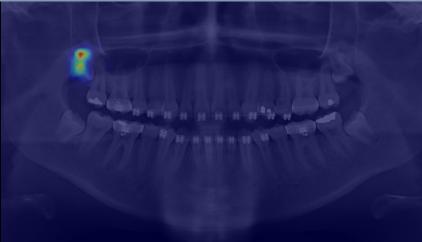
Leveraging CAM Algorithms for Explaining Medical Semantic Segmentation

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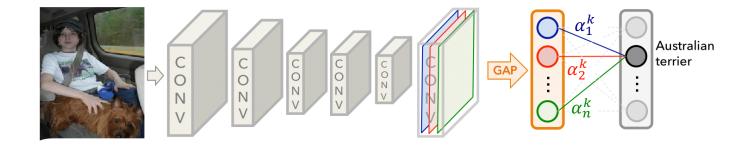


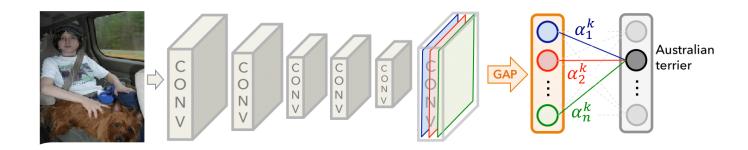




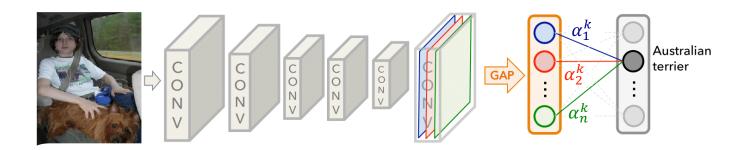








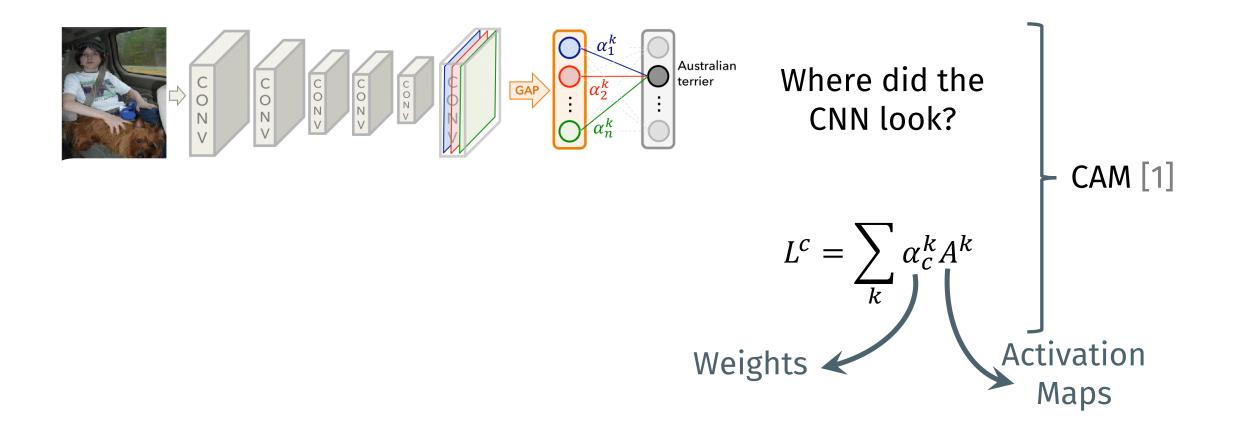
Where did the CNN look?

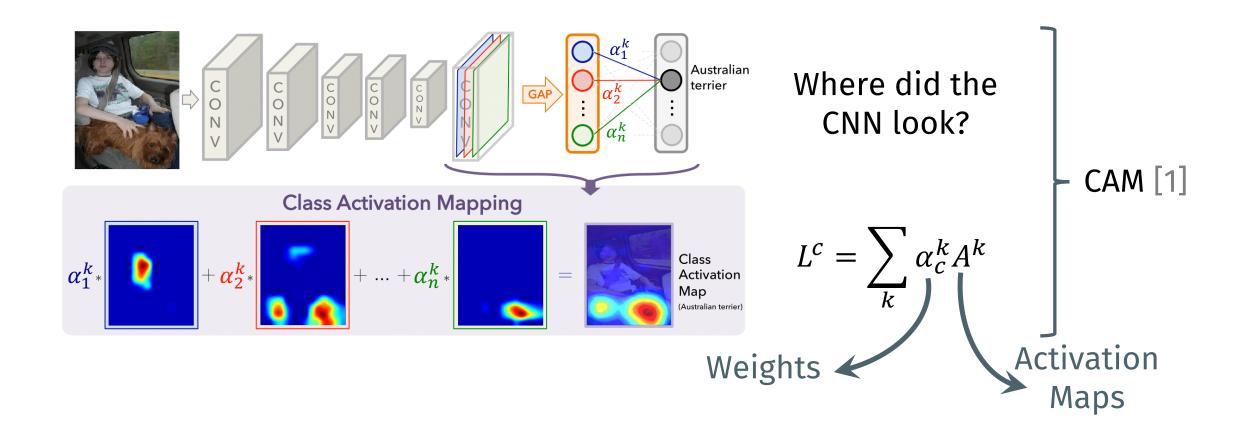


Where did the CNN look?

