1 Coupling ML and VIP

- Santner, J., Unger, M., Pock, T., Leistner, C., Saffari, A., and Bischof, H. (2009). Interactive texture segmentation using random forests and total variation. In *BMVC*, pages 1–12 This is one instance of using a random forest to parameterize a variational image segmentation model.
- Ranftl, R. and Pock, T. (2014). *A Deep Variational Model for Image Segmentation*, pages 107–118. Springer International Publishing The paper describes a method of combining CNN(5 layers) with a final variational/inference layer. The inference layer has a single neuron and tries to learn appropriate weight and lamda together. They work with changing the objective function for back propogation(little complex).
- Taylor, G., Burmeister, R., Xu, Z., Singh, B., Patel, A., and Goldstein, T. (2016). Training neural networks without gradients: A scalable ADMM approach. *CoRR*, abs/1605.02026 The paper describes training in neural networks using as iterations in ADMM. They split the loss function by introducing new variables and removing dependency of one layer on other. **This can be one of the approach to split CNN and VIP training.**
- Gould, S., Fernando, B., Cherian, A., Anderson, P., Santa Cruz, R., and Guo, E. (2016). On Differentiating Parameterized Argmin and Argmax Problems with Application to Bi-level Optimization. *ArXiv e-prints* The paper describes an approach to use gradient descent for bilevel optimisation problems, where the lower level problem is argmin/argmax problem. The approach need the objective function to be first and second order differentiable.
- Knöbelreiter, P., Reinbacher, C., Shekhovtsov, A., and Pock, T. (2016). End-to-End Training of Hybrid CNN-CRF Models for Stereo. *ArXiv e-prints* The CNN + VIP is modelled as a bilevel optimization problem. They derive an optimization algorithm usin Structured SVM and subgradient approximation to train joint CNN and VIP .
- Riegler, G., Ferstl, D., Rüther, M., and Bischof, H. (2016a). A deep primal-dual network for guided depth super-resolution. *CoRR*, abs/1607.08569
- Riegler, G., Rüther, M., and Bischof, H. (2016b). Atgv-net: Accurate depth super-resolution. *CoRR*, abs/1607.07988 We combine a deep fully convolutional network with a non-local variational method in a deep primal-dual network. They consider the primal-dual network as an additional layer in CNN. They call the method ATGV-Net and train it end-to-end by unrolling the optimization procedure of the variational method.
- Parikh, N. and Boyd, S. (2014). Proximal algorithms. *Found. Trends Optim.*, 1(3):127–239 Decription of proximal algorithm. The paper introduces Moreau envelope and its use to compute gradients of non-differentiable function.

- Borgerding, M. and Schniter, P. (2016). Onsager-corrected deep learning for sparse linear inverse problems. *CoRR*, abs/1607.05966
- Polson, N. G., Willard, B. T., and Heidari, M. (2015). A Statistical Theory of Deep Learning via Proximal Splitting. *ArXiv e-prints*
- Gal, Y. and Ghahramani, Z. (2015). On modern deep learning and variational inference. In *Advances in Approximate Bayesian Inference workshop, NIPS*
- Ochs, P., Ranftl, R., Brox, T., and Pock, T. (2015). Bilevel optimization with nonsmooth lower level problems. In *International Conference on Scale Space and Variational Methods in Computer Vision*, pages 654–665. Springer
- Calatroni, L., Chung, C., De Los Reyes, J. C., Schönlieb, C.-B., and Valkonen, T. (2015). Bilevel approaches for learning of variational imaging models. *ArXiv e-prints*

2 Convolution Neural Networks

- Introduction
  "http://cs231n.github.io/neural-networks-2/"
- Maninis, K., Pont-Tuset, J., Arbeláez, P. A., and Gool, L. J. V. (2016). Deep retinal image understanding. *CoRR*, abs/1609.01103 This method is used for our imeplementaion of Image segmentation using CNN.
- Long, J., Shelhamer, E., and Darrell, T. (2014). Fully convolutional networks for semantic segmentation. *CoRR*, abs/1411.4038
- Gonda, F., Verena Kaynig, R. T., Daniel Haehn, Jeff Lichtman, T. P., and Pfister, H. (2016). Icon: An interactive approach to train deep neural networks for segmentation of neuronal structures. *CoRR*, abs/1610.09032 Interactive approach for training CNN using scribbles for segmentation purpose.
- Havaei, M., Axel Davy, D. W., Antoine Biard, A. C. C., Yoshua Bengio, C. P., and Pierre-Marc Jodoin, H. L. (2015). Brain tumor segmentation with deep neural networks. *CoRR*, abs/1505.03540 They explore in particular differerent architectures based on Convolutional Neural Networks (CNN), i.e. DNNs specifically adapted to image data.
- Xie, W., Noble, J. A., and Zisserman, A. (2015). Microscopy cell counting with fully convolutional regression networks. In *MICCAI 1st Workshop on Deep Learning in Medical Image Analysis* This paper concerns automated cell counting in microscopy images. The approach we take is to adapt Convolutional Neural Networks (CNNs) to regress a cell spatial density map across the image.

