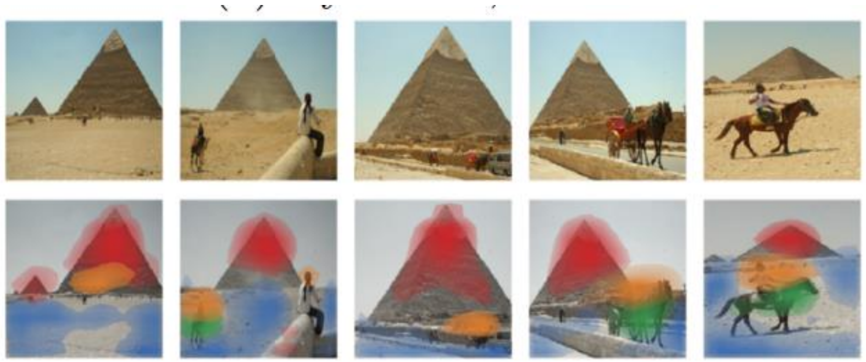
Introduction

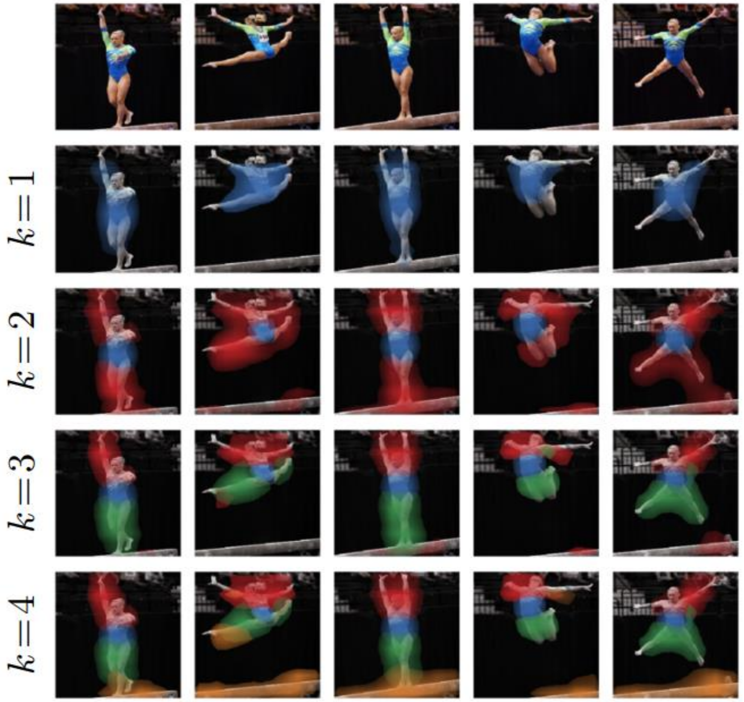
Deep Feature Factorization For Concept Discovery

In The Euopean Conference on Computer Vision (ECCV), 2018.





(a) Gymnastics1



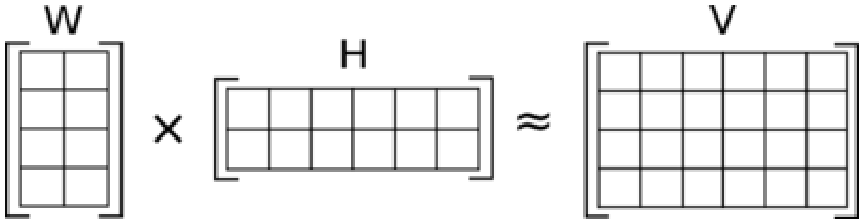
Project goal : Factorization part에 대한 개선 통해, Object co-segmentation과 Part co-segmentation 성능을 개선 함.

Related works

Matrix Factorization 기반 차원 축소 방법들

1. Non-negative matrix factorization

- Lee and Seung (1999, 2000) 이 multiplicative update algorithm을 개발하여 많이 사용되기 시작됨.
- Parts based representation (해석력이 좋다.)

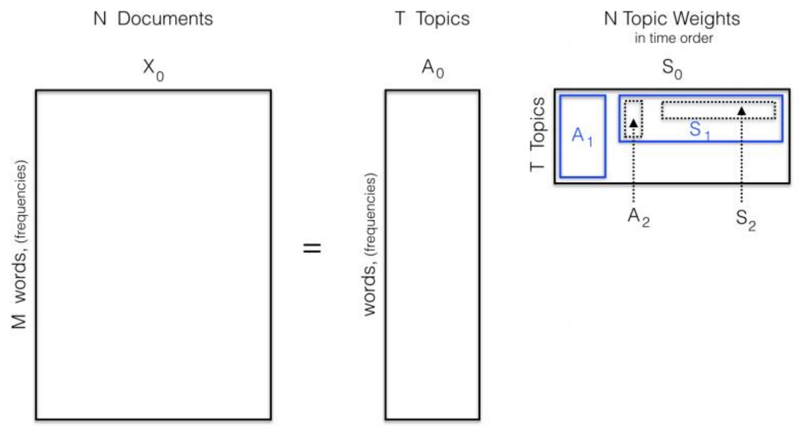


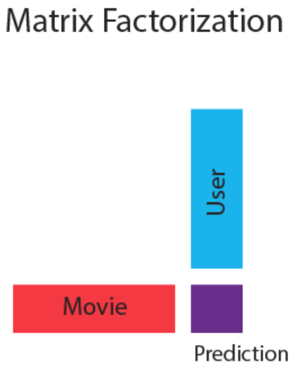
$$\min_{W,H} ||V - WH||_F, \text{ subject to } W \geq 0, H \geq 0.$$

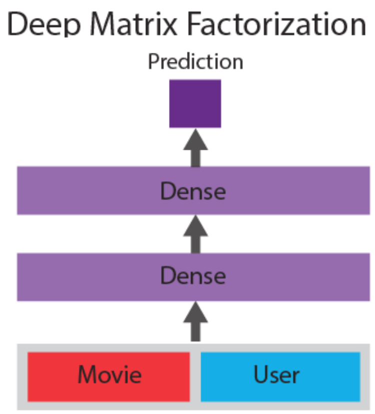
2. Semi NMF

$$\min_{G^T G = I, G \geq 0} || X_{\pm} - F_{\pm} G_{+}^{T} ||^2$$

3. Deep Semi NMF, Deep Matrix Factorization, Deep NMF







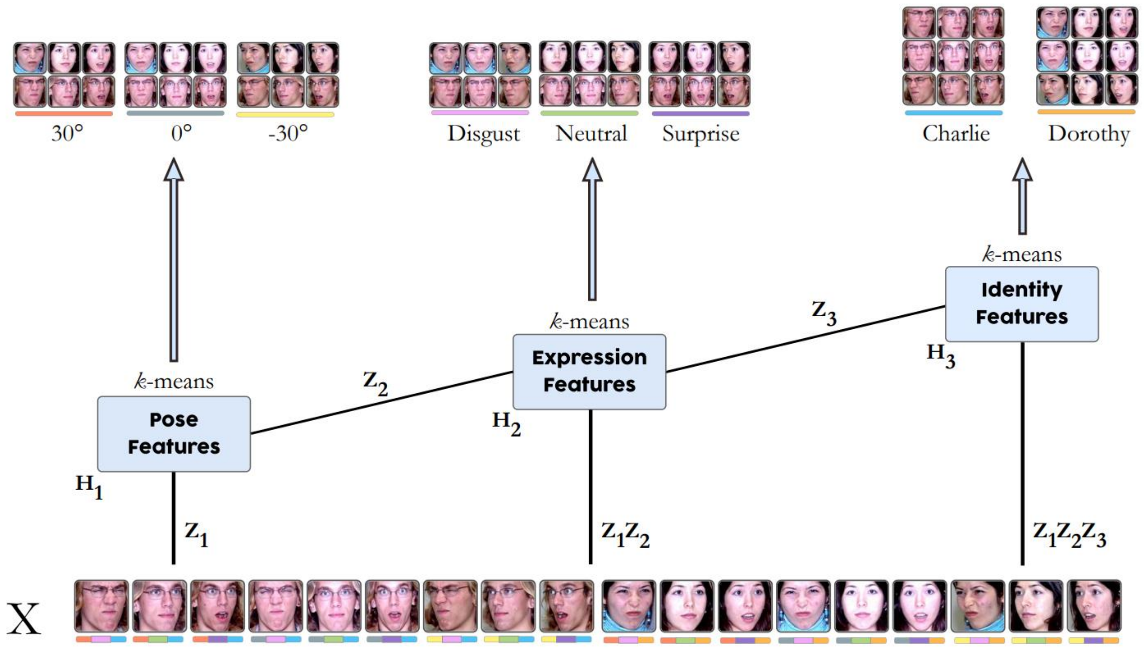
$$C^* = \frac{1}{2}\|\boldsymbol{X} - \boldsymbol{Z}_1 g\left(\boldsymbol{Z}_2\, g\left(\cdots g\left(\boldsymbol{Z}_m \boldsymbol{H}_m\right)\right)\right)\|_F^2$$

\+ Regularization Term
\+ 등등

A **deep** matrix factorization method for learning attribute representations
G Trigeorgis, K Bousmalis, S Zafeiriou... - IEEE transactions on ..., 2016 - ieeexplore.ieee.org
... and the intermediate hidden represen- tations that are implied, allowing for a better higher-leve feature representation H. In this work, we propose **Deep Semi-NMF**, a novel approach that is able to factorize a matrix into multiple factors in an unsupervised fashion— see Fig ...
☆ 99 87회 인용 관련 학술자료 전체 10개의 버전 Web of Science: 43

[PDF] A **deep semi-nmf** model for learning hidden representations
G Trigeorgis, K Bousmalis, S Zafeiriou... - ... Conference on Machine ..., 2014 - jmlr.org
Semi-NMF is a matrix factorization technique that learns a low-dimensional representation of a dataset that lends itself to a clustering interpretation. It is possible that the mapping between this new representation and our original features contains rather complex ...
☆ 99 100회 인용 관련 학술자료 전체 11개의 버전 »