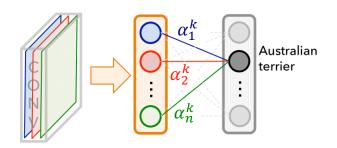
$$L^c = \sum_k \alpha_c^k A^k$$

CAM [1]





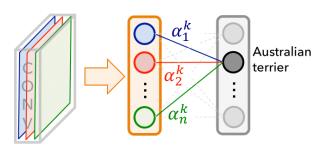
HiRes / Grad CAM - Extensions to CAM



$$\alpha_c^k = weights$$

$$L_{CAM}^{c} = \sum_{k} \alpha_{c}^{k} A^{k}$$
 CAM [1]

HiRes / Grad CAM - Extensions to CAM



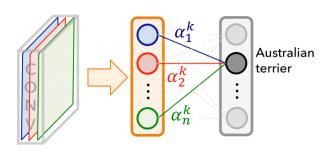
$$\alpha_c^k = weights$$

$$L_{CAM}^{c} = \sum_{k} \alpha_{c}^{k} A^{k}$$
 CAM [1]

$$\alpha_c^k = \frac{1}{N} \sum_{u,v} \frac{\partial y^c}{\partial A_{uv}^k}$$

Australian terrier
$$\alpha_c^k = \frac{1}{N} \sum_{u,v} \frac{\partial y^c}{\partial A_{uv}^k} \qquad L^c = ReLU\left(\sum_k \alpha_c^k A^k\right) - \text{Grad CAM [3]}$$

HiRes / Grad CAM – Extensions to CAM



$$\alpha_c^k = weights$$

$$L_{CAM}^{c} = \sum_{k} \alpha_{c}^{k} A^{k}$$
 CAM [1]

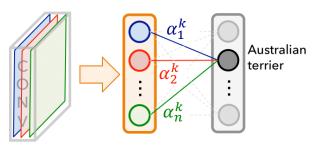
$$\alpha_c^k = \frac{1}{N} \sum_{u,v} \frac{\partial y^c}{\partial A_{uv}^k}$$

Australian terrier
$$\alpha_c^k = \frac{1}{N} \sum_{u,v} \frac{\partial y^c}{\partial A_{uv}^k} \qquad L^c = ReLU\left(\sum_k \alpha_c^k A^k\right) - \text{Grad CAM [3]}$$

$$\alpha_c^k = \sum_{u,v} \frac{\partial y^c}{\partial A_{uv}^k}$$

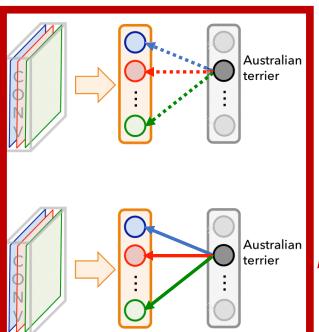
Australian terrier
$$\alpha_c^k = \sum_{u,v} \frac{\partial y^c}{\partial A_{uv}^k} \qquad L^c = ReLU\left(\sum_k \alpha_c^k A^k\right) - \text{HiRes CAM [4]}$$

HiRes / Grad CAM – Extensions to CAM



$$\alpha_c^k = weights$$

$$L_{CAM}^{c} = \sum_{k} \alpha_{c}^{k} A^{k}$$
 CAM [1]



$$\alpha_c^k = \frac{1}{N} \sum_{u,v} \frac{\partial y^c}{\partial A_{uv}^k}$$

Australian terrier
$$\alpha_c^k = \frac{1}{N} \sum_{u,v} \frac{\partial y^c}{\partial A_{uv}^k} \qquad L^c = ReLU\left(\sum_k \alpha_c^k A^k\right)$$
 Fix inaccuracies

$$\alpha_c^k = \sum_{u,v} \frac{\partial y^c}{\partial A_{uv}^k}$$

Australian terrier
$$\alpha_c^k = \sum_{u,v} \frac{\partial y^c}{\partial A_{uv}^k} \qquad L^c = ReLU\left(\sum_k \alpha_c^k A^k\right) \quad \text{HiRes CAM [4]}$$

Overview - CAMs for Classification Tasks

Classification

CAM [1]

Grad CAM [3]

Grad CAM++ [9]

XGrad CAM [10]