- Lai, M. (2015). Deep learning for medical image segmentation Patch-based 3-D image segmentation. May be good for small training data-set. Good paper to understand basic tricks used in Neural networks and their reason. Example: use of patches, tri-planar patches, concept of pre-trainig

- Turaga SC, M. J., Jain V, R. F., Helmstaedter M, B. K., and Denk W, S. H. (2010). Convolutional networks can learn to generate affinity graphs for image segmentation. *MIT Press journals*, pages 511–538 3-D segmentation using graphCut methods. The affinity between pixels is generated using 3-D CNN. Uses Volumetric electron microscope data of neurons. CNN - 3 layers only using fully segmented images

- David A. Van Valen, Takamasa Kudo, K. M. L. (2016). Deepcell software DeepCell is a program for segmenting individual cells in microscopy images using deep learning. Image segmentation is frequently the analysis bottleneck in single-cell live-cell imaging experiments. This program describes our efforts to approach this problem using deep learning. Description in http://journals.plos.org/ploscompbiol/article?id=10.1371/journal.pcbi.1005177

- MIT (2012). Isbi challenge: Segmentation of neuronal structures in em stacks http://people.idsia.ch/ juergen/deeplearningwinsbraincontest.html: Winner of contest uses Deep learning for automated segmentation.

  http://journal.frontiersin.org/article/10.3389/fnana.2015.00142/full

- Parag, T., Ciresan, D. C., and Giusti, A. (2015). Efficient classifier training to minimize false merges in electron microscopy segmentation. In *The IEEE International Conference on Computer Vision (ICCV)*

- Masci, J., Giusti, A., Ciresan, D., Fricout, G., and Schmidhuber, J. (2013). A fast learning algorithm for image segmentation with max-pooling convolutional networks. In *2013 IEEE International Conference on Image Processing*, pages 2713–2717

- Ciresan, D., Giusti, A., Gambardella, L. M., and Schmidhuber, J. (2012). Deep neural networks segment neuronal membranes in electron microscopy images. In Pereira, F., Burges, C. J. C., Bottou, L., and Weinberger, K. Q., editors, *Advances in Neural Information Processing Systems 25*, pages 2843–2851. Curran Associates, Inc

3 Variational Image Processing

- Chambolle, A., T. Pock, H. B., and Cremers, D. (2009). A convex relaxation approach for computing minimal partitions. *CVPR*, pages 810–817 This paper formulates optimization problem for multi-class segmentation using Potts model and solves it using Primal-dual algo. Different options for convex relaxation of optimization problem.

- Lefkimmiatis, S., Roussos, A., Maragos, P., and Unser, M. (2015). Structure tensor total variation. *SIAM Journal on Imaging Sciences*, 8(2):1090–1122 The proposed regularization family, termed as structure tensor total variation (STV), penalizes the eigenvalues of the structure tensor and is suitable for both grayscale and vector-valued images. It generalizes several existing variational penalties, including the total variation seminorm and vectorial extensions of it. Meanwhile, thanks to the structure tensor's ability to capture first-order information around a local neighborhood, the STV functionals can provide more robust measures of image variation. Further, we prove that the STV regularizers are convex while they also satisfy several invariance properties w.r.t. image transformations.

4 Object detection

- Ren, S., He, K., Girshick, R., and Sun, J. (2015). Faster r-cnn: Towards real-time object detection with region proposal networks. In Cortes, C., Lawrence, N. D., Lee, D. D., Sugiyama, M., and Garnett, R., editors, *Advances in Neural Information Processing Systems 28*, pages 91–99. Curran Associates, Inc

- Girshick, R. B. (2015). Fast R-CNN. *CoRR*, abs/1504.08083

- Girshick, R. B., Donahue, J., Darrell, T., and Malik, J. (2013). Rich feature hierarchies for accurate object detection and semantic segmentation. *CoRR*, abs/1311.2524

- Uijlings, J., van de Sande, K., Gevers, T., and Smeulders, A. (2013). Selective search for object recognition. *International Journal of Computer Vision*

- Tensorflow implementation of Faster-RCNN
  https://github.com/smallcorgi/Faster-RCNN_TF
  https://github.com/zplizzi/tensorflow-fast-rcnn

- Training on another dataset
  https://github.com/rbgirshick/fast-rcnn/pull/21/files

  https://github.com/zeyuanxy/fast-rcnn/blob/master/help/train/README.md

  http://sgsai.blogspot.ch/2016/02/training-faster-r-cnn-on-custom-dataset.html

  https://github.com/sergeyk/selective_search_ijcv_with_python

  https://github.com/deboc/py-faster-rcnn/blob/master/help/Readme.md

5 Random Forest

- Efficient Online Random Forests:
  https://github.com/balajiln/mondrianforest

- This is the original implementation of the Online Random Forest algorithm
https://github.com/amirsaffari/online-random-forests

- Adding new classes:
Incremental Learning of NCM Forests.
http://www.idiap.ch/ fleuret/SMLD/2014/SMLD2014_-_Marko_Ristin-Kaufmann_-
_Incremental_Learning_of_NCM_Forests_for_Large-Scale_Image_Classification.pdf

  https://bitbucket.org/markoristin/