Deep Semi NMF



얼굴 방향

$$X^{\pm} \approx Z_1^{\pm} H_1^{+}$$

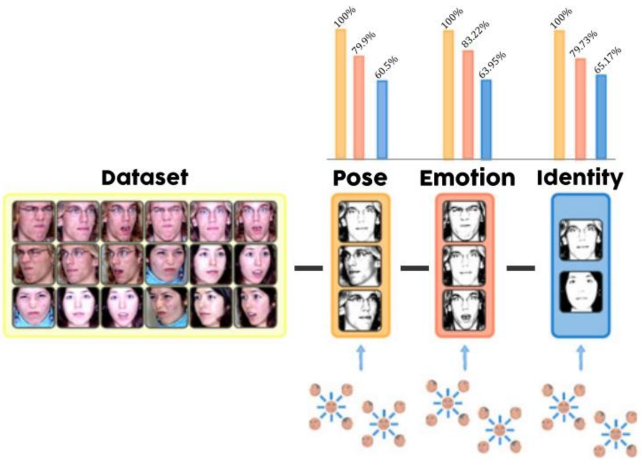
얼굴 표정

$$X^{\pm} \approx Z_1^{\pm} Z_2^{\pm} H_2^{+}$$

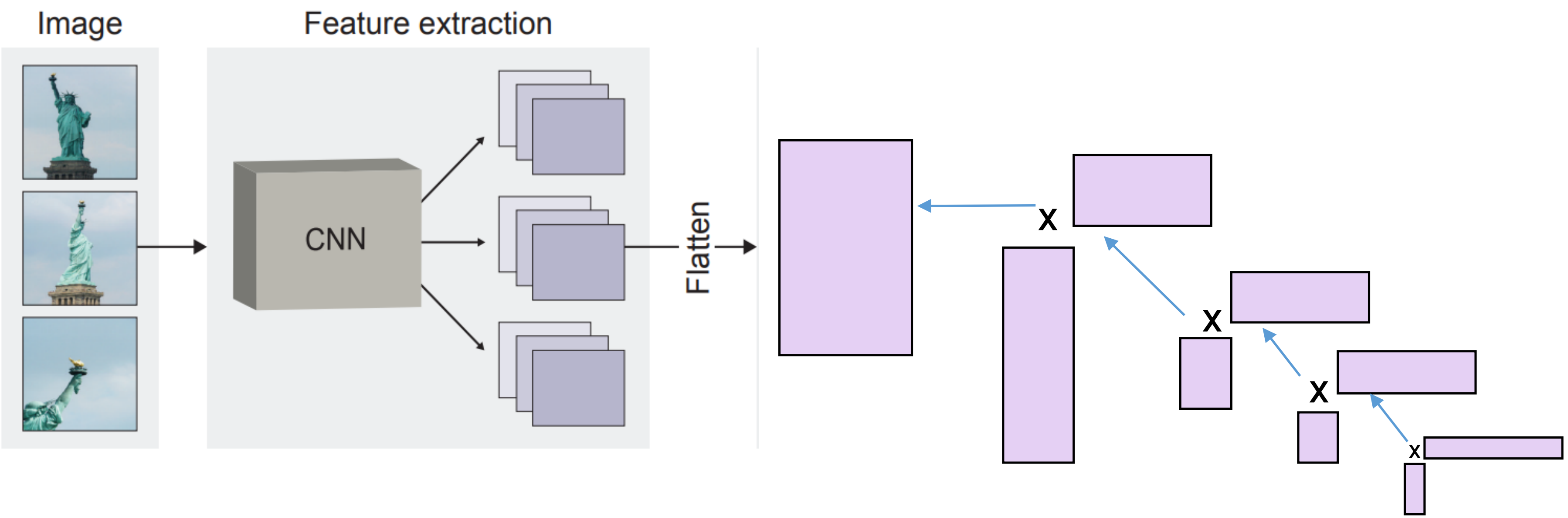
$$X^{\pm} \approx Z_1^{\pm} Z_2^{\pm} Z_3^{\pm} H_3^{+}$$

인물 classification

각 레이어 마다 Face image에 대해 hidden representations(얼굴 방향, 표정, 인물 분류)을 표현 할 수 있다고 가정.



Method

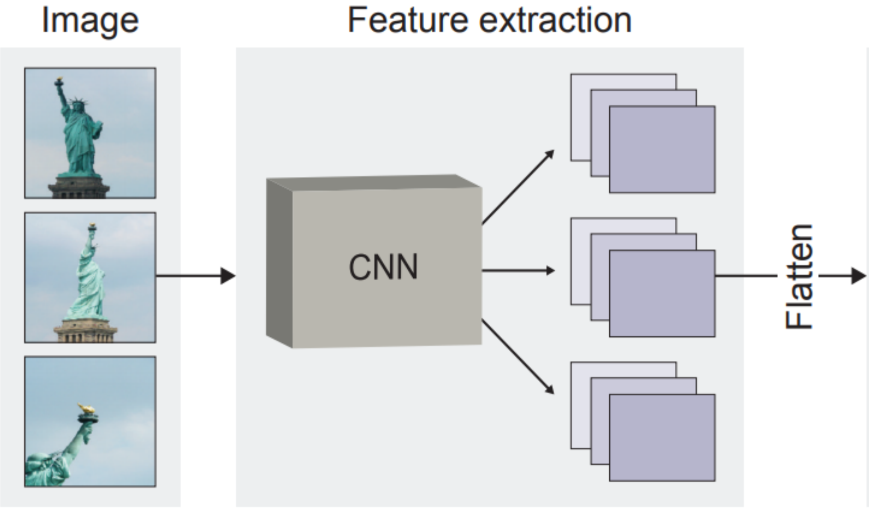


$$C^* = \frac{1}{2}\|\boldsymbol{X} - \boldsymbol{Z}_1 g\left(\boldsymbol{Z}_2\, g\left(\cdots g\left(\boldsymbol{Z}_m \boldsymbol{H}_m\right)\right)\right)\|_F^2$$

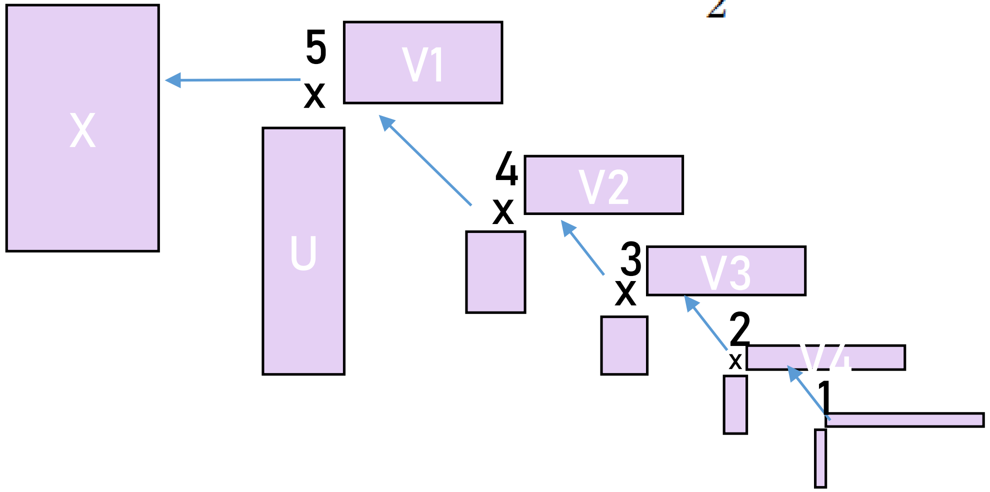
기존의 NMF 기반 모델은 linear dimension reduction 방식이 었음.
Multi layer 와 activation function을 추가하여 Non-linear dimension reduction을 통해 Complex한 이미지에 대해 latent features을 뽑을 수 있을 것으로 기대.

Project goal : Factorization part에 대한 개선 통해, Object co-segmentation과 Part co-segmentation 성능을 개선 함.

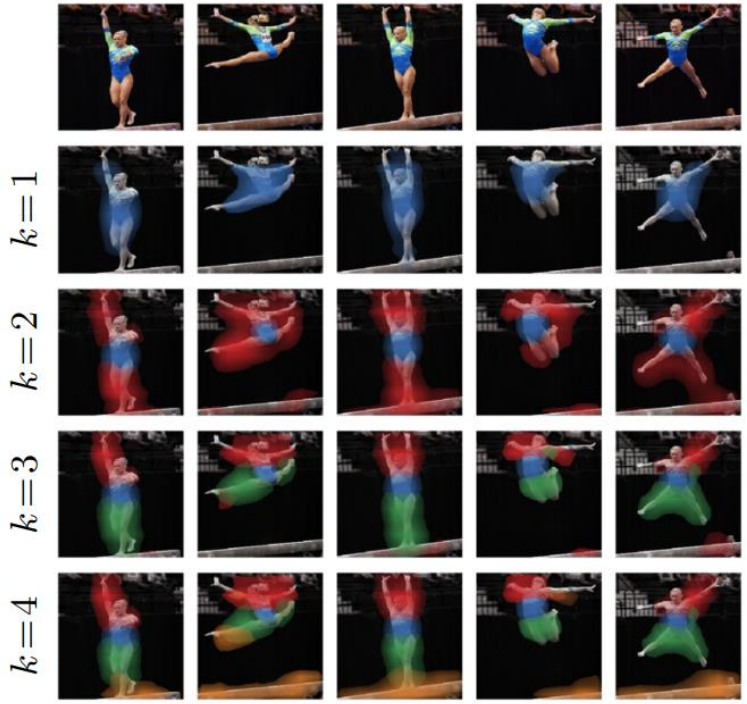
Method



$$C^* = \frac{1}{2}\|\boldsymbol{X} - \boldsymbol{Z}_1 g\left(\boldsymbol{Z}_2\, g\left(\cdots g\left(\boldsymbol{Z}_m \boldsymbol{H}_m\right)\right)\right)\|_F^2$$