•••

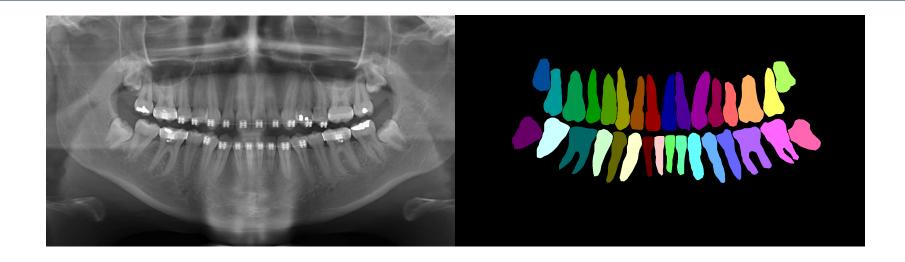
Eigen CAM [11]

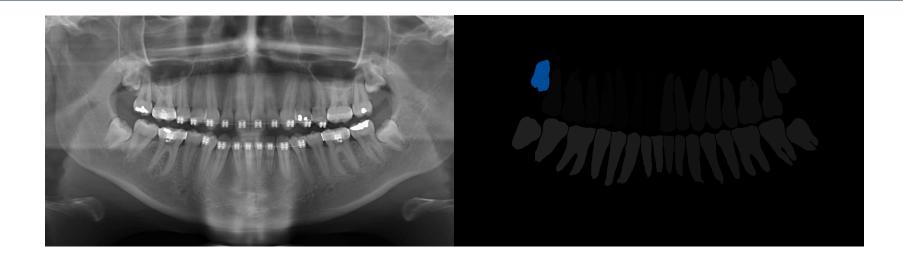
Layer CAM [12]

HiRes CAM [4]

Classification	Segmentation
CAM [1]	n/a
Grad CAM [3]	Seg-Grad CAM [2]
Grad CAM++ [9]	n/a
XGrad CAM [10]	n/a
•••	•••
Eigen CAM [11]	n/a
Layer CAM [12]	n/a
HiRes CAM [4]	n/a

Segmentation
n/a
Seg-Grad CAM [2]
n/a
n/a
•••
n/a
n/a
n/a



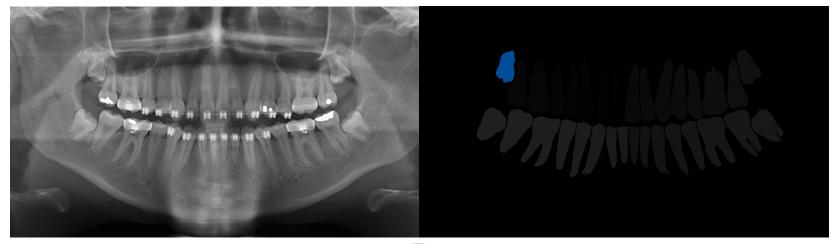


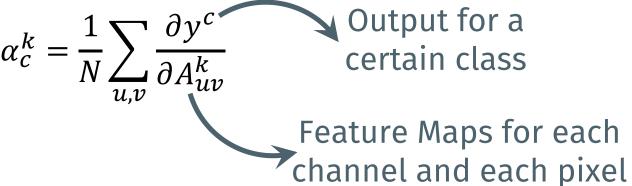


$$\alpha_c^k = \frac{1}{N} \sum_{u,v} \frac{\partial y^c}{\partial A_{uv}^k}$$



$$\alpha_c^k = \frac{1}{N} \sum_{uv} \frac{\partial y^c}{\partial A_{uv}^k}$$
 Output for a certain class







 $\alpha_c^k = \frac{1}{N} \sum_{u,v} \frac{\partial y^c}{\partial A_{uv}^k}$

Number of Pixels

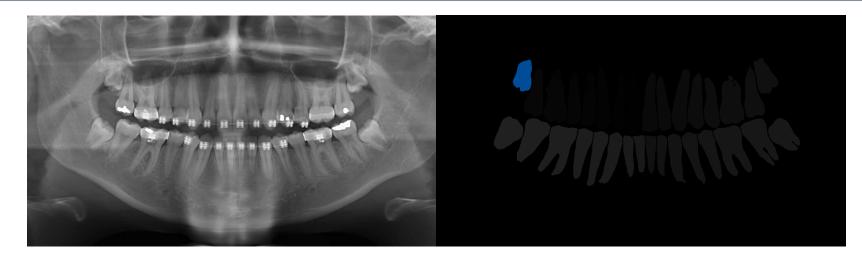
Output for a certain class

Feature Maps for each channel and each pixel



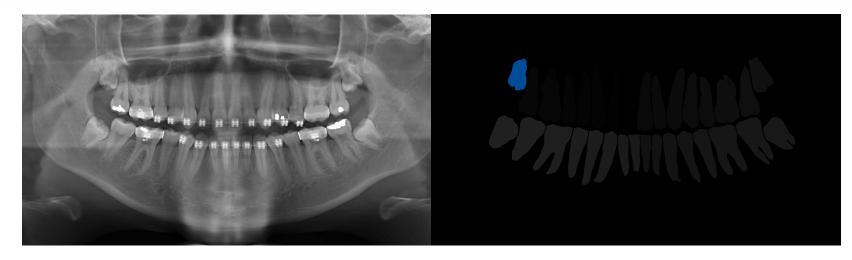
$$\alpha_c^k = \frac{1}{N} \sum_{u,v} \frac{\partial y^c}{\partial A_{uv}^k}$$

