OMB No. 0925-0001/0002 (Rev. 08/12 Approved Through 8/31/2015)

BIOGRAPHICAL SKETCH

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NAME: Wu, Ying Nian

eRA COMMONS USER NAME (credential, e.g., agency login): ynwu

POSITION TITLE: Professor

EDUCATION/TRAINING (Begin with baccalaureate or other initial professional education, such as nursing, include postdoctoral training and residency training if applicable. Add/delete rows as necessary.)

| INSTITUTION AND LOCATION | DEGREE(if applicable) | Completion DateMM/YYYY | FIELD OF STUDY |
| --- | --- | --- | --- |
| Harvard University | A.M. | 11/1993 | Statistics |
| Harvard University | Ph.D. | 11/1996 | Statistics |
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**A. Personal Statement**

As a statistician, my research expertise is on statistical modeling and learning, with applications in computational vision and computational biology. I will be able to contribute to all the statistical aspects of the proposed project, which requires considerable efforts and innovations in developing novel statistical models and associated learning algorithms, as well as theoretical analysis of the statistical methods. For the past decade, I have worked with biologists on various high throughput data. For example, I worked with Bing Ren on ChIP-chip data. We developed a statistical model for this type of data. We also developed a model fitting algorithm for identifying the protein binding sites. I also worked with Dr. Ying Xi on alternative splicing data. We developed a EM algorithm for probabilistic reconstructions of full-length isoforms from splice graphs. More recently, we developed rMATS method for robust and flexible detection of differential alternative splicing from RNA-seq data.

1. Shen, S., Park, J. W., Lu, Z. X., Lin, L., Henry, M. D., **Wu, Y. N**., Zhou, Q., Xing, Y. (2014) rMATS: robust and flexible detection of differential alternative splicing from replicate RNA-seq data, *Proceedings of National Academy of Science*, published on line, in press.
2. Xing, Y. Yu, T., **Wu, Y. N.**, Roy, M., Kim, J. and Lee C. (2006), An expectation-maximization algorithm for probabilistic reconstructions of full-length isoforms from splice graphs. *Nucleic Acid Research*, 34, 3150-3160.
3. Zheng, M., Barrera, L. O., B. Ren, and **Wu, Y. N.** (2007) ChIP-chip: data, model, and analysis. *Biometrics*, 63, 787-796.
4. Kim, T. H, Barrera, L. O., Zheng, M., Qu, C., Singer, M. A., Richmand, T. A., **Wu, Y. N**., Green, R. G. and Ren, B. (2005) A High-resolution map of active promoters in the human genome, *Nature*, 436, 876-880.

**B. Positions and Honors**

**Positions and Employment**

2006-now Professor, Department of Statistics, UCLA

2001-2006 Associated Professor, Department of Statistics, UCLA

1999-2001 Assistant Professor, Department of Statistics, UCLA

1997-1999 Assistant Professor, Department of Statistics, University of Michigan

1996/1997 Visitor, Bell Labs, Lucent Technologies

**Honors and Awards**

Honorable Mention for David Marr Prize, International Conference on Computer Vision, 2007.

Honorable Mention for David Marr Prize, International Conference on Computer Vision, 1999.

**Other Experience and Professional Activities**

Associate editor, *Journal of the American Statistical Association*, Theory and Method, 2011-present.

Associate editor, *Stat*, 2012-present.

Associate editor, *Electronic Journal of Statistics*, 2013-present.

Guest editors for the special issue on “Generative Models for Vision” for the journal *Computer Vision and Image Understanding*, 2014.

NSF panel, 2012. NSF panel, 2009.

**C. Contribution to Science**

**1. Generative models**

My research program centers on developing generative models and associated learning algorithms, with applications in computational vision. Generative models enable us to learn useful features and representations from the data in an unsupervised or semi-supervised manner. They also enable us to learn more accurately from the data, and the learned features and representations can be more interpretable and explicit than those learned by discriminative models, especially if the learned models are sparse. Recently we have developed generative models that are based on or are closely related to the convolutional neural networks (CNN). In particular, we have developed the deep FRAME (Filters, Random field, And Maximum Entropy) models using CNN filters. We have also developed the sparse FRAME models by merging two important themes in image representation, namely wavelet sparse coding and Markov random field.

1. Lu, Y., Zhu, S. C., and **Wu, Y. N**. (2015) Learning FRAME models using CNN filters. *AAAI Conference on Artificial Intelligence*, accepted.

2. Xie, J., Lu, Y., Zhu, S. C., and **Wu, Y. N.** (2015) Inducing wavelets into random fields via generative boosting. *Journal of Applied and Computational Harmonic Analysis*, in press.

3. Xie, J., Hu, W., Zhu, S. C., and **Wu, Y. N.** (2015). Learning sparse FRAME models for natural image patterns. *International Journal of Computer Vision*, 112, 221-238.

