Probabilistic Modelling for Detecting Outliers in Medical Images

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Motivation

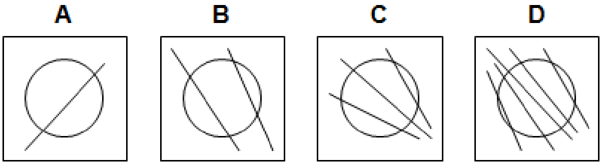


Image credit: http://www.graduatewings.co.uk & https://www.elementai.com

Quantifying Normality - Toy Example

Let's model the distribution of the height of people:

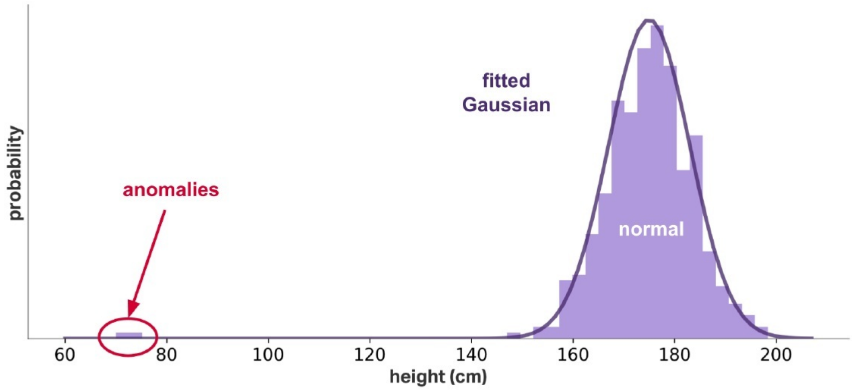
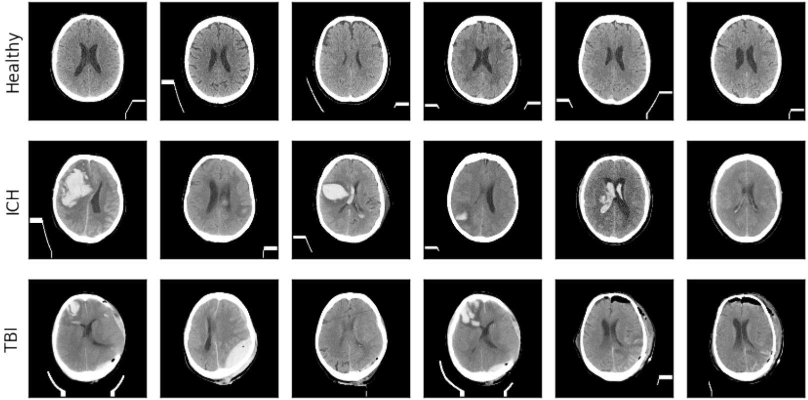


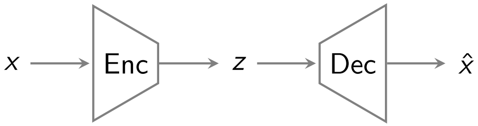
Image credit: https://www.elementai.com

Treating Lesion Detection as Outlier Detection



: Pawlowski, et al. MIDL 2018

Pixel-wise Outlier Detection

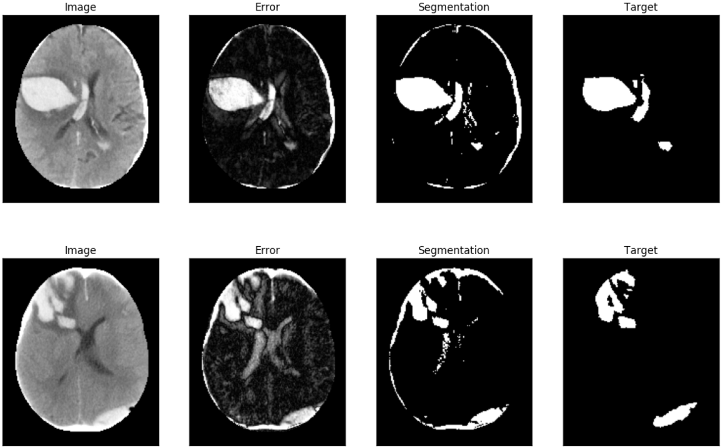


- Autoencoder learns about data distribution
- Latent code z of VAEs informs about probability of single instance

