Geospatial Artificial Intelligence (GeoAI)

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Introduction

Nowadays, artificial intelligence (AI) is bringing tremendous new opportunities and challenges to geospatial research. Its fast development is powered by theoretical advancement, big data, computer hardware (e.g., the graphics processing unit, or GPU), and high-performance computing platforms that support the development, training, and deployment of AI models within a reasonable amount of time. Recent years have witnessed significant advances in geospatial artificial intelligence (GeoAI), which is the integration of geospatial studies and AI, especially machine learning and deep learning methods and the latest AI technologies in both academia and industry. GeoAI can be regarded as a study subject to develop intelligent computer programs to mimic the processes of human perception, spatial reasoning, and discovery about geographical phenomena and dynamics; to advance our knowledge; and to solve problems in human environmental systems and their interactions, with a focus on spatial contexts and roots in geography or geographic information science (GIScience). Thus, it would require the knowledge of AI theory, programming and computation practices as well as geographic domain knowledge to be competent in GeoAI research. There have already been increasingly collaborative GeoAI studies for GIScience, remote sensing, physical environment, and human society. It is a good time to provide a key reference list for educators, students, researchers, and practitioners to keep up with the latest GeoAI research topics. This bibliographical entry will first review the historical roots for AI in geography and GIScience and then list up to ten selective recent works with annotations that briefly describe their importance for each topic of interest in the GeoAI landscape, ranging from fundamental spatial representation learning to spatial predictions and to various advancements in cartography, earth observation, social sensing, and geospatial semantics.

Historical Roots and General Overviews

The intersection of AI and geographic studies is not completely new; its historical roots are described in Smith 1984; Couclelis 1986; Openshaw 1992; Openshaw and Openshaw 1997; and Janowicz, et al. 2020. Before the recent explosion of deep learning studies by LeCun, et al. 2015, major AI developments included theoretical speculations in the 1950s and 1960s (see Buchanan 2005); artificial neural networks (ANN), heuristic search, knowledge-based expert systems, neurocomputing and artificial life (e.g., cellular automata) in the 1980s; genetic programming, fuzzy logics, and development of hybrid intelligent systems in the 1990s; and ontology and web semantics for geographic information retrieval (GIR) in the 2000s. All of these developments have contributed to the research themes of GeoAI. One key question that drives contributions in GeoAI is why spatial is special in AI. One answer might be because geographic location is often the key for linking heterogeneous data sets that have been intensively used for training advanced AI models (more information in Hu, et al. 2019b). In addition, what are the key geographical questions that we can now address better using AI rather than traditional approaches? What are the unsolved problems that can now be solved with AI? Are there any new theories or intelligent approaches to building models and data pipelines in geographic information systems (GIS)? Geographers and computer scientists have made great efforts in contributing to these topics in recent publications, such as in a special issue on artificial intelligence techniques for geographic knowledge discovery in the *International Journal of Geographical Information Science* (Janowicz, et al. 2020) and in the ACM SIGSPATIAL GeoAI workshops (2017, 2018, 2019), as described in Hu, et al. 2019a, as well as discussions in the American Association of Geographers (AAG) GeoAI and Deep Learning symposiums (2018, 2019, 2020).

Buchanan, B. G. "A (Very) Brief History of Artificial Intelligence." ***AI Magazine*** **26.4 (2005): 53–53.**

Profound thoughts in philosophy, fiction, and imagination and early inventions and technology advancements in electronics, engineering, and many other disciplines have influenced AI.

Couclelis, H. "Artificial Intelligence in Geography: Conjectures on the Shape of Things to Come." ***Professional Geographer*** **38.1 (1986): 1–11.**

Couclelis broadens the discussion of AI in geography after Smith 1984 from more theoretical dimensions of the computational approach, and introduces the discrete-structure hierarchy as a universal framework for multilevel analytical representation.

Hu, Y., S. Gao, D. Lunga, W. Li, S. Newsam, and B. Bhaduri. "GeoAI at ACM SIGSPATIAL: Progress, Challenges, and Future Directions." ***SIGSPATIAL Special*** **11.2 (2019a): 5–15.**

Reviews the research articles published in the 2017, 2018, and 2019 SIGSPATIAL GeoAI workshops, and summarizes a wide range of topics, such as geospatial image processing, transportation modeling, public health, and digital humanities. A list of GeoAI research directions is also suggested.

Hu, Y., W. Li, D. Wright, et al. Artificial Intelligence Approaches. In ***The Geographic Information Science and Technology Body of Knowledge (3rd Quarter 2019 Edition)*****. Edited by John P. Wilson. Ithaca, NY: University Consortium for Geographic Information Science, 2019b.**

Authors review recent developments of AI in geospatial studies, with a focus on machine learning and deep learning approaches, and introduce a variety of applications, such as automatic recognition of natural terrain features from remote sensing images, land cover classification, and spatiotemporal habitats modeling.