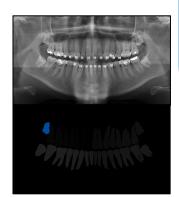
$$y^{c,new} = \sum_{i,j \in \mathcal{M}} y_{i,j}^c$$



$$\alpha_c^k = \frac{1}{N} \sum_{u,v} \frac{\partial y^c}{\partial A_{uv}^k}$$

$$y^{c,new} = \sum_{i,j \in \mathcal{M}} y^{c}_{i,j}$$
Set of Pixel Indices

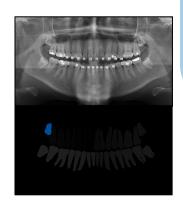




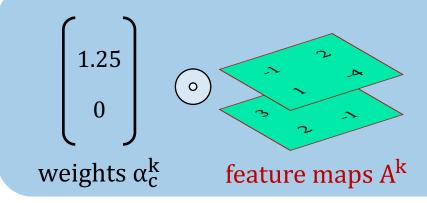
Input and Pixelset \mathcal{M}

$$\begin{bmatrix} 1.25 \\ 0 \end{bmatrix}$$
 weights α_c^k

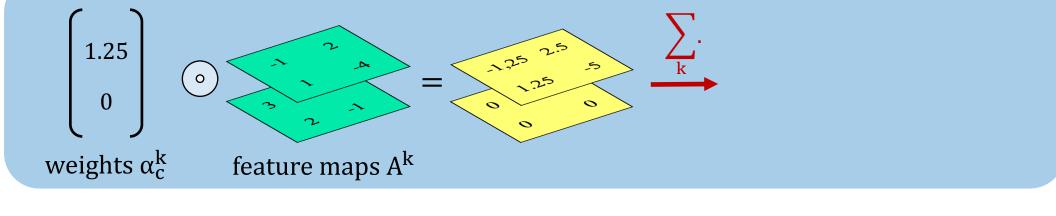
$$L^{c} = ReLU\left(\sum_{k} \alpha_{c}^{k} A^{k}\right)$$

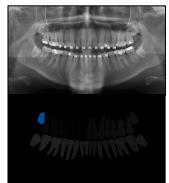


Input and Pixelset \mathcal{M}



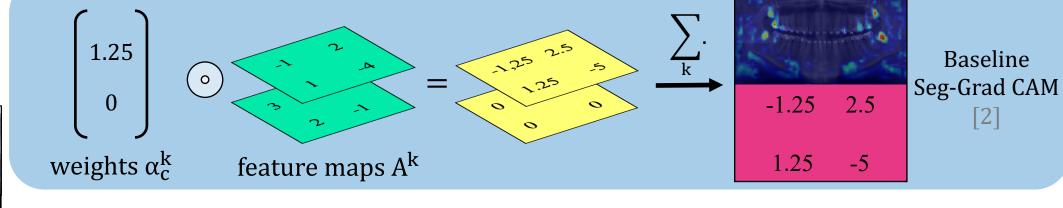
$$L^{c} = ReLU\left(\sum_{k} \alpha_{c}^{k} A^{k}\right)$$

