# Generative modelling and feature interpretation using VAEs and GANs

## 1. General Info

Project Title: **Generative modelling and feature interpretation using conditional VAEs**

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## 2. Project Abstract

Conditional generative modeling of vertebral segmentation masks employing two popular, deep-learning based generative models: generative adversarial networks (GAN) and variational autoencoders (VAE). At the end of the project, the students will have a grasp on popular generative models, the difference between VAEs and GANs, the challenges involved in conditional generation, latent space analysis, and lastly, conditional feature interpretation. The project deals with vertebrae, specifically binary vertebral masks, of two public datasets and one in-house dataset from Klinikum rects der Isar. The developed techniques will consequently be fine-tuned for use in clinically relevant tasks of fracture detection and classification, improved segmentation etc.

## 3. Background and Motivation

Osteoporotic vertebral fractures cause pain and spinal deformities in the short term but have catastrophic consequences in the long term (8-fold higher mortality). This is because spine is the reason why all the internal organs stay in place and function as they should. However, according to a 2014 study ~70% of vertebral fractures went undiagnosed, mainly due to the vagueness of the symptoms associated with the fracture's incidence. A computer-aided diagnosis is required for effectively identifying these fractures. Given a perfectly segmented vertebral mask, one can easily identify if it is fractured or not. So can a deep network. However, data is the key. It is challenging to get troves of fractured vertebral masks to train a network.

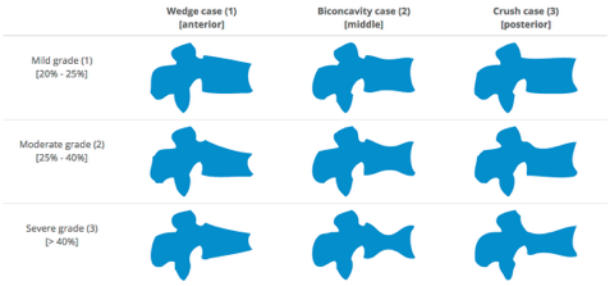


*Figure 1: A subset of fracture types and grades shown with masks: http://lit.fe.uni-lj.si/xVertSeg*

As a first step in this direction, we resort to 'generating' vertebral segmentation masks. We employ naive variational autoencoders (VAE) and generative adversarial networks (GAN) for this task, thereby comparing both of them in terms of their generation capability and latent space modeling. It should be noted that the generation should be in 3D and at resolution high enough to for capturing a fracture. Following this, in order to have more control over our generation, we implement 'conditional' variants of VAE and GAN with the conditions being the classes of the vertebra, viz. cervical, thoracic, and lumbar.

Please send the completed document to the course organizer, Dr. Shadi Albarqouni (shadi.albarqouni@in.tum.de), before the project proposal deadline on Sept. 27th, preferably earlier. Proposals will be evaluated before assigning the projects.

4. **Technical Prerequisites**
   - Strong programming in Python (pref. OOP skills)
   - Tensorflow and Tensorboard
   - Basics of probability theory (eg. Bayes rule, common density functions)
5. **Benefits:**
   - Hands-on exposure to the currently trending GANs and VAEs.
   - Clinical relevance of the problem statement will act as inspiration for solving similar issues
   - A refresher for probability in deep learning.
6. **Students' Tasks Description**

Students' tasks would be the following:

- Understand the difference between GAN and VAE
- Implement GAN and VAE.
- Extend the implementations to conditional generation.

**Group 1: 3D Generative adversarial networks**

**Group 2: 3D Variational Autoencoders**

7. **Work-packages and Time-plan:**

| | Description | #Students | From | To |
|---|---|---|---|---|
| **WP1** | Familiarize with the literature for GAN and VAE. Understand the fundamental similarities and differences | 4 | | |
| **WP2** | Familiarize with TensorFlow, implement basic versions of both architectures on MNIST. | 2+2 | | |
| **M1** | Intermediate Presentation I | 4 | 20.11.2018 | |
| **WP3** | Switch to the vertebrae dataset. Extend earlier GAN to 3D. Investigate for a stable implementation of GAN | 2 | | |
| **WP4** | Switch to the vertebrae dataset. Extend earlier VAE to 3D. Fine-tune training parameters. | 2 | | |
| **M2** | Intermediate Presentation II | 4 | 18.12.2018 | |
| **WP5** | Choose the better of both: GAN or VAE. Work on its conditional variant. | 2 | | |
| **WP6** | Explore latent space of naive model. (Interpolation, t-SNE etc.) | 2 | | |
| **WP7** | Extend latent space analysis to conditional model and draw parallels. | 4 | | |
| **M3** | Final Presentation | 4 | 29.01.2018 | |

8. **References**


- Vertebral fractures: http://lit.fe.uni-lj.si/xVertSeg/overview.php
- NIPS 2016 Tutorial: Generative Adversarial Networks: https://arxiv.org/abs/1701.00160
- Tutorial on Variational Autoencoders: https://arxiv.org/abs/1606.05908
- Biffi et al. "Learning Interpretable Anatomical Features Through Deep Generative Models: Application to Cardiac Remodeling. In: MICCAI (2018).


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