Janowicz, K., S. Gao, G. McKenzie, Y. Hu, and B. Bhaduri. "GeoAI: Spatially Explicit Artificial Intelligence Techniques for Geographic Knowledge Discovery and Beyond." ***International Journal of Geographical Information Science*** **34.4 (2020): 625–636.**

Reviews state-of-the-art research on GeoAI for geographic knowledge discovery, explains how a change in data culture is fueling the rapid growth of GeoAI, and points to future research directions. Also calls for the development of spatially explicit models and the sharing of high-quality geospatial data sets for advancing reproducible GeoAI research.

LeCun, Y., Y. Bengio, and G. Hinton. "Deep Learning." ***Nature*** **521.7553 (2015): 436–444.**

A high-level review from worldwide lead researchers on deep convolutional neural networks and recurrent neural networks that have brought about breakthroughs in processing images, video, speech, and audio.

Openshaw, S. "Some Suggestions concerning the Development of Artificial Intelligence Tools for Spatial Modelling and Analysis in GIS." ***Annals of Regional Science*** **26.1 (1992): 35–51.**

Key landmarks in the development process of AI tools for spatial modeling and analysis in GIS may include (1) demonstrations of new technology with pedagogic data support, (2) empirical evidences that new AI methods outperform traditional approaches, (3) new methods work in data rich environment in GIS, and (4) incorporation of AI procedures in general analysis and modeling.

Openshaw, S., and C. Openshaw. ***Artificial Intelligence in Geography*****. Chichester, UK: John Wiley & Sons, 1997.**

A milestone book project in GeoAI that introduces key principles of AI, with applications in geography, urban planning, and GIS. It mainly covers the contemporary AI methods and technologies in the 1970s–1990s, including heuristic search, expert systems, intelligent knowledge-based systems, neurocomputing, ANN, artificial life, genetic algorithms, and fuzzy systems.

Smith, T. R. "Artificial Intelligence and Its Applicability to Geographical Problem Solving." ***Professional Geographer*** **36.2 (1984): 147–158.**

Smith summarizes the applicability of AI to geographical problem solving, research, and practices, with a focus on individual and aggregated intelligent spatial decision-making from both cognitive and engineering perspectives.

Spatially Explicit AI Models

The location uncertainty, spatial heterogeneity, and dependence, along with other spatial characteristics in geographic information, make spatial thinking and the use of spatial concepts crucial as the first citizen when developing spatially explicit AI models (More information can be found in Kuhn 2012; Zhu, et al. 2018; and Janowicz, et al. 2020—the latter cited under Historical Roots and General Overviews). Therefore, the integration of AI technologies and methods with geography and GIS is not a one-way street. Location is a key to integrate and synthesize multi-source data layers, and geographic domain knowledge and spatial concepts contribute to the development of different contextual spaces (i.e., mobility space and social space) and play an important role in the development of AI models. Being a spatially explicit model requires meeting one of the four spatial tests (see Goodchild 2001 and Janowicz, et al. 2020, the latter cited under Historical Roots and General Overviews): (1) invariance test, (2) representation test, (3) formulation test, and (4) outcome test. Spatially explicit models incorporating spatial contexts (Yan, et al. 2018) can outperform traditional nonspatial machine learning models in many tasks, such as image classification, geographic knowledge graph summarization (Yan, et al. 2019), and geographic question-answering problems (Mai, et al. 2019). Furthermore, some recently developed machine learning, and particularly deep learning, methods are also motivated by GIS and geography, such as deep compositional spatial models (Zammit-Mangion, et al. 2019), spatially conditioned generative adversarial nets (SpaceGAN) (Klemmer, et al. 2019), a GeoGAN with reconstruction and style losses (Ganguli, et al. 2019), and a LSTM-TrajGAN for trajectory privacy protection (Rao, et al. 2020).

Ganguli, S., P. Garzon, and N. Glaser. "GeoGAN: A Conditional GAN with Reconstruction and Style Loss to Generate Standard Layer of Maps from Satellite Images. Preprint arXiv:1902.05611. Ithaca, NY: Computer Research Repository (CoRR), 2019.

Develops a GeoGAN with new pixel-wise reconstruction loss and style loss design to create stylish maps from satellite images.

Goodchild, M. "Issues in Spatially Explicit Modeling." In ***Proceedings of the Agent-Based Models of Land-Use and Land-Cover Change: Report and Review of an International Workshop, Irvine, CA, 2001*****. Edited by D. C. Parker, T. Berger, and S. M. Manson, 12–15. Bloomington, IN: LUCC Focus 1 Office.**

Goodchild introduces the four tests for spatially explicit modeling: invariance test, representation test, formulation test, and outcome test.