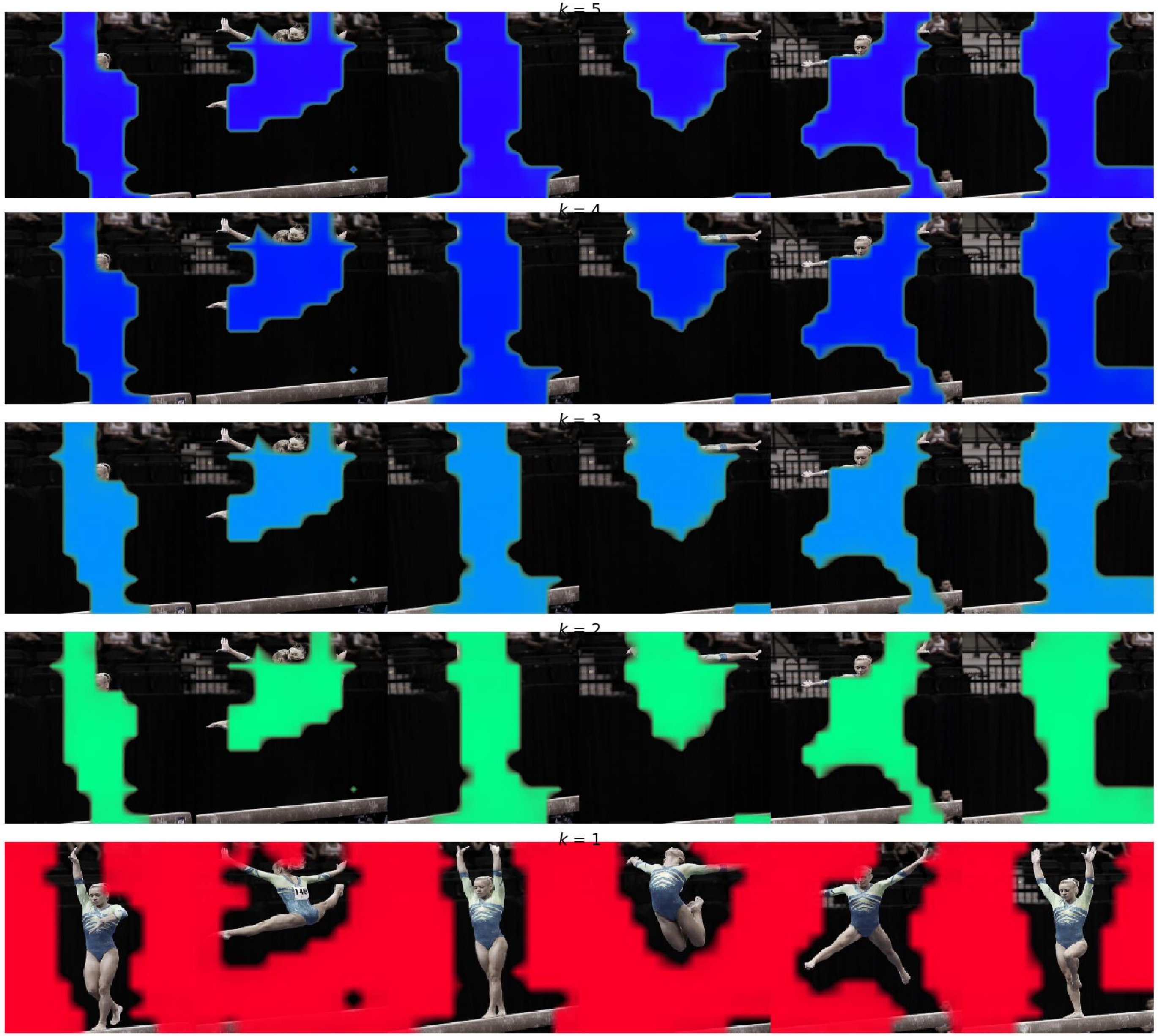
(a) Gymnastics1



각 deep NMF layer 을 5,4,3,2,1로 차원 축소하여,
각 레이어 마다 이미지의 특징을 추출하기를 기대 (왼쪽 이미지)

Result & Analysis

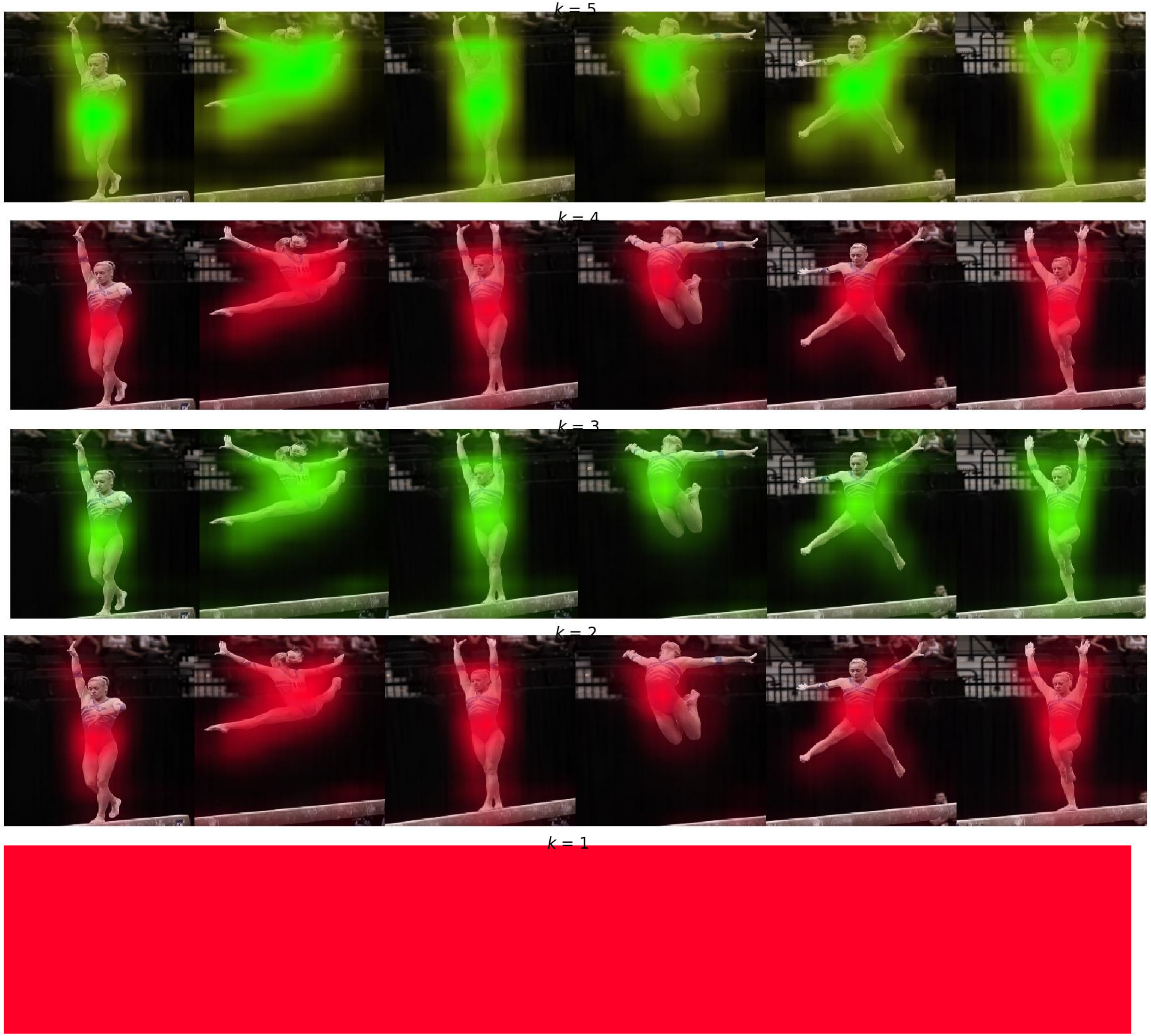
Experiment 1
- Activation function : Sigmoid