$\Rightarrow$ Pixelwise reconstruction error informs about probability of image region: $p(\mathrm{outlier}) \propto |x - \hat{x}|$

: Pawlowski, et al. MIDL 2018

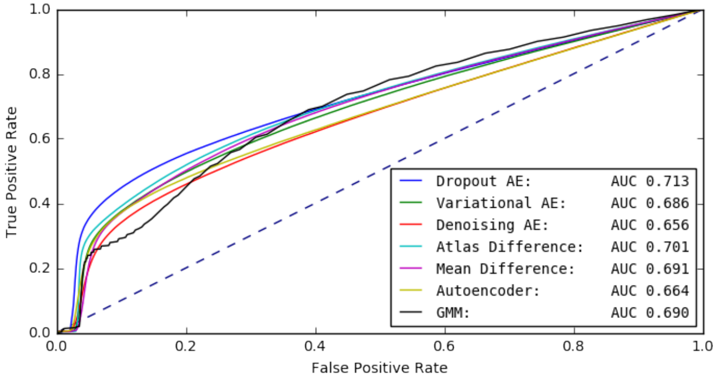
Segmenting Lesions



Possible segmentations by thresholding output of Dropout AE. Top: ICH, bottom: TBI

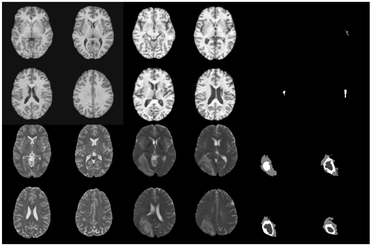
: Pawlowski, et al. MIDL 2018

Results - Intracranial Hemorrhages



: Pawlowski, et al. MIDL 2018

Application to MRI

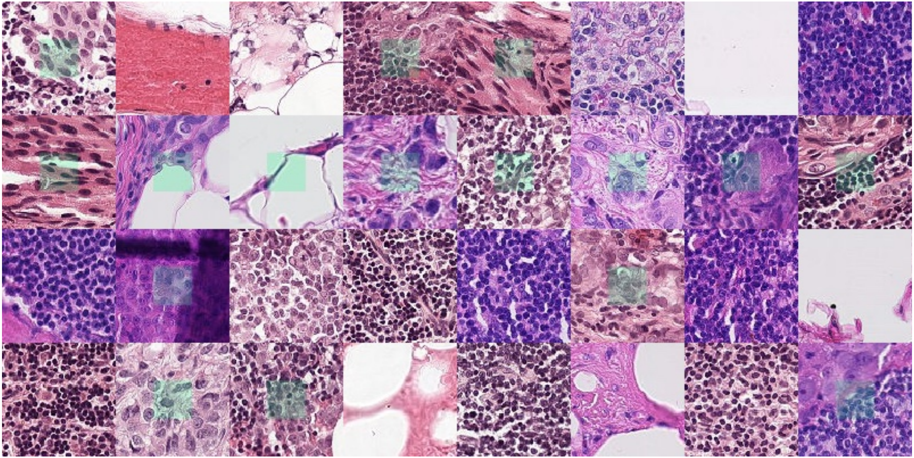


Example images: Healthy (CamCAN), Unhealthy (BraTS & ATLAS), Segmentations

Models	Latent variables z	BraTS-T2w (whole tumor) AUC	BraTS-T2w (whole tumor) mDSC	ATLAS-T1w AUC	ATLAS-T1w mDSC
mean	-	0,65	0.20	0.46	0.02
AE	256	0.63	0.41	0.49	0.03
DAE (σ=0.5)	256	0.59	0.29	0.41	0.06
VAE-128	(2,2,64)	0.69	0.42	0.64	0.08
VAE-BBB-128	(2,2,64)	0.69	0.40	0.67	0.05
VAE-256	(4,4,64)	0.67	0.40	0.66	0.08
AAE-128	(2,2,64)	0.70	0.41	0.63	0.06
AAE-256	(4,4,64)	0.67	0.38	0.60	0.04
α-GAN-128	128	0.66	0.35	0.60	0.05
α-GAN-256	256	0.67	0.37	0.60	0.04
GMM (λ_{out}=0.01)	-	0.80	0.22	0.78	0.17
GMM (λ_{out}=0.001)	-	0.79	0.21	0.77	0.17
U-net (supervised)	-	-	0.80	-	0.50

: Chen, et al., arXiv:1806.05452

Detecting Cancerous Tissue on Histopathology