Klemmer, K., A. Koshiyama, and S. Flennerhag. "Augmenting Correlation Structures in Spatial Data Using Deep Generative Models." Preprint arXiv:1905.09796. Ithaca, NY: Computer Research Repository (CoRR), 2019.

Introduces a generative model for geospatial domains SpaceGAN that learns neighborhood structures and enriches spatial representation of each data point rather than mere spatial coordinates. Using synthetic and real-world prediction tasks, the research suggests that SpaceGAN can be used as a tool for artificially inflating sparse geospatial data and improving generalization of geospatial models.

Kuhn, W. "Core Concepts of Spatial Information for Transdisciplinary Research." ***International Journal of Geographical Information Science*** **26.12 (2012): 2267–2276.**

Kuhn proposes a set of ten core concepts of spatial information: location, neighborhood, field, object, network, event, granularity, accuracy, meaning, and value. These concepts can be used across multiple disciplines for enabling spatial analysis and spatial model development.

Mai, G., B. Yan, K. Janowicz, and R. Zhu. "Relaxing Unanswerable Geographic Questions Using a Spatially Explicit Knowledge Graph Embedding Model." In *Geospatial Technologies for Local and Regional Development: Proceedings of the 22nd AGILE Conference on Geographic Information Science (AGILE)*. Edited by edited by Phaedon Kyriakidis, Diofantos Hadjimitsis, Dimitrios Skarlatos, Ali Mansourian, 21–39. Cham, Switzerland: Springer, 2019.

Reviews the uniqueness of geographic question-answering problems and presents a spatially explicit translational knowledge graph embedding model called TransGeo, which is further applied to relax and rewrite unanswerable geographic questions.

Rao, J., S. Gao, Y. Kang, and Q. Huang. "LSTM-TrajGAN: A Deep Learning Approach to Trajectory Privacy Protection." In *Proceedings of the 11th International Conference on Geographic Information Science, Poznan, Poland: GIScience 2021*. Edited by Krzysztof Janowicz and Judith A. Verstegen, 12:1–12:17. Saarbrücken, Germany: Schloss Dagstuhl, 2020.

Proposes a novel deep learning framework, LSTM-TrajGAN, to generate privacy-preserving synthetic trajectory data for data sharing and publication. A spatially explicit loss metric function, TrajLoss, is introduced to measure the trajectory similarity for model training and optimization.

Yan, B., K. Janowicz, G. Mai, and R. Zhu. "xNet+ SC: Classifying Places Based on Images by Incorporating Spatial Contexts." In *Proceedings of the 10th International Conference on Geographic Information Science (GIScience 2018)*. Edited by S. Winter, A. Griffin, and M. Sester, 17:1–17:15. Saarbrücken, Germany: Schloss Dagstuhl, 2018.

The paper demonstrates how utilizing the rich information embedded in spatial contexts can substantially improve the classification of place types from images and outperform state-of-the-art deep learning models such as CNN and ResNet.

Yan, B., K. Janowicz, G. Mai, and R. Zhu. "A Spatially Explicit Reinforcement Learning Model for Geographic Knowledge Graph Summarization." *Transactions in GIS* 23.3 (2019): 620–640.

Proposes a novel graph summarization method by incorporating spatially explicit components into a reinforcement learning framework for geographic knowledge graphs interlinking large-scale places, actors, events, and objects.

Zammit-Mangion, A., T. L. J. Ng, Q. Vu, and M. Filippone. "Deep Compositional Spatial Models." Preprint arXiv:1906.02840. Ithaca, NY: Computer Research Repository (CoRR), 2019.

Through simulation studies, the proposed deep compositional spatial models show strong capacity to model nonstationary and anisotropic spatial data.

Zhu, A. X., G. Lu, J. Liu, C. Z. Qin, and C. Zhou. "Spatial Prediction Based on Third Law of Geography." *Annals of GIS* 24.4 (2018): 225–240.

A thorough discussion about the laws in geography. After the First Law (spatial dependence) and the Second Law (spatial heterogeneity) in geography, this paper presents a new thinking about spatial prediction based on the Third Law of geography that focuses on the similarity of geographic configuration of locations. The discussion offers insights into future development of GeoAI models.