Result & Analysis

Experiment 2

- Activation function : ReLu
- Sigmoid에 비해 경계가 strict하지 않음



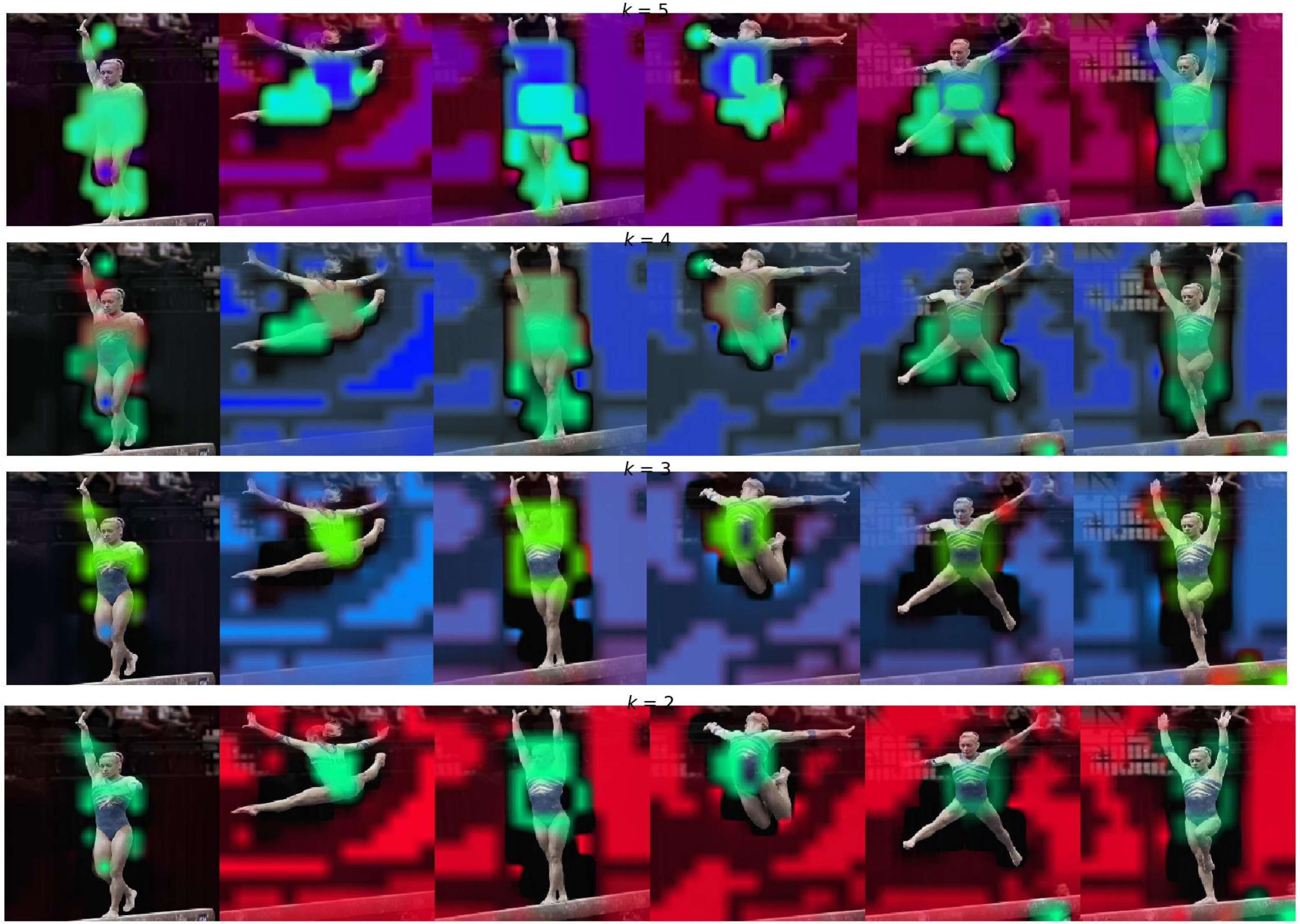
Result & Analysis

Experiment 3

- Activation function : Sigmoid
- 각 레이어의 아웃풋에 activation을 빼고 heatmap을 그림.

$$g\left(\boldsymbol{Z}_m \boldsymbol{H}_m\right) \longrightarrow \left(\boldsymbol{Z}_m \boldsymbol{H}_m\right)$$

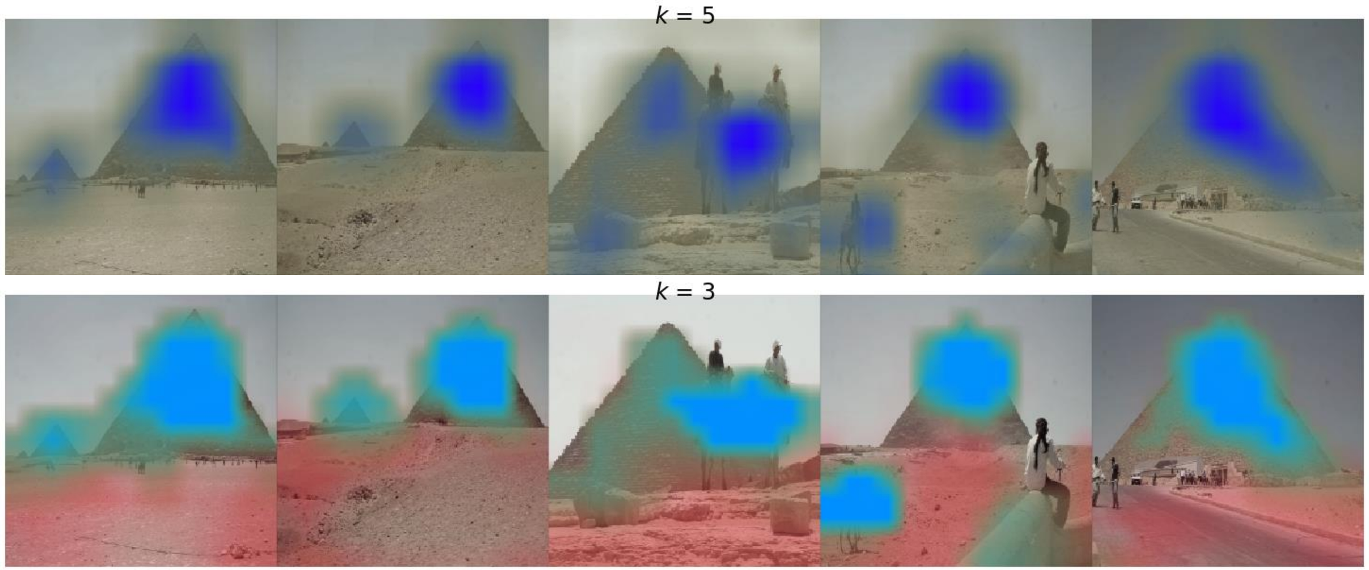
- 이전 보다 다양한 features들이 확인됨.



Result & Analysis

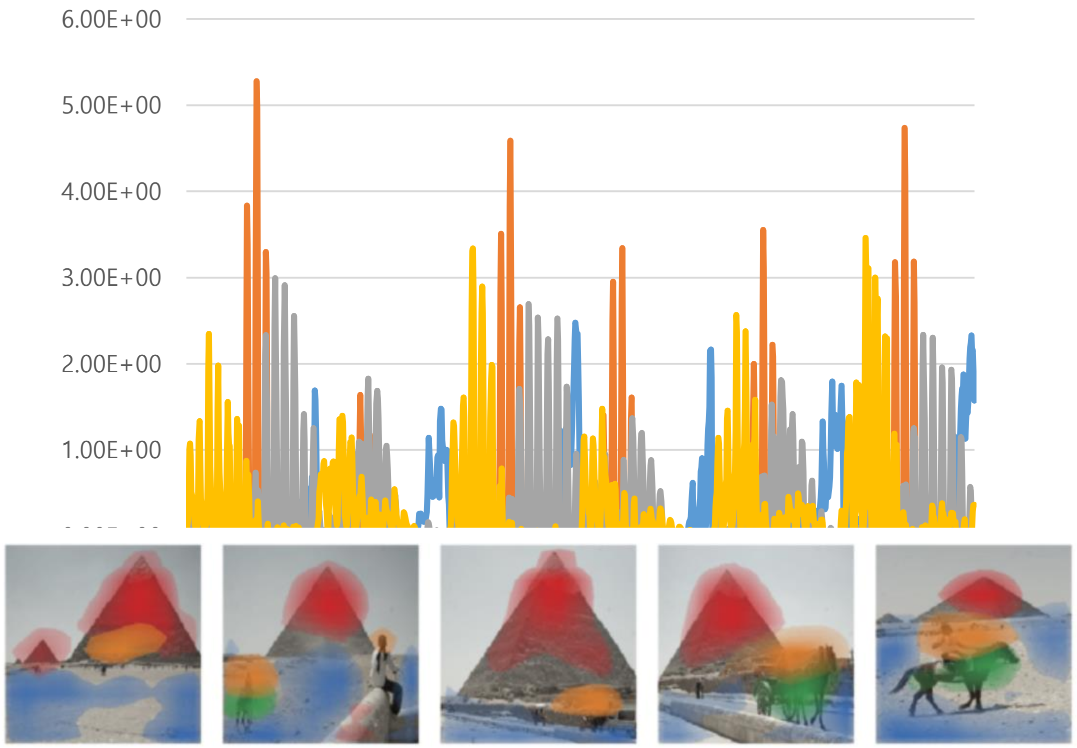
Experiment 4

- 다른 이미지에서도 5개의 차원이 있지만, 한가지의 색(feature)로만 표현 됨.