4. Dai, J., Lu, Y., and **Wu, Y. N.** (2015) Generative modeling of convolutional neural networks. *International Conference on Learning Representations.* An expanded version has been accepted by a special issue on big data in *Statistics and Its Interfaces*.

**2. Unsupervised learning**

We have developed unsupervised learning methods for learning dictionaries of models of image patterns from training images without any labeling or annotations. The models are the active basis models that I and my co-authors have developed before, and they can be considered deformable templates for the image patterns. The unsupervised learning generates sparse representations of the images using the models or templates selected from the learned dictionary, and these models are very much like “visual words” for describing the images. We call the representation the “compositional sparse coding” because each image is decomposed into a small number of active basis models, which are in turn decomposed into a small number of constituent wavelets. We have applied the learning method to tasks such as co-segmentation and domain adaption and obtained state of the art results. We have also developed learning method for unsupervised learning of hierarchical active basis models.

1. Yi,H.,Hu,W.,Zi,Z.,Zhu,S.C.,and **Wu,Y.N**.(2014)Unsupervisedlearningofcompositional sparse code for natural images. *Quarterly of Applied Mathematics*, 72, 373-406.

2. Dai. J., **Wu, Y. N**., Zhou, J., and Zhu, S. C. (2013) Co-segmentation and co-sketch by unsupervised learning. *Proceedings of International Conference of Computer Vision*.

3. Dai, J., Hong, Y., Hu, W., Zhu, S. C., and **Wu, Y. N.** (2014) Unsupervised learning of dic- tionaries of hierarchical compositional models. *Proceedings of IEEE Conference on Computer Vision and Pattern Recognition.*

**4. Wu, Y. N.,** Si, Z., Gong, H., and Zhu, S. C. (2010) Learning active basis model for object detection and recognition. *International Journal of Computer Vision*, 90, 198-235.

**3. Statistical computing**

We have developed computational methods for Bayesian and likelihood-based inference. In particular, we have developed a Bayesian method for sparse group selection. We have also developed parameter expanded EM and data augmentation algorithms for accelerating the traditional EM and data augmentation algorithms. Such methods have proven to be useful for many statistical models, including linear mixed-effects models, factor analysis models, probit models etc.

1. Chen, R. B., Chu, C. H., Yuan, S. and **Wu, Y. N.** (2015) Bayesian sparse group selection. *Journal of Computational and Graphical Statistics*. In press.

2. Pinheiro J., Liu, C., and **Wu, Y. N.** (2001) Efficient algorithms for robust estimation in linear mixed-effects models using the multivariate t-distribution. *Journal of Computational and Graphical Statistics*, 10, 249-276.

3. Liu, C., Rubin, D. B., and **Wu, Y. N.** (1998) Parameter expansion to accelerate EM - the PX-EM algorithm. *Biometrika*, 85, 755-770.

4. Liu, J. S. and **Wu, Y. N.** (1999) Parameter expansion for data augmentation. *Journal of the American Statistical Association*, 94, 1264-1274.

**4. Markov random field models**

We have developed a class of Markov random field models for texture patterns. This class of models have greatly expanded the traditional Markov random field models and unified various research themes in texture modelling and analysis. We have also established the equivalence of this class of models with image ensembles that are characterized by spatial statistics. In addition, we have also developed statistical models for dynamic textures.

1. Doretto, G., Chiuso, A, **Wu, Y. N**. and Soatto, S., (2003) Dynamic textures. *International Journal of Computer Vision*. 51, 91-109.

2. **Wu, Y. N**., Zhu, S. C., and Liu, X. (2000) Equivalence of Julesz ensembles and FRAME models. *International Journal of Computer Vision*, 38, 245-261.

3. Zhu, S. C., **Wu, Y. N**., and Mumford, D. B. (1998) Minimax entropy principle and its application to texture modeling. *Neural Computation*, 9, 1627-1660.

4. Zhu, S. C., **Wu, Y. N**., and Mumford, D. B. (1997) Filter, Random field, And Maximum Entropy (FRAME): towards a unified theory for texture modeling. *International Journal of Computer Vision*, 27, 107-126.

**Complete List of Published Work in Google Scholar**:

https://scholar.google.com/citations?hl=en&user=7k\_1QFIAAAAJ&view\_op=list\_works

**D. Research Support**

Ongoing Research Support

DMS 1310391 (PI Wu) 07/01/13-06/30/15

NSF

*Learning Compositional Sparse Coding Models for Natural Images*

Role: PI

N00014-10-1-0933 (PI Zhu)                                                   08/01/10-07/31/16

ONR

*Knowledge Representation, Reasoning and Learning for Understanding Scenes and Events*

Role: Co-PI

N00014-10-1-0933 (PI Zhu)                                                    06/29/15-09/28/18

DARPA

*Knowledege Representation from Heterogeneous Data for Quantitative and Qualitative Reasoning in Autonomy*

Role: Co-PI

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