Spatial Representation Learning

The success of many machine learning algorithms generally depends on the quality of data representation or feature engineering (see Bengio, et al. 2013). Thus, latent feature learning or representation learning for spatially explicit AI techniques by considering spatial constraints and relationships have attracted much attention in GeoAI (see Janowicz, et al. 2020, cited under Historical Roots and General Overviews). Researchers have utilized representation learning for latent geospatial feature representation, such as Place2Vec for place types, built environment, and region representation (Yan, et al. 2017; Zhang, et al. 2017; Liu, et al. 2019; Zhai, et al. 2019), Road2Vec embedding for road segments and traffic prediction (Deng, et al. 2016; Liu, et al. 2017), Mot2Vec embedding for mobility and visit traces (Crivellari and Beinat 2019), Tile2Vec embedding for remote sensing data (Jean, et al. 2019), and multi-scale location encoding Space2Vec for spatial feature distributions (Mai, et al. 2020).

Bengio, Y., A. Courville, and P. Vincent. "Representation Learning: A Review and New Perspectives." ***IEEE Transactions on Pattern Analysis and Machine Intelligence*** **35.8 (2013): 1798–1828.**

Reviews key concepts and progress in the area of unsupervised feature learning and deep learning. Also outlines new perspectives for learning good data representations, computing representations (i.e., inference), and the connections between representation learning, density estimation, and manifold learning (an approach to nonlinear dimensionality reduction).

Crivellari, A., and E. Beinat. "From Motion Activity to Geo-Embeddings: Generating and Exploring Vector Representations of Locations, Traces and Visitors through Large-Scale Mobility Data." ***ISPRS International Journal of Geo-Information*** **8.3 (2019): 134.**

Mot2Vec is proposed to derive multidimensional vector representations of locations, traces, and visitors through an unsupervised machine learning approach, which enables direct comparison of locations' connectivity, provides analogous similarity distributions for places of the same type, and identifies common human movement behaviors.

Deng, D., C. Shahabi, U. Demiryurek, L. Zhu, R. Yu, and Y. Liu. "Latent Space Model for Road Networks to Predict Time-Varying Traffic." In ***Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*****. Edited by Balaji Krishnapuram, and Mohak Shah,1525–1534. New York: Association for Computing Machinery, 2016.**

A latent space modeling framework for road networks (LSM-RN) is proposed for more accurate and scalable traffic prediction by utilizing both topology similarity and temporal correlations.

Liu, K., S. Gao, P. Qiu, X. Liu, B. Yan, and F. Lu. "Road2vec: Measuring Traffic Interactions in Urban Road System from Massive Travel Routes." ***ISPRS International Journal of Geo-Information*** **6.11 (2017): 321.**

The proposed Road2Vec can quantify the implicit spatial interactions among road segments based on real-world vehicle operating data. Such embedding techniques capturing underlying heterogeneous and nonlinear traffic properties can be used for more accurate short-term traffic forecasting along road networks.

Liu, X., C. Andris, and S. Rahimi. "Place Niche and Its Regional Variability: Measuring Spatial Context Patterns for Points of Interest with Representation Learning." ***Computers, Environment and Urban Systems*** **75 (2019): 146–160.**

Proposes a representation learning model using spatial contexts to explore place niche patterns and demonstrates potential for information retrieval and place recommendation tasks.

Jean, N., S. Wang, A. Samar, G. Azzari, D. Lobell, and S. Ermon. "Tile2Vec: Unsupervised Representation Learning for Spatially Distributed Data." In ***Proceedings of the 33rd AAAI Conference on Artificial Intelligence*****. Edited by AAAI, 3967–3974. Palo Alto, CA: AAAI Press, 2019.**

Proposes an unsupervised representation learning algorithm Tile2Vec that extends the distributional context hypothesis from natural language to spatially distributed data such as remote sensing images.

Mai, G., K. Janowicz, B. Yan, R. Zhu, L. Cai, and N. Lao. "Multi-Scale Representation Learning for Spatial Feature Distributions Using Grid Cells." In ***Proceedings of the International Conference on Learning Representations, Addis Ababa, Ethiopia, April*****,** ***26–***

***30*, *2020*. OpenReview.net.**

A novel representation learning model called Space2Vec is proposed to encode the absolute positions and spatial relationships of places. Experiment results show that such a multiscale spatial representation model outperforms traditional models in POI type prediction and image classification tasks.

Yan, B., K. Janowicz, G. Mai, and S. Gao. "From ITDL to Place2Vec: Reasoning about Place Type Similarity and Relatedness by Learning Embeddings from Augmented Spatial Contexts." In *Proceedings of the 25th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems*. Edited by Erik Hoel, et al., 1–10. New York: Association for Computing Machinery, 2017.

A novel method to augment the spatial contexts of POI types using a distance-binned, information-theoretic approach is proposed to generate place-type embeddings. It outperforms non-spatial Word2Vec and other representation models using three different machine and human intelligence evaluation tasks and strongly correlates with human assessments of POI type similarity.