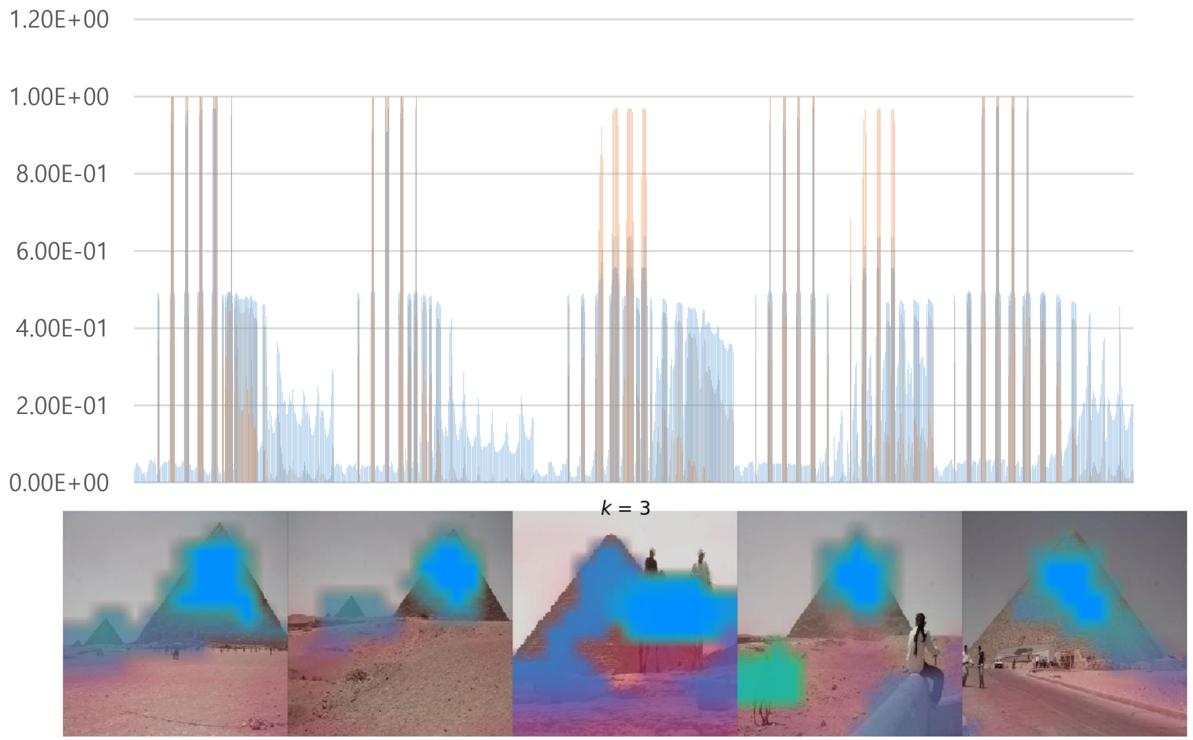


Result & Analysis

논문 (vgg19, NMF)에서의 차원 축소 결과

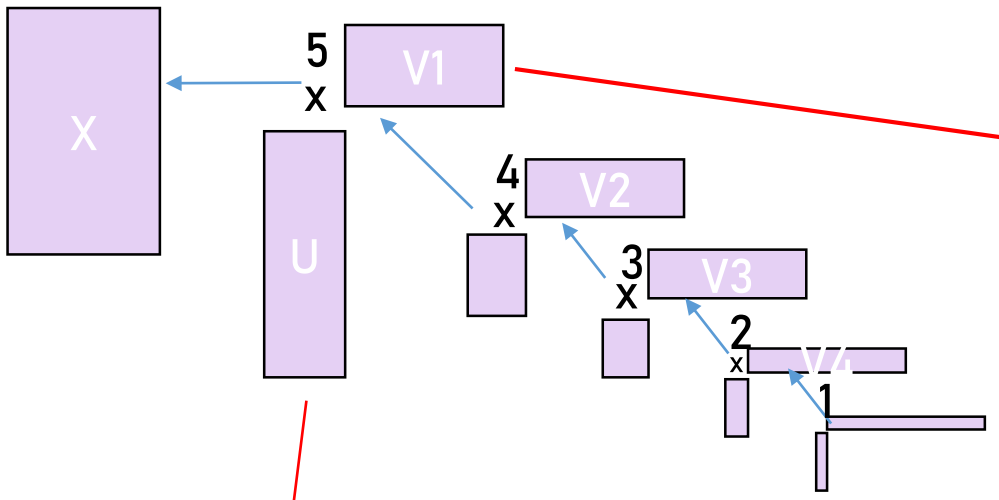


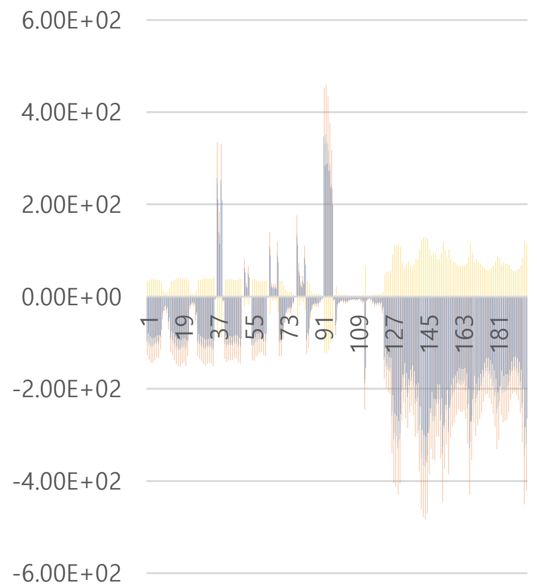
Vgg19, deep semi NMF에서의 차원 축소 결과

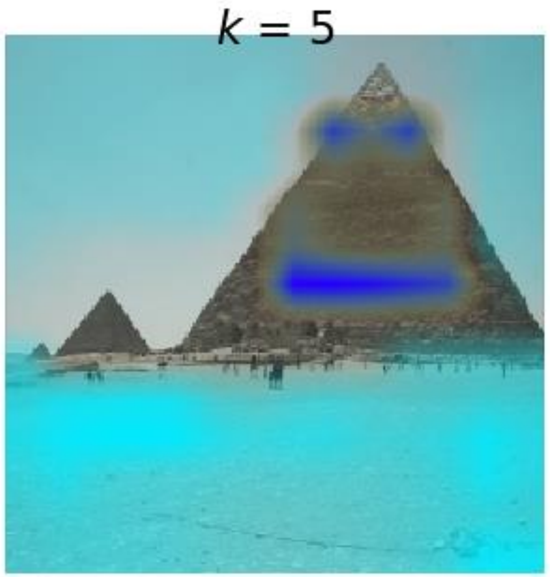


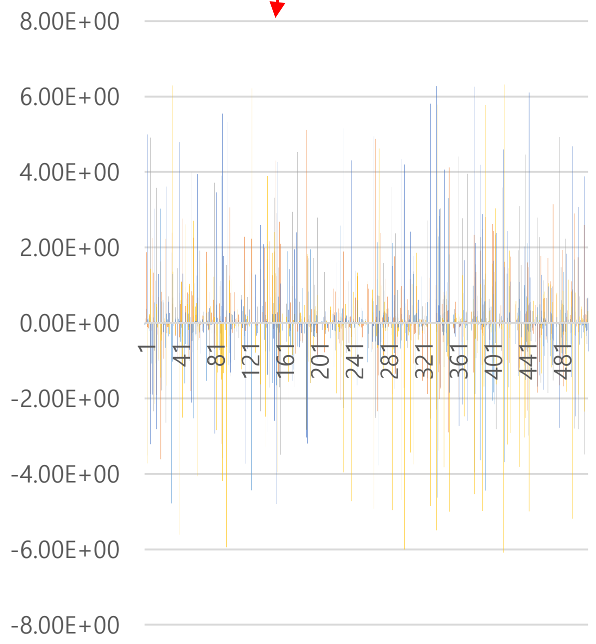
- 색(features) 마다 distribution에 차이가 크지 않아 heatmap에서 색이 겹쳐 표현됨.

Result & Analysis



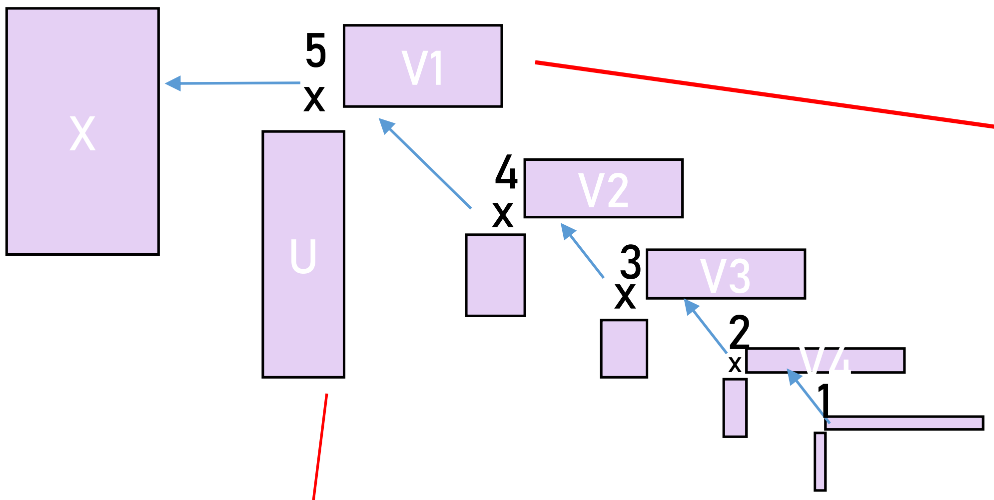


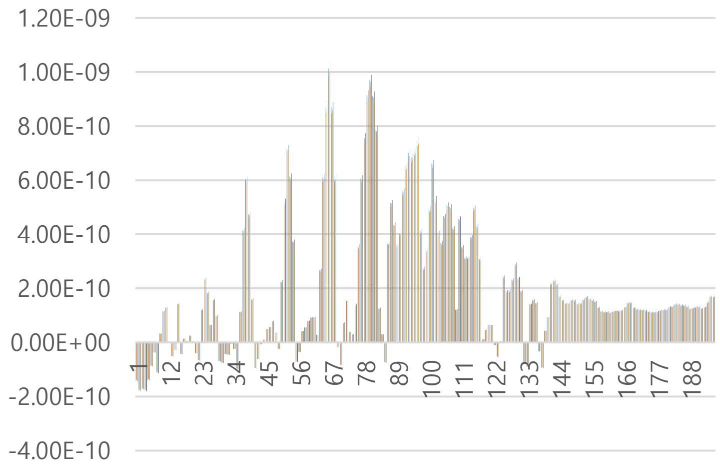


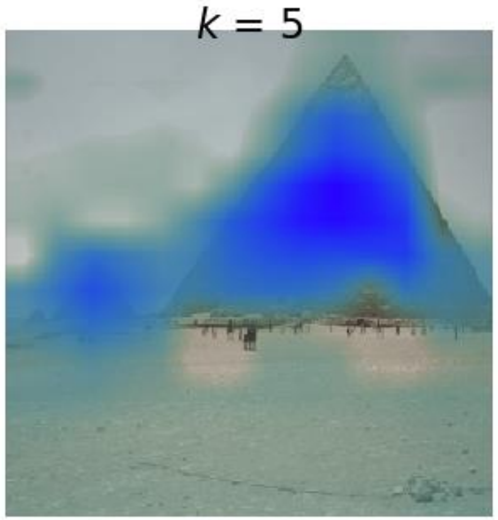


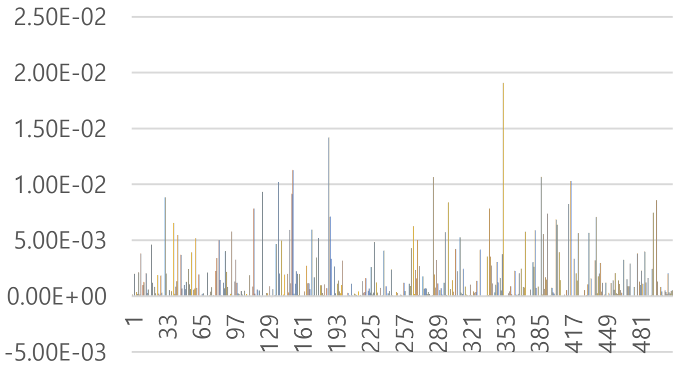
- 차원축소 된 U와 V1의 분포를 확인 한 결과,
U X V1 -> X 로 reconstruct하기 위해 U만 집중 적으로 학습하는 것을 관찰함.
(U의 feature에 대한 분포를 다양하게 함)