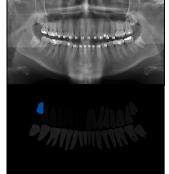




Input and Pixelset \mathcal{M}

$$L^{c} = ReLU\left(\sum_{k} \alpha_{c}^{k} A^{k}\right)$$





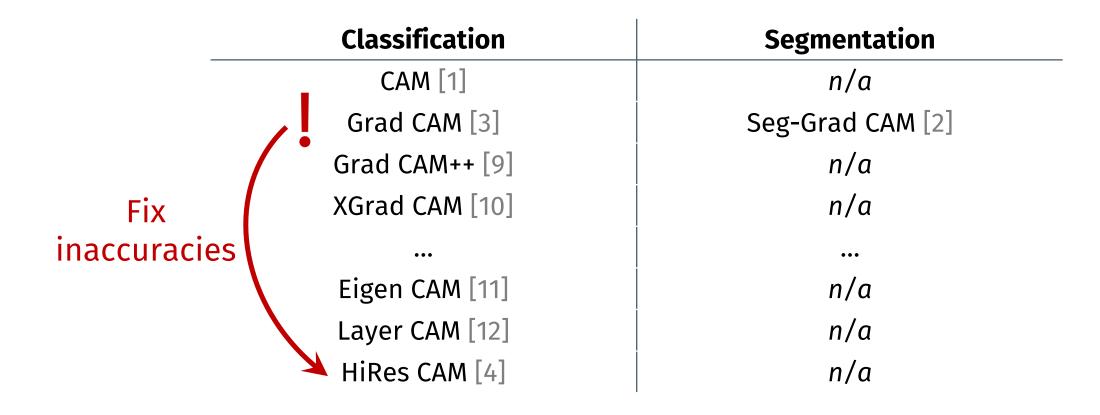
Input and Pixelset \mathcal{M}

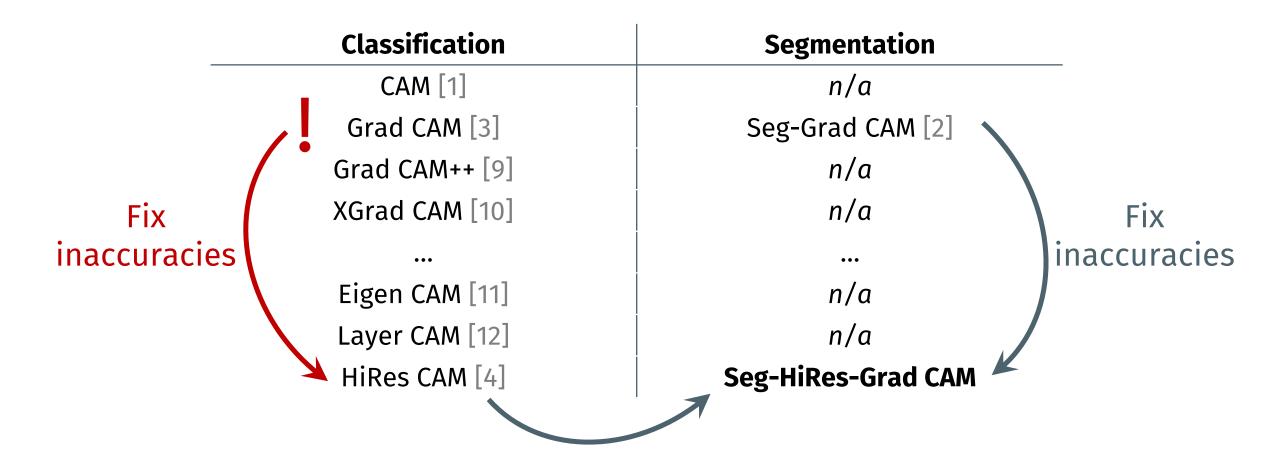
$$L^{c} = ReLU\left(\sum_{k} \alpha_{c}^{k} A^{k}\right)$$

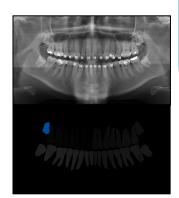
* ReLU not visualized to ensure a better comparability later on

Classification	Segmentation
CAM [1]	n/a
Grad CAM [3]	Seg-Grad CAM [2]
Grad CAM++ [9]	n/a
XGrad CAM [10]	n/a
•••	•••
Eigen CAM [11]	n/a
Layer CAM [12]	n/a
HiRes CAM [4]	n/a

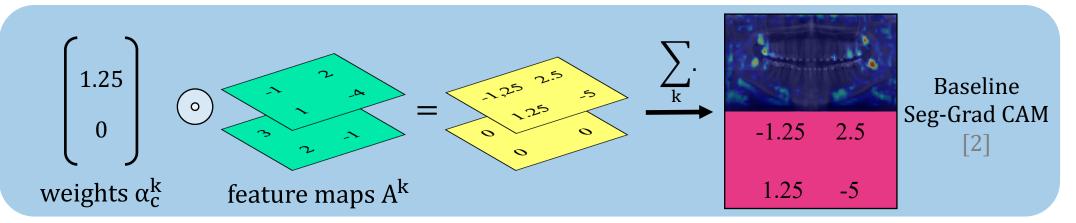
Classification	Segmentation
CAM [1]	n/a
Grad CAM [3]	Seg-Grad CAM [2]
Grad CAM++ [9]	n/a
XGrad CAM [10]	n/a
•••	•••
Eigen CAM [11]	n/a
Layer CAM [12]	n/a
HiRes CAM [4]	n/a







Input and Pixelset \mathcal{M}

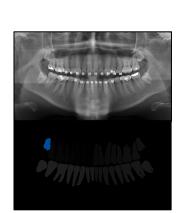


$$\alpha_c^k = \frac{1}{N} \sum_{u,v} \frac{\partial y^c}{\partial A_{uv}^k}$$

$$c,new = \sum_{i,j \in \mathcal{M}} y_{i,j}^c$$

$$\alpha_c^k = \frac{1}{N} \sum_{u,v} \frac{\sum_{i,j \in \mathcal{M}} y_{i,j}^c}{\partial A_{uv}^k}$$