Zhai, W., X. Bai, Y. Shi, Y. Han, Z. R. Peng, and C. Gu. "Beyond Word2vec: An Approach for Urban Functional Region Extraction and Identification by Combining Place2vec and POIs." *Computers, Environment and Urban Systems* 74 (2019): 1–12.

Combines Place2Vec representation learning of POIs and clustering approaches for urban functional region identification and neighborhood classification.

Zhang, C., K. Zhang, Q. Yuan, et al. "Regions, periods, activities: Uncovering urban dynamics via cross-modal representation learning." In *Proceedings of the 26th International Conference on World Wide Web*. Edited by Rick Barrett and Rick Cummings, 361–370. New York: Association for Computing Machinery, 2017.

A new cross-modal representation learning method for uncovering urban dynamics with massive geotagged social media data is developed. It jointly embeds all spatial, temporal, and textual dimensions into data representations.

Spatial Prediction and Interpolation

The basic idea of spatial prediction is to estimate the values of a geographic variable at unknown locations using known location values or multivariate data analysis (see more details in Zhu, et al. 2018, cited under Spatially Explicit AI Models). Spatial interpolation is one type of spatial prediction functionality in GIS. Traditional methods of spatial interpolation include Inverse Distance Weighting (IDW) and Triangulated Irregular Networks (TIN). Innovative use of machine learning and deep learning in spatial prediction includes, for example, new development of spatial interpolation methods using conditional generative adversarial neural networks (Zhu, et al. 2020), interpolation and prediction of activity locations from sparsely sampled mobile phone location data (Li, et al. 2019; Li, et al. 2020), classification of GPS noise levels using convolutional neural networks (CNN) for accurate distance estimation (Murphy, et al. 2017), traffic sign recognition for traffic rule updating (Xing, et al. 2019), and enhancing trip distribution prediction (Pourebrahim, et al. 2018). In addition, many human activities happen along road networks. Thus, spatiotemporal prediction of traffic flows, urban mobility patterns, and crimes also attracts large attention (more information in Zhang, et al. 2019; Zhao, et al. 2019; Ren, et al. 2020; and Zhang and Cheng 2020).

Li, M., S. Gao, F. Lu, and H. Zhang. "Reconstruction of Human Movement Trajectories from Large-Scale Low-Frequency Mobile Phone Data." *Computers, Environment and Urban Systems* 77 (2019): 101346.

A machine learning-based multi-criteria data partitioning trajectory reconstruction method (MDP-TR) is proposed to interpolate and reconstruct human movement trajectories from large-scale low-frequently sampled mobile phone location data. One key concept for designing this intelligent method is considering the similarity among multiple trajectories and the temporal patterns of missing location data.

Li, M., F. Lu, H. Zhang, and J. Chen. "Predicting Future Locations of Moving Objects with Deep Fuzzy-LSTM Networks." ***Transportmetrica A: Transport Science*** **16.1 (2020): 119–136.**

A novel trajectory prediction method called the trajectory predictor with fuzzy-long short-term memory network (TrjPre-FLSTM) is introduced by overcoming the sharp boundary limitation and considering period movement patterns of individual trajectories.

Murphy, J., Y. Pao, and A. Haque. "Image-Based Classification of GPS Noise Level Using Convolutional Neural Networks for Accurate Distance Estimation." In ***Proceedings of the 1st Workshop on Artificial Intelligence and Deep Learning for Geographic Knowledge Discovery*****. Edited by Huina Mao, Yingjie Hu, Song Gao, and Grant McKenzie, 10–13. New York: Association for Computing Machinery, 2017.**

A CNN approach to classifying the noise level of the input ride-sharing GPS data on any given route is proposed to reduce the distance errors between the predicted and ground-truth traces of actual ride data and to find the best estimate of the driving path.

Pourebrahim, N., S. Sultana, J. C. Thill, and S. Mohanty. "Enhancing Trip Distribution Prediction with Twitter Data: Comparison of Neural Network and Gravity Models." In ***Proceedings of the 2nd ACM SIGSPATIAL International Workshop on AI for Geographic Knowledge Discovery*****. Edited by Yingjie Hu, Song Gao, Shawn Newsam, and Dalton Lunga, 5–8. New York: Association for Computing Machinery, 2018.**

Compares the performance of artificial neural networks and the gravity model in predicting the home-work commuting flows between census tracts of the New York City. The models use population, employment, distance, and number of geotagged-tweets in the origin-destination zones as variables. It shows that adding the social media information may improve the model performance in trip distribution prediction.