Examples of histopathology patches; green patches indicate cancerous patches.

Image credit: Veeling, et al. arXiv:1806.03962

Normalising Flows

We model $p(x)$ using invertible transformations $f(x)$ on some base distribution $\pi(u)$: $p(x) = \pi\left(f^{-1}(x)\right)\left|\det \frac{\partial f^{-1}}{\partial x}\right|$

We can approximate complex distributions by stacking simple transformations:

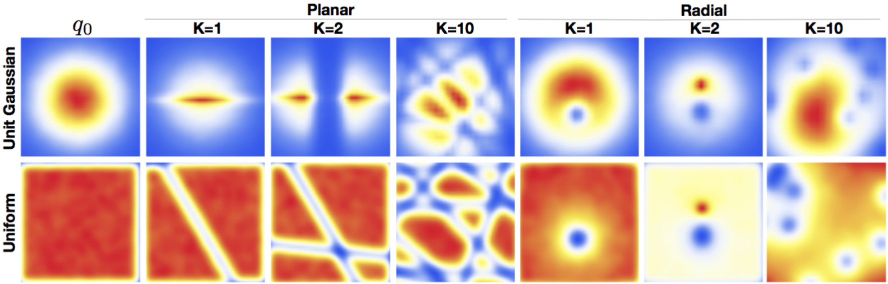


Image credit: Rezende & Mohamed. NeurIPS 2015

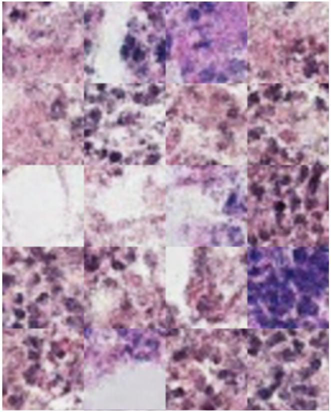
Results

Method	Gaussian	RealNVP	VAE	ResNet@572	ResNet
AUROC	0.32	0.68	0.52	0.67	0.86

We compare the AUROC for:

- RealNVP (Dinh, et al. ICLR 2017) on 32×32 px centre patches
- A Gaussian baseline fitted to each colour channel
- A supervised ResNet-50 with varying unhealthy examples
- VAE as described before

Synthethic patches:



: Pawlowski, et al. AI4CC @ ICLR 2020

Conclusion

- Outlier detection can find medically relevant abnormalities
- VAEs seem to rely on intensity rather than including contextual information
- Normalising Flows offer more principled way to find outliers

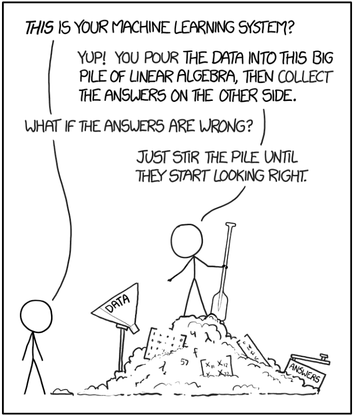


Image credit: XKCD

Thanks!

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