* ReLU not visualized to ensure a better comparability later on



Input and Pixelset
$$\mathcal{M}$$

$$\alpha_c^k = \frac{1}{N} \sum_{u,v} \frac{\partial y^c}{\partial A_{uv}^k}$$

$$y^{c,new} = \sum_{i,j \in \mathcal{M}} y_{i,j}^c$$

$$\alpha_c^k = \frac{\sum_{i,j \in \mathcal{M}} y_{i,j}^c}{\partial A^k}$$



Input and Pixelset
$$\mathcal{M}$$

$$\alpha_c^k = \frac{1}{N} \sum_{u,v} \frac{\partial y^c}{\partial A_{vv}^k}$$

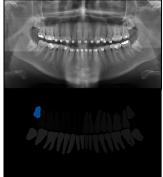
$$\alpha_c^k = \sum_{i,j \in \mathcal{M}} y_{i,j}^c$$

$$\alpha_c^k = \frac{1}{N} \sum_{u,v} \frac{\partial y^c}{\partial A_{vv}^k}$$

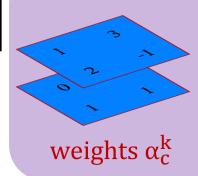
$$\alpha_c^k = \frac{1}{N} \sum_{u,v} \frac{\partial y^c}{\partial A_{vv}^k}$$

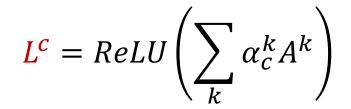
$$y^{c,new} = \sum_{i,j \in \mathcal{M}} y_{i,j}^c$$

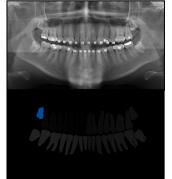
$$\alpha_c^k = \frac{\sum_{i,j \in \mathcal{M}} y_{i,j}^c}{\partial A^k}$$