Ren, Y., H. Chen, Y. Han, T. Cheng, Y. Zhang, and G. Chen. "A Hybrid Integrated Deep Learning Model for the Prediction of Citywide Spatio-Temporal Flow Volumes." ***International Journal of Geographical Information Science*** **34.4 (2020): 802–823.**

Introduces a long short-term memory neural network into the ST-ResNet to form a hybrid integrated deep learning model to predict urban traffic flows.

Xing, T., Y. Gu, Z. Song, et al. "A Traffic Sign Discovery Driven System for Traffic Rule Updating." In ***Proceedings of the 3rd ACM SIGSPATIAL International Workshop on AI for Geographic Knowledge Discovery*****. Edited by Song Gao, et al. 52–55. New York: Association for Computing Machinery, 2019.**

A deep learning-based traffic sign recognition system for traffic rule updating (such as no left/right/U- turn, no parking, and speed limit) is developed by DiDi Chuxing. The object detection and classification based on deep neural networks and a model compression method are deployed on their driving vehicle recorders.

Zhang, F., L. Wu, D. Zhu, and Y. Liu. "Social Sensing from Street-Level Imagery: A Case Study in Learning Spatio-Temporal Urban Mobility Patterns." ***ISPRS Journal of Photogrammetry and Remote Sensing*** **153 (2019): 48–58.**

A deep convolutional neural network (DCNN) is developed to identify high-level scene features from street view images that can explain up to 66.5 percent of the hourly variation of taxi trips along urban road networks. It presents a smart approach to bridge the gaps between the physical sensing and human activity sensing.

Zhang, Y., and T. Cheng. "Graph Deep Learning Model for Network-Based Predictive Hotspot Mapping of Sparse Spatio-Temporal Events." ***Computers, Environment and Urban Systems*** **79 (2020): 101403.**

Proposes a gated localized diffusion neural network (GLDNet) for predictive hotspots of sparse spatiotemporal events along road networks. A case study using crime data in Chicago is conducted to validate the effectiveness of the GLDNet model.

Zhao, L., Y. Song, C. Zhang, et al. “T-GCN: A Temporal Graph Convolutional Network for Traffic Prediction.” *IEEE Transactions on Intelligent Transportation Systems* 21.9 (2019): 3848–3858.

A novel temporal graph convolutional network T-GCN is proposed for traffic prediction, which uses the GCN to learn complex topological structures for capturing spatial dependence and uses the gated recurrent unit to learn dynamic changes of traffic data for capturing temporal dependence.

Zhu, D., X. Cheng, F. Zhang, X. Yao, Y. Gao, and Y. Liu. “Spatial Interpolation Using Conditional Generative Adversarial Neural Networks.” *International Journal of Geographical Information Science* 34.4 (2020): 735–758.

A novel deep learning architecture named “conditional encoder-decoder generative adversarial neural networks” (CEDGANs) is proposed for spatial interpolation tasks. A case study on digital elevation models (DEMs) shows that the CEDGANs outperform benchmark spatial interpolation methods in both accuracy and visual fidelity because it can capture local geographical structure patterns.

AI in Cartography and Mapping

Recent research demonstrates great potential for implementing AI techniques, especially deep learning for cartographic design and map style transferring (see Xu and Zhao 2018; Kang, et al. 2019; Huang, et al. 2019), detection and extraction of map features, symbols, and texts (Li and Hsu 2020; Duan, et al. 2018; Duan, et al. 2020; Xie, et al. 2020; Yan, et al. 2020), and cartographic generalization (Touya, et al. 2019; Feng, et al. 2019). These directions for the use of AI in cartography are outlined as follows. First, the use of generative adversarial networks (GAN) can be extended to other mapping contexts, such as helping cartographers deconstruct the most salient stylistic elements that constitute the unique look and feel of existing designs and using this information to improve cartographic designs. Second, the topology of geographic features needs to be well retained and the map symbols and texts may require separate pattern recognition models from styling to get better outcomes. Finally, integration of AI with cartographic design may fully or partially automate the map generalization process.

Duan, W., Y. Y. Chiang, C. A. Knoblock, S. Leyk, and J. H. Uhl. “Automatic Generation of Precisely Delineated Geographic Features from Georeferenced Historical Maps Using Deep Learning.” In *Proceedings of the AutoCarto/UCGIS 2020*. Edited by S. M. Freundschuh and D. Sinton, 59–63. Albuquerque, NM: Cartography and Geographic Information Society, 2018.

The research compared the performance of two DCNN models for extracting geographic features from scanned historical maps. The context module that does not use pooling layers can maintains the spatial resolution of the input historical maps (images) and thus generate fewer false positives than the fully convolutional networks (FCNs).

