**Homework #4:**

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**Title of research (official):**

Applications of Machine & Deep Learning in GIS – Spatiotemporal data mining

**Interests:**

My thesis is focused on paper survey of overhead imagery processing & recognition using machine and deep learning algorithms and models, such as CNN (Convolutional Neural Network) for static images, and LSTM-RNN (Long Short-Term Memory RNN) for videos and time series data. With the AI, there are some uses in GIS:

* Some researchers use CNN to identify and classify outdoor events occurred in an overhead image (i.e, vehicular racing, marathon, etc.)
* Some researchers use LSTM-RNN to identify, classify, predict the damage of, and respond to the disasters, and analyse their post-action damage.
* In survey engineering, some researchers use CNN observe changes in land use, crop growth, and construction progresses.
* To make GPS based pathfinding more accurate, Spatiotemporal Data Mining is often utilized in several papers to train the pathfinding ML/DL-architectures.
* All the papers referred, may be added & updated in the future, involve GIS, Computer Vision (CV), and spatiotemporal data mining.

**Research project Description (More to be added):**

According to Doshi et al, 2018 [1], We propose to identify disaster-impacted areas by comparing the change in man-made features extracted from satellite imagery. Using a pre-trained semantic segmentation model from [2] we extract man-made features, the pre- and post-event images on the “before, during and after” imagery of the event-affected area.

According to Amit et al. [3], CNN is a sequence of layers, the convolution layer (who detects features from a data image), the pooling layer (downsamples the input), and the FC layer (who classifies the features detected earlier). with ReLU as the main activation function of the network. Further explained in the section 2 of [3].

Iglovikov et al. 2017 [4], used an FC-CNN named U-NET, along with an embedded multispectral sensor, which detects frequency reflection by the objects, to detect geo-features in satellite images and yielded satisfying results.

According to Bochkovskiy et al. [5], with the help of YOLO V.4, and TensorFlow Keras, CNN’s performance in image recognition is improved. So that it would be our main CNN model in this thesis. We hope that our deep learning model, written in Python, will work as the goals above.

In Terms of video and sequence type photos (such as slideshow), however, the use of LSTM-RNN is needed. According to Fang et al. [6], LSTM is excellent at predicting flood because it could process time series data.

According to Li et al, 2018. [7], spatiotemporal forecasting is a crucial task for a learning system that operates in a dynamic environment. It can be useful in pathfinding, autonomous vehicles, logistics, city planning etc. They used a Diffusion Convolutional Recurrent Neural Network (DCRNN) model to forecast the road traffic within a specific space and timeframe (The dataset was METR-LA, 2014). Diffusion convolution extracts the traffic features, and the RNN processes the traffic volumes in sequence.

Yu et al, 2018. [8] proposed a Spatiotemporal Graph Convolutional Networks (STGCN), to tackle the time series prediction problem in traffic domain. They formulated the problem on graphs and build the model with complete convolutional structures, enabling much faster training speed with fewer parameters. Compared with existing models, STGCN more effectively captured comprehensive spatiotemporal correlations through modeling multi-scale traffic networks and consistently outperforms state-of-the-art baselines on various real-world traffic datasets.

Correa et al, 2017 [9] performed a spatiotemporal data mining of Taxi vs Uber ridership in NYC, 2014+15. According to the heatmap inside the paper, the ridership for both taxi systems depended on several factors – such as personal income, education, jobs, car ownership etc. With 3 spatial models for ridership prediction – linear, spatial error and spatial lag models, the last one outperformed not only the first 2 algorithms, but also yielded a considerable accuracy and performance.

**Project Phases:**

* May/June <-(CURRENT PHASE)
  + Perform Literature Reviews, Python coding & other essential skills
* July
  + Perform even deeper LR + coding practice + Validation runs.
* August/September
  + Custom Model Design, Training & Testing
* October
  + Final Validation Runs
* November
  + Result & Analysis
  + Writing a paper.
* December
  + Finish the paper.
* January
  + Defence oral exam

**To be determined/confirmed by the supervisor:**

* Official Title
* Dataset for:
  + Training
  + Testing
  + Validation
    - Kaggle: Taxi vs Uber Data
* Models & Architectures
  + LSTM
  + No. & Types/Roles of hidden layers
  + Activation Functions
  + Etc.
* Quantitative Metrics
  + K1 Score
  + Accuracy
  + Etc
  + R^2.

**Progresses:**

Current Phase: Literature Review and Essential Skill Training

**References:**

[1] Doshi, J., Basu, S. and Pang, G., 2018. From satellite imagery to disaster insights. *arXiv preprint arXiv:1812.07033*.

[2] Doshi, Jigar. 2018. Residual Inception Skip Network for Binary Segmentation. Pages 216–219 of:

Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops.  
  
[3] Amit, S.N.K.B. and Aoki, Y., 2017, September. Disaster detection from aerial imagery with convolutional neural network. In 2017 International Electronics Symposium on Knowledge Creation and Intelligent Computing (IES-KCIC) (pp. 239-245). IEEE.

[4] V. Iglovikov, S. Mushinskiy, and V. Osin, “Satellite Imagery Feature Detection using Deep Convolutional Neural Network: A Kaggle Competition,” vol. June, 2017.

[5] A. Bochkovskiy, C.-Y. Wang, and H.-Y. M. Liao, “Yolov4: Optimal speed and accuracy of object detection,” ArXiv, vol. abs/2004.10934, 2020.

[6] Fang, Z., Wang, Y., Peng, L. and Hong, H., 2020. Predicting flood susceptibility using LSTM neural networks. *Journal of Hydrology*, [online] p.125734. Available at: <https://doi.org/10.1016/j.jhydrol.2020.125734> [Accessed 18 April 2021].

[7] Li, Y., Yu, R., Shahabi, C., & Liu, Y. (2017). Diffusion convolutional recurrent neural network: Data-driven traffic forecasting. *arXiv preprint arXiv:1707.01926*.

[8] Yu, B., Yin, H., & Zhu, Z. (2017). Spatio-temporal graph convolutional networks: A deep learning framework for traffic forecasting. *arXiv preprint arXiv:1709.04875*.

[9] Correa, D., Xie, K., & Ozbay, K. (2017). Exploring the taxi and Uber demand in New York City: An empirical analysis and spatial modeling. In *96th Annual Meeting of the Transportation Research Board, Washington, DC*.