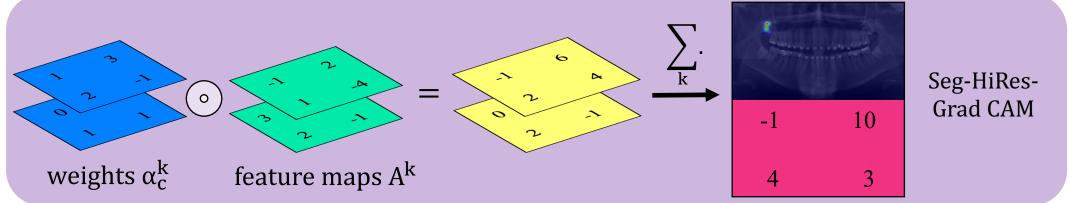
Input and Pixelset \mathcal{M}



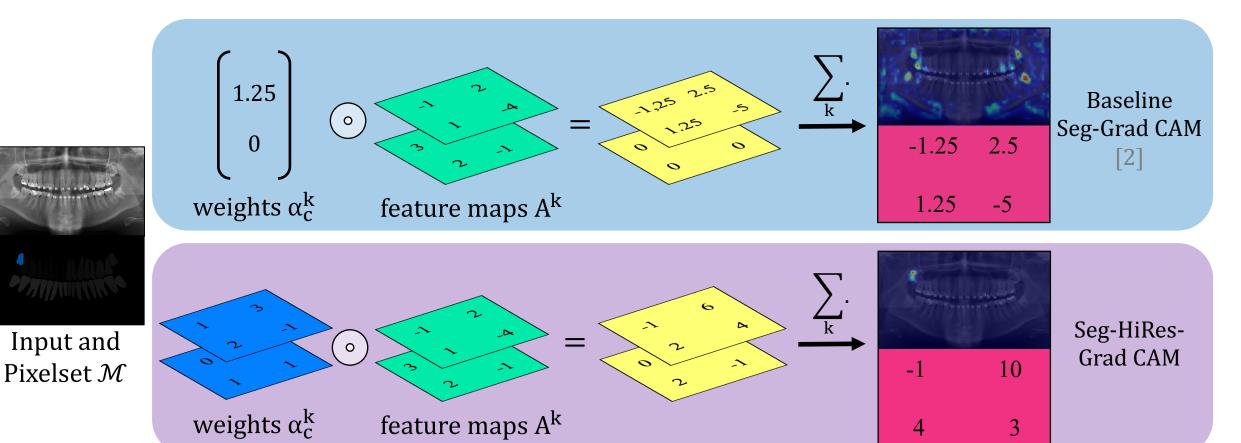




Input and Pixelset \mathcal{M}



* ReLU not visualized to ensure a better comparability later on

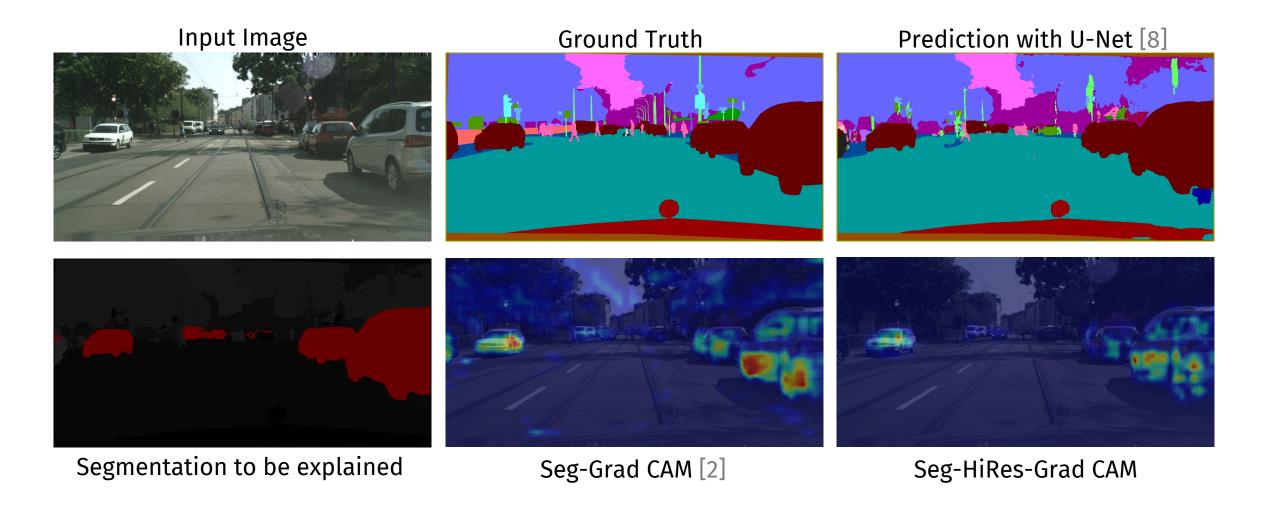


* ReLU not visualized to ensure a better comparability

Examples with OPG [5]

Input Image **Ground Truth** Prediction with U-Net [8] Segmentation to be explained Seg-Grad CAM [2] Seg-HiRes-Grad CAM

Examples with Cityscapes [6]



- Examples which are not explainable at all
- o Dimensions of feature map must be large enough

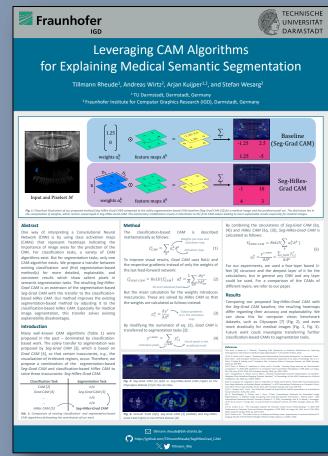
- Examples which are not explainable at all
- o Dimensions of feature map must be large enough
- Future Work could include ...
 - ... different CNNs
 - ... 3D segmentation tasks
 - ... transfer to further classification-based CAM methods

- Examples which are not explainable at all
- Dimensions of feature map must be large enough
- Future Work could include ...
 - ... different CNNs
 - ... 3D segmentation tasks
 - ... transfer to further classification-based CAM methods
- Seg-HiRes-Grad CAM can lift the SOTA of classification-based CAM methods to segmentation tasks

Thank you for your attention!

Feel free to ask questions & to stop by at the poster sessions!













References I

- [1] B. Zhou, A. Khosla, À. Lapedriza, A. Oliva, and A. Torralba, "Learning Deep Features for Discriminative Localization," in 2016 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2016, Las Vegas, NV, USA, June 27-30, 2016, IEEE Computer Society, 2016, pp. 2921–2929.
- [2] K. Vinogradova, A. Dibrov, and G. Myers, "Towards Interpretable Semantic Segmentation via Gradient-Weighted Class Activation Mapping (Student Abstract)," in Proceedings of the AAAI Conference on Artificial Intelligence, Apr. 2020, pp. 13943–13944.
- [3] R. R. Selvaraju, M. Cogswell, A. Das, R. Vedantam, D. Parikh, and D. Batra, "Grad-CAM: Visual Explanations from Deep Networks via Gradient-Based Localization," in IEEE International Conference on Computer Vision, ICCV 2017, Venice, Italy, October 22-29, 2017, IEEE Computer Society, 2017, pp. 618–626.
- [4] R. L. Draelos and L. Carin, "Use HiResCAM instead of Grad-CAM for faithful explanations of convolutional neural networks," ArXiv, Nov. 2021.
- [5] G. Jader, J. Fontineli, M. Ruiz, K. Abdalla, M. Pithon, and L. Oliveira, "Deep Instance Segmentation of Teeth in Panoramic X-Ray Images," in 31st SIBGRAPI Conference on Graphics, Patterns and Images, SIBGRAPI 2018, Paraná, Brazil, October 29 Nov. 1, 2018, IEEE Computer Society, 2018, pp. 400–407.
- [6] M. Cordts et al., "The Cityscapes Dataset for Semantic Urban Scene Understanding," in 2016 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2016, Las Vegas, NV, USA, June 27-30, 2016, IEEE Computer Society, 2016, pp. 3213–3223.
- [7] N. Heller et al., "The state of the art in kidney and kidney tumor segmentation in contrast-enhanced CT imaging: Results of the KiTS19 Challenge," Medical Image Analysis, p. 101821, 2020.