Duan, W., Y. Y. Chiang, S. Leyk, J. H. Uhl, and C. A. Knoblock. “Automatic Alignment of Contemporary Vector Data and Georeferenced Historical Maps Using Reinforcement Learning.” *International Journal of Geographical Information Science* 34.4 (2020): 824–849.

The research introduces a novel reinforcement learning approach to annotate precise locations of geographic features on historical scanned maps. The proposed automatic vector-to-raster alignment algorithm enables efficient searches for matching features without pre-processing steps, such as extracting specific feature signatures (e.g., road intersections) in aligning various features (roads, water lines, and railroads) with high accuracy.

Feng, Y., F. Thiemann, and M. Sester. “Learning Cartographic Building Generalization with Deep Convolutional Neural Networks.” *ISPRS International Journal of Geo-Information* 8.6 (2019): 258.

The research employs DCNN and GAN for cartographic generalizations (with a focus on building generalization in digital maps). The performance of three network architectures—U-net, residual U-net, and GAN for building generalization in multiple map scales—are compared using OpenStreetMap. The residual U-net is found to outperform the other two models in the building generalization experiments.

Huang, X., D. Xu, Z. Li, and C. Wang. “Translating Multispectral Imagery to Nighttime Imagery via Conditional Generative Adversarial Networks.” Preprint arXiv:2001.05848. Ithaca, NY: Computer Research Repository (CoRR), 2019.

The Pix2Pix GAN is employed to translate multispectral imagery derived from Landsat 8 into nighttime images with the style of the Visible Infrared Imaging Radiometer Suite (VIIRS) product.

Kang, Y., S. Gao, and R. E. Roth. “Transferring Multiscale Map Styles Using Generative Adversarial Networks.” *International Journal of Cartography* 5.2–3 (2019): 115–141.

A novel framework using AI for map style transfer applicable across multiple map scales is proposed. The research identifies and transfers styles from a target group of visual examples, including Google Maps, OpenStreetMap, and artistic paintings, to unstylized GIS vector data using two conditional GAN models (Pix2Pix and CycleGAN).

Li, W., and C. Y. Hsu. “Automated Terrain Feature Identification from Remote Sensing Imagery: A Deep Learning Approach.” *International Journal of Geographical Information Science* 34.4 (2020): 637–660.

A new deep convolutional neural network (DCNN) approach is introduced to automatically detect and extract terrain features from 12,000 remotely sensed images (1,000 original images and 11,000 derived images from data augmentation).

Touya, G., X. Zhang, and I. Lokhat. “Is Deep Learning the New Agent for Map Generalization?” *International Journal of Cartography* 5.2–3 (2019): 142–157.

The authors discuss key issues in the use of machine learning and deep learning models in the automatic map generalization process. Data enrichment and automatic evaluation of the model outputs are two key steps.

Xie, Y., J. Cai, R. Bhojwani, S. Shekhar, and J. Knight. “A Locally-Constrained YOLO Framework for Detecting Small and Densely-Distributed Building Footprints.” *International Journal of Geographical Information Science* 34.4 (2020): 777–801.

A novel Locally-Constrained (LOCO) You-Only-Look-Once deep learning framework by incorporating spatial characteristics is proposed to detect small and densely distributed building footprints from satellite images.

Xu, C., and B. Zhao. “Satellite Image Spoofing: Creating Remote Sensing Dataset with Generative Adversarial Networks.” In *10th International Conference on Geographic Information Science (GIScience 2018)*. Edited by S. Winter, A. Griffin, and M. Sester, 67.1–67.6. Saarbrücken, Germany: Schloss Dagstuhl, 2018.

The CycleGAN model is employed to transfer remote sensing image styles and geographic features of different cities from one place to another, which also shows the capability of GAN in extracting feature patterns from their spatial distribution structures in cities.

Yan, X., T. Ai, M. Yang, and X. Tong. “Graph Convolutional Autoencoder Model for the Shape Coding and Cognition of Buildings in Maps.” *International Journal of Geographical Information Science* (Online First, 25 May 2020).

A graph convolutional autoencoder (GCAE) model consisting of the graph convolution and unsupervised auto-encoder learning architecture is proposed to classify building shapes such as E- shape, T-shape, and U-shape, and support shape matching and retrieval in digital maps.

Deep Learning in Earth Observation

Recent advancement in deep learning has revolutionized multiple domains in both scientific and practical ways (see LeCun, et al. 2015, cited under Historical Roots and General Overviews). Researchers find that the integration of spatiotemporal features extracted from remote sensing big data with deep learning models offers capabilities for a better understanding of data-driven and physical process-based Earth system science (as described by Reichstein, et al. 2019 and Zhu, et al. 2017), including various Earth observation applications such as land cover and land use classification (Scott, et al. 2017; Huang, et al. 2018), air quality monitoring (Li, et al. 2017), soil mapping (Behrens, et al. 2018), environmental parameter retrieval (Yuan, et al. 2020), flood mapping for natural disaster response (Peng, et al. 2019), and transportation infrastructure extraction (Tao, et al. 2019).