Result & Analysis





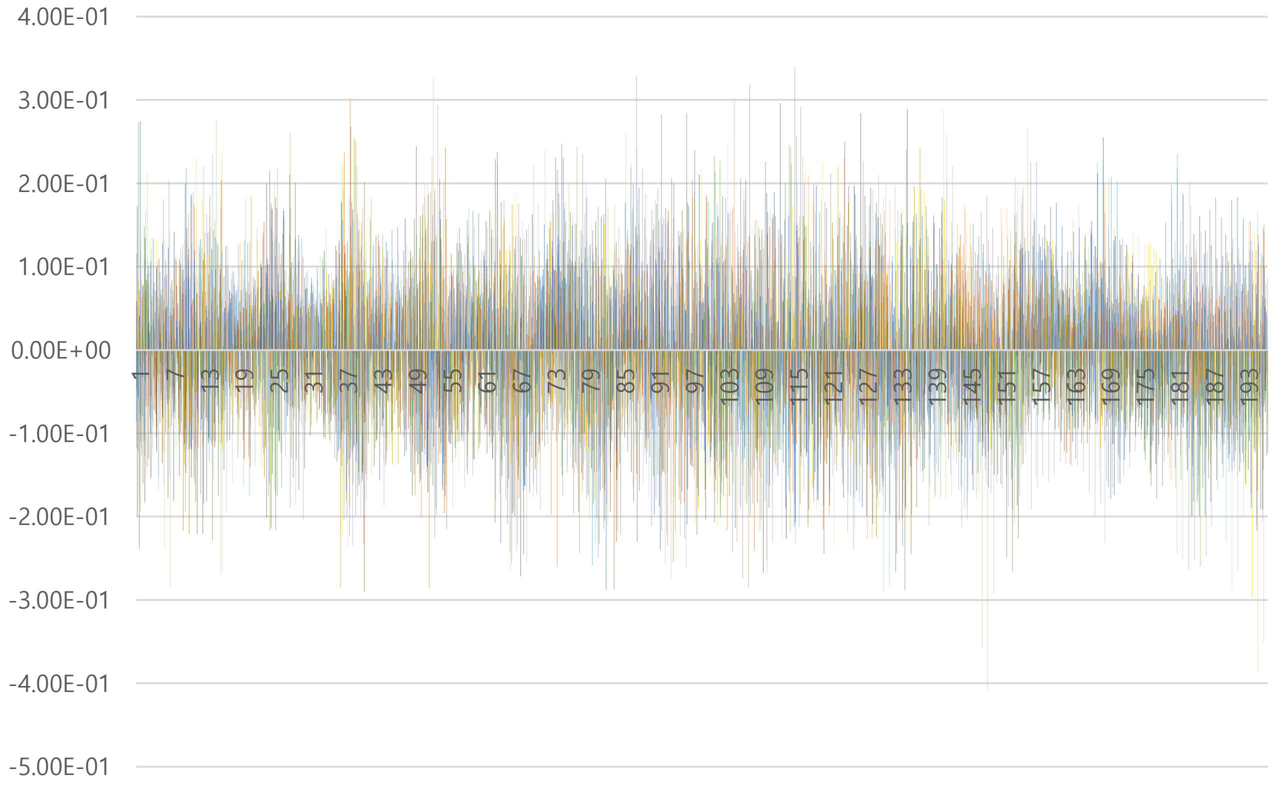




- U에 대한 L2 norm weight을 주어서 U만 학습되는 것을 방지하였지만, 결과는 크게 다르지 않았음.

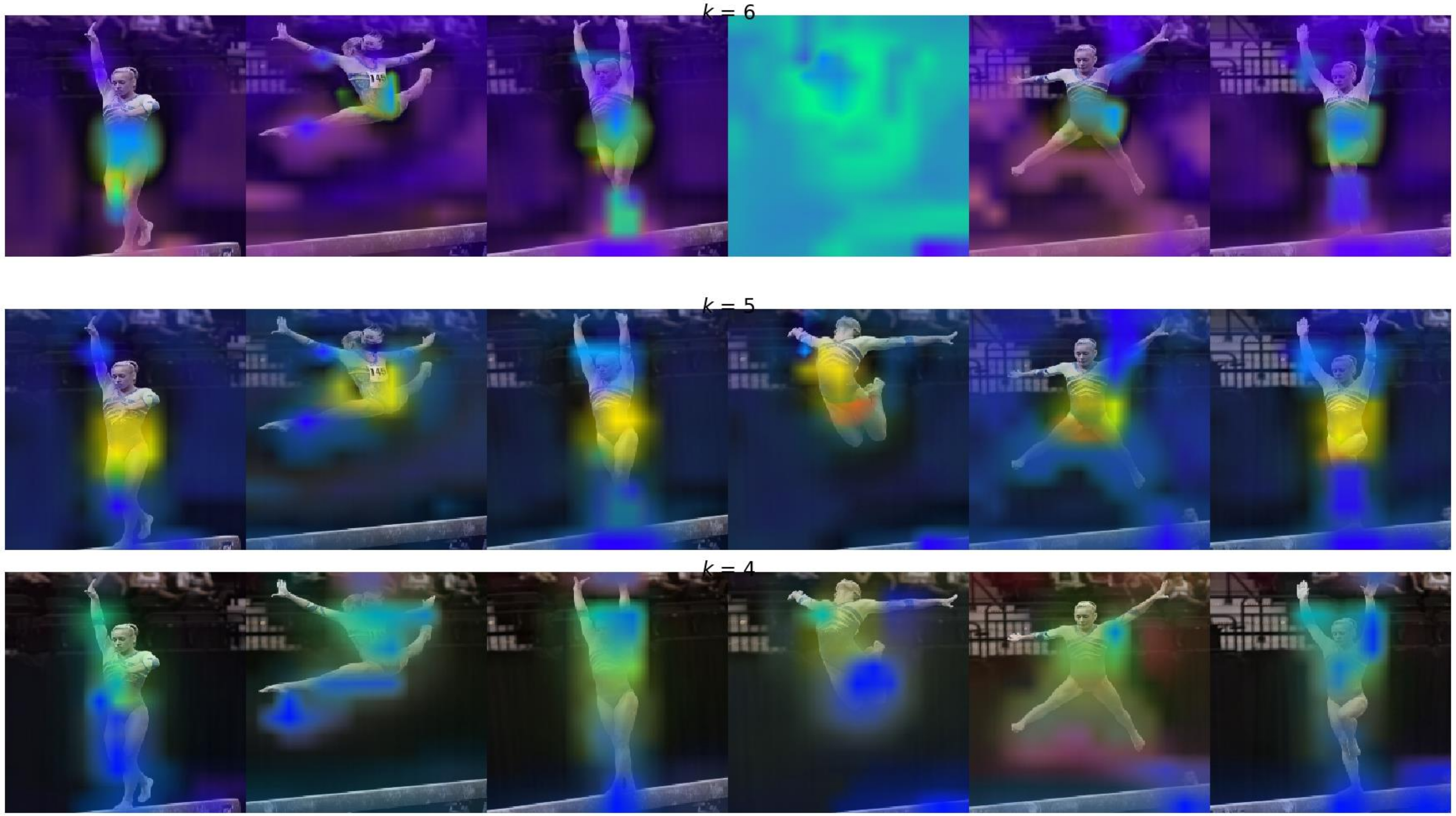
Result & Analysis

- 색(features) 별 분포 차이가 크지 않는 문제의 원인을 찾기 위해 여러시도를 해 봄
- 차원을 작은 수가 아닌 큰 수(59)로 줄이니 분포가 차이가 많이 남.



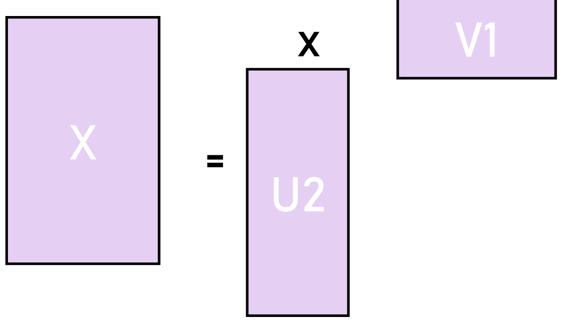
Result & Analysis

- Layer을 (5,4,3,2,1) 에서 (6,5,4)로 변경함.
- 분포 차이가 있지만, 논문 정도의 segmentation 성능은 나오지 않음.

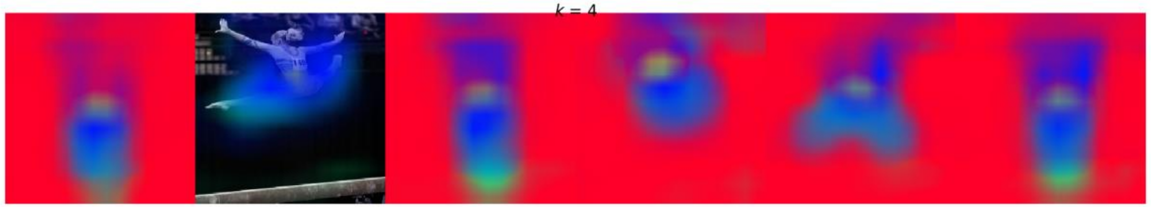


Result & Analysis

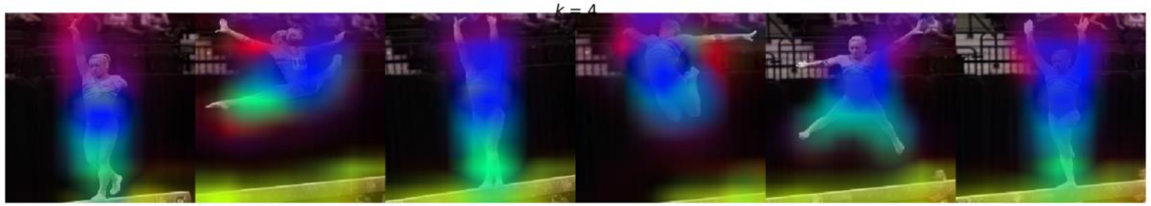
- 레이어가 1개인 모델로 돌아가 여러 시도를 해봄.
- (+) : 학습 할때 variable이 양수 값만 가지도록 constraint를 줌.
- 조건을 변경해가며 결과를 확인함.