References II

[8] O. Ronneberger, P. Fischer, and T. Brox, "U-Net: Convolutional Networks for Biomedical Image Segmentation," in Medical Image Computing and Computer-Assisted Intervention - MICCAI 2015 - 18th International Conference Munich, Germany, October 5 - 9, 2015, Proceedings, Part III, N. Navab, J. Hornegger, W. M. W. III, and A. F. Frangi, Eds., in Lecture Notes in Computer Science, vol. 9351. Springer, 2015, pp. 234–241.

[9] A. Chattopadhay, A. Sarkar, P. Howlader, and V. N. Balasubramanian, "Grad-CAM++: Generalized Gradient-Based Visual Explanations for Deep Convolutional Networks," in 2018 IEEE Winter Conference on Applications of Computer Vision (WACV), 2018, pp. 839–847. doi: 10.1109/WACV.2018.00097.

[10] R. Fu, Q. Hu, X. Dong, Y. Guo, Y. Gao, and B. Li, "Axiom-based Grad-CAM: Towards Accurate Visualization and Explanation of CNNs," in 31st British Machine Vision Conference 2020, BMVC 2020, Virtual Event, UK, September 7-10, 2020, BMVA Press, 2020.

[11] M. B. Muhammad and M. Yeasin, "Eigen-CAM: Class Activation Map using Principal Components," in 2020 International Joint Conference on Neural Networks, IJCNN 2020, Glasgow, United Kingdom, July 19-24, 2020, IEEE, 2020, pp. 1–7.

[12] P.-T. Jiang, C.-B. Zhang, Q. Hou, M.-M. Cheng, and Y. Wei, "LayerCAM: Exploring Hierarchical Class Activation Maps for Localization," IEEE Trans. Image Process., vol. 30, pp. 5875–5888, 2021.

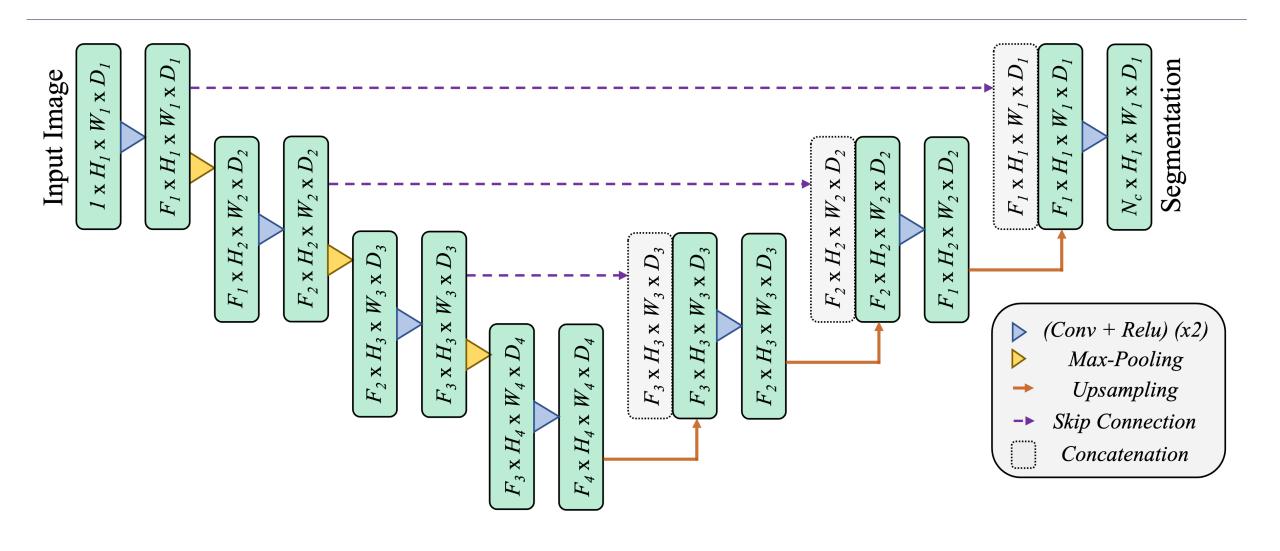
Backup Slides







U-Net



Examples with KITS23 [7]