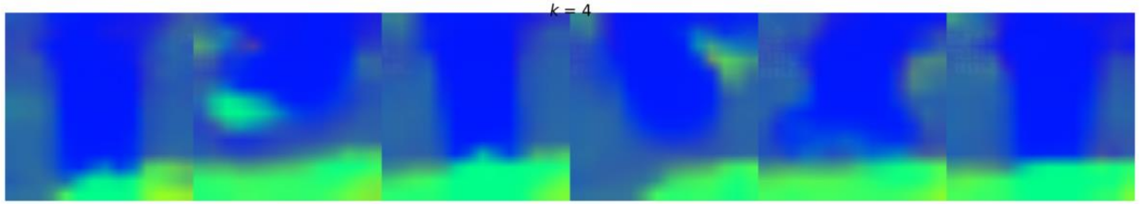
U2, V1



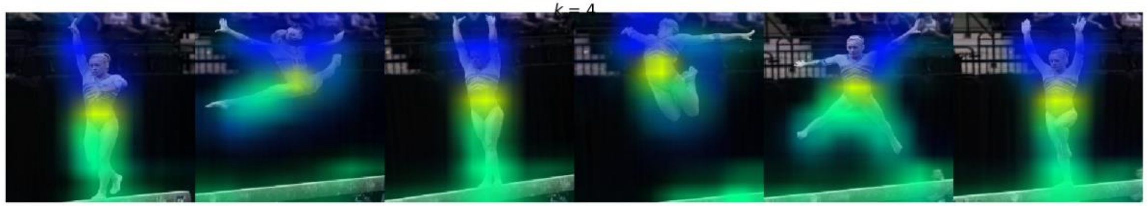
U2, sigmoid(V1)
Result : None



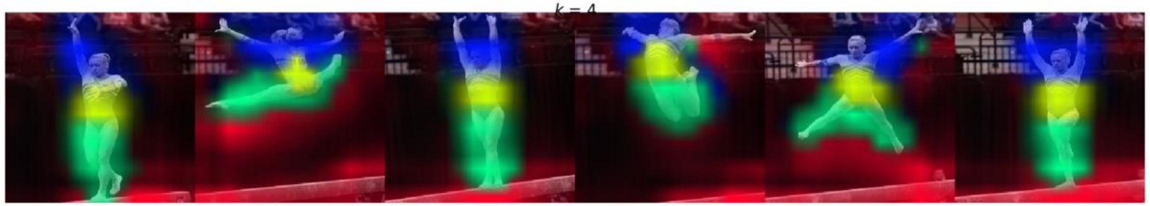
U2, sigmoid(V1)
Result : with sigmoid



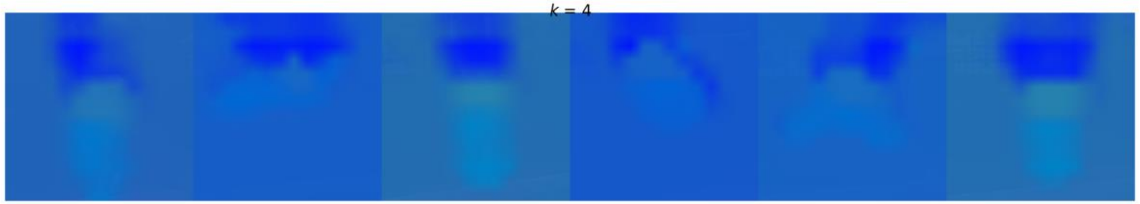
U2(+), V1(+)



U2(+), sigmoid(V1(+))
Result : None

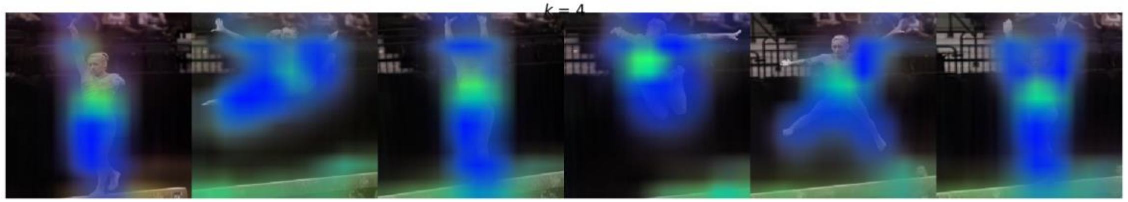


U2(+), sigmoid(V1(+))
Result : with sigmoid

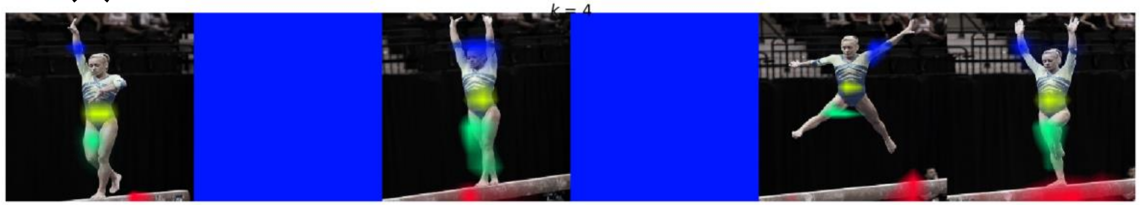


Result & Analysis

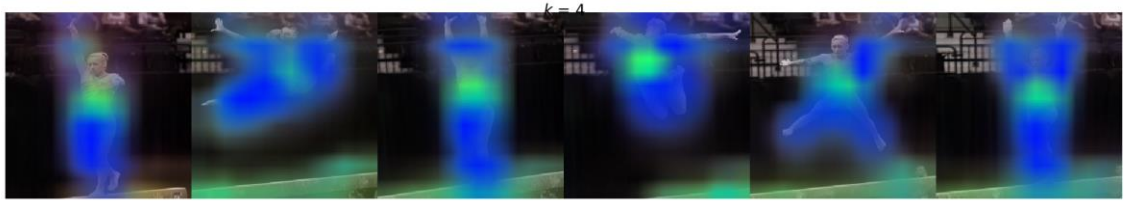
U2, V1(+)



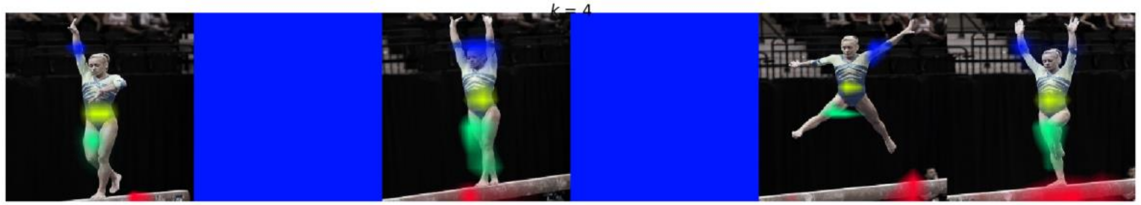
U2(+), V1



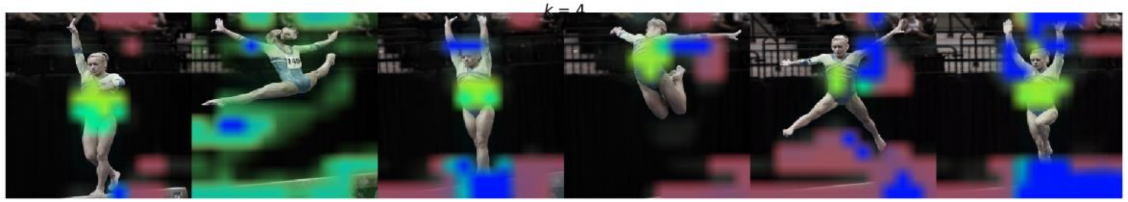
U2, sigmoid(V1(+))
Result : None



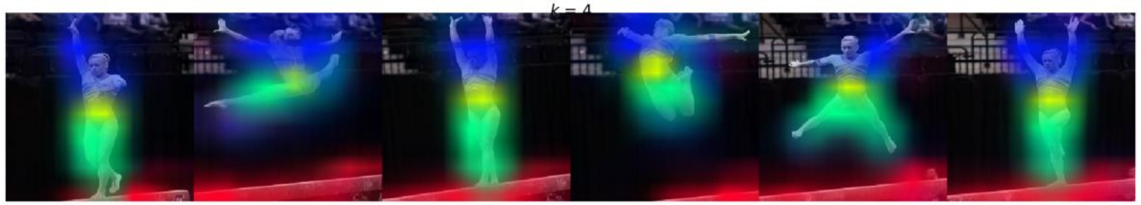
U2(+), sigmoid(V1)
Result : None



U2, sigmoid(V1(+))
Result : with sigmoid



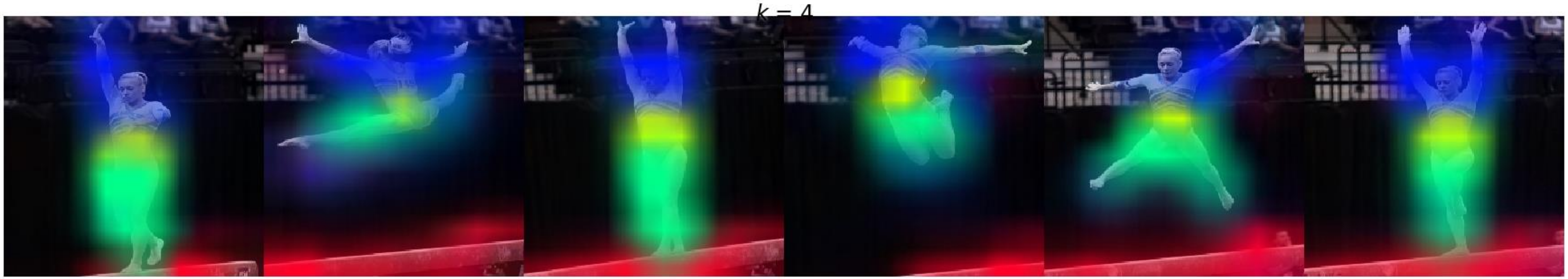
U2(+), sigmoid(V1)
Result : with sigmoid



이 조건에서 가장 segmentation이 잘 되었음.

Result & Analysis

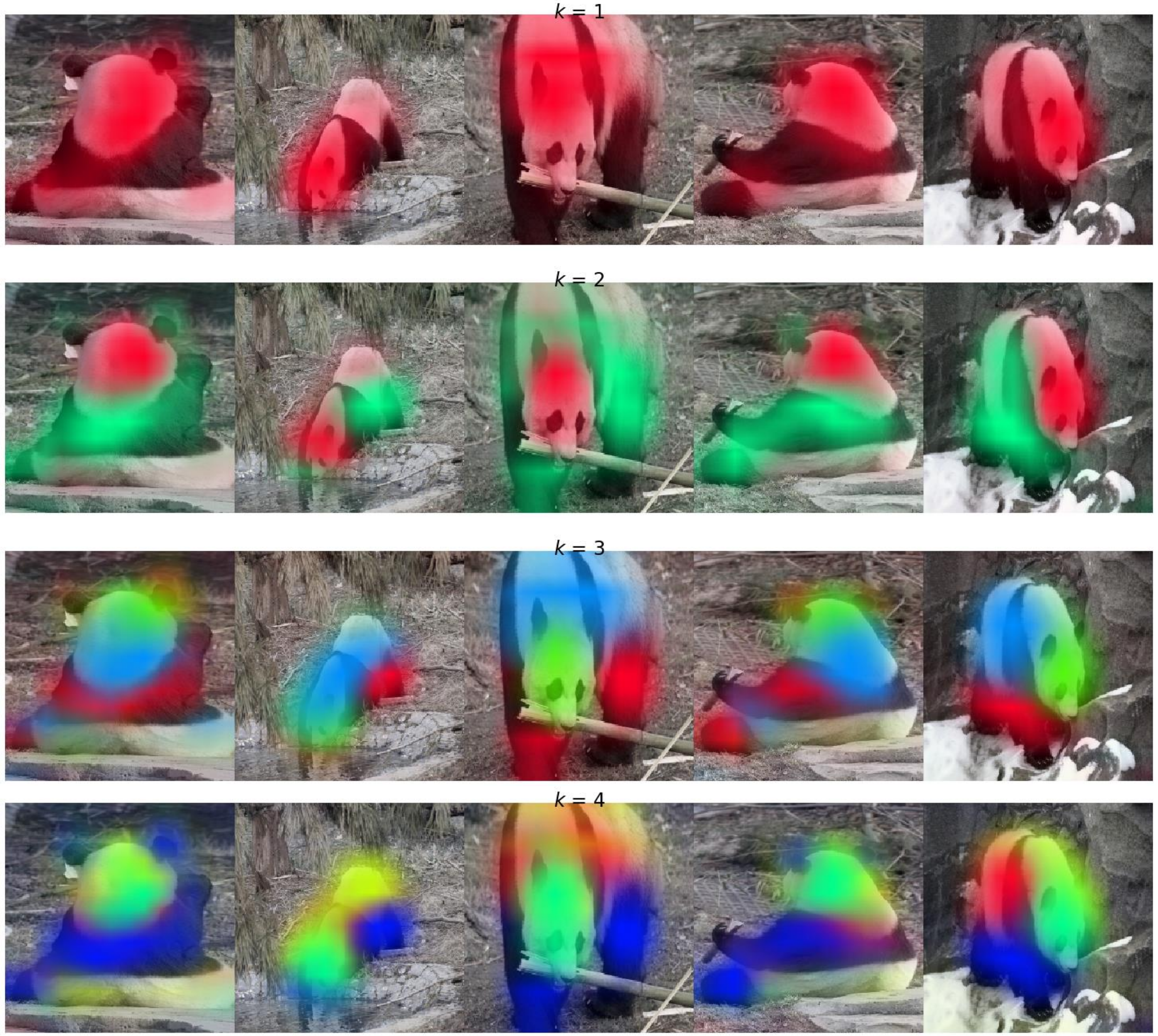
U2(+), sigmoid(V1)
Result sigmoid   mIoU : 0.654652239208446



Baseline   mIoU : 0.649336232593925

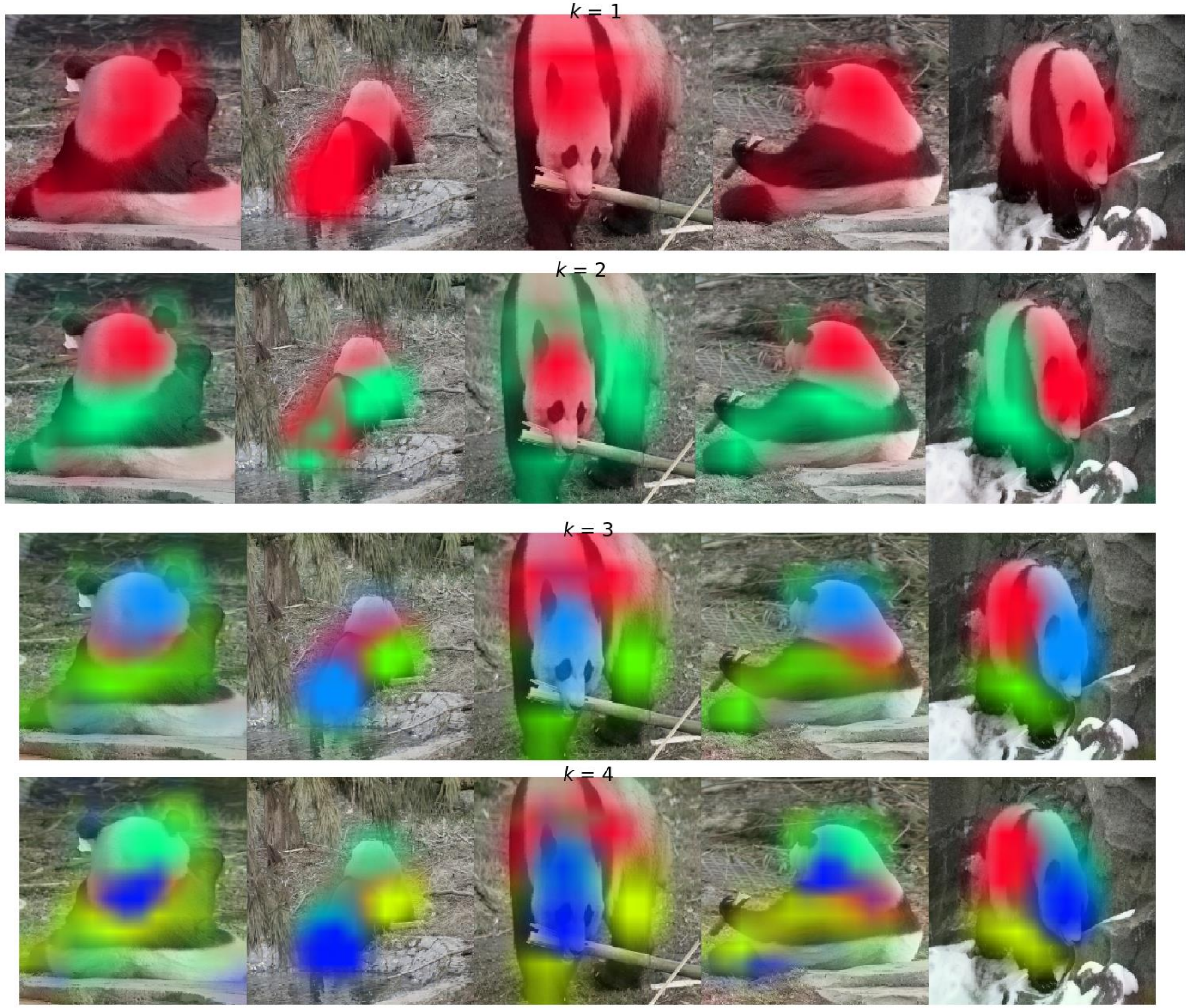
Baseline figure

Baseline



mIoU : 0.5656613257346442

U2(+), sigmoid(V1)
Result sigmoid



mIoU : 0.5764818387798333

Conclusion

Summarize
- Deep layer을 가진 차원 축소 모델을 사용하여, 레이어 마다 차원축소 결과를 확인 하고자 함. 하지만, deep한 경우 차원이 너무 작으면 색상(features)별 분포 차이가 크지 않았다.
- Baseline의 MF part는 NMF (Lee and Seung ,1999)의 multiplicative update algorithm을 사용함.
  이 프로젝트에서 구현한 모델에서는 non-linear activation functio과 non-negative constraints을 주었으며, Adam 으로 학습하였다.
- Baseline 보다 mIoU 결과가 약간 증가 하였음.

논문 open source
- pytorch
- pre-trained model(vgg19) + NMF + heatmap visualization

mIoU calculate (open source)

My code (tensorflow)
1 layer NMF include activation function
Deep semi NMF or Deep NMF