Behrens, T., K. Schmidt, R. A. MacMillan, and R. A. V. Rossel. "Multi-scale Digital Soil Mapping with Deep Learning." ***Scientific Reports*** **8.1 (2018): 1–9.**

The research introduces a mixed-scaling method with deep learning for digital soil mapping that overcomes some issues (such as neighbor size and decomposition artifact) when using traditional terrain feature construction methods and preserves the landscape features across multiple scales.

Huang, B., B. Zhao, and Y. Song. "Urban Land-Use Mapping Using a Deep Convolutional Neural Network with High Spatial Resolution Multispectral Remote Sensing Imagery." ***Remote Sensing of Environment*** **214 (2018): 73–86.**

A semi-transfer deep convolutional neural network (STDCNN) approach is proposed to overcome some limitations when applying traditional DCNN methods in remote sensing, such as no more than three multispectral channels, limited training samples, and uniform decomposition of large images. The proposed STDCNN model is used to generate high accuracy urban land-use maps from WorldView-2 and WorldView-3 high spatial resolution (HSR) remote sensing images.

Li, T., H. Shen, Q. Yuan, X. Zhang, and L. Zhang. "Estimating Ground-Level PM2.5 by Fusing Satellite and Station Observations: A Geo-Intelligent Deep Learning Approach." ***Geophysical Research Letters*** **44.23 (2017): 11–985.**

A GeoAI approach that incorporates geographical correlation into a deep belief network learning architecture is proposed to estimate the spatial distribution of ground level PM2.5 concentration by fusing satellite and station observation data. Experiments in China show that the proposed Geoi-DBN model outperforms other traditional nonspatial neural networks.

Reichstein, M., G. Camps-Valls, B. Stevens, M. Jung, J. Denzler, and N. Carvalhais. "Deep Learning and Process Understanding for Data-Driven Earth System Science." ***Nature*** **566.7743 (2019): 195–204.**

This perspective paper summarizes state-of-the-art machine learning approaches to geoscientific tasks, such as weather forecasts, land-use change detection, atmospheric flux prediction, and physical transport modeling. It identifies five major challenges for the successful adoption of deep learning approaches in the geosciences: interpretability, physical consistency, complex and uncertain data, limited labels, and computational demand. It calls for a hybrid modeling approach with coupling physical process models with data-driven machine learning.

Scott, G. J., M. R. England, W. A. Starms, R. A. Marcum, and C. H. Davis. "Training Deep Convolutional Neural Networks for Land-Cover Classification of High-Resolution Imagery." ***IEEE Geoscience and Remote Sensing Letters*** **14.4 (2017): 549–553.**

To overcome the limited label issue in deep-learning-based land-cover classification using remote-sensing image data, the research employs two techniques in conjunction with DCNN: transfer learning with fine-tuning technique, and data augmentation technique tailored specifically for improving network training of remote sensing imagery. Three different DCNNs derived from CaffeNet, GoogLeNet, and ResNet50 all show high land-cover classification accuracies on two different remote sensing data sets.

Peng, B., Z. Meng, Q. Huang, and C. Wang. "Patch Similarity Convolutional Neural Network for Urban Flood Extent Mapping Using Bi-temporal Satellite Multispectral Imagery." ***Remote Sensing*** **11.21 (2019): 2492.**

The research develops a new patch similarity convolutional neural network (PSNet) using satellite multispectral surface reflectance imagery instead of raw pixel digital numbers before and after flooding with a 3-meter spatial resolution, which can mitigate the influence of inconsistent illumination caused by varied weather conditions at different times of data collection. Experiments on two hurricane-related flooding events show high accuracy and recall of the proposed model.

Tao, C., J. Qi, Y. Li, H. Wang, and H. Li. "Spatial Information Inference Net: Road Extraction Using Road-Specific Contextual Information." ***ISPRS Journal of Photogrammetry and Remote Sensing*** **158 (2019): 155–166.**

A spatial information inference structure that enables multidirectional message passing between pixels is integrated into a deep-learning-based semantic segmentation framework for road information extraction from very-high-resolution (VHR) satellite imagery. It shows the importance of preserving different levels (the global-level, local-level and object-level) of contextual information in semantic segmentation to keep the continuity of the extracted road networks.

Yuan, Q., H. Shen, T. Li, et al. "Deep Learning in Environmental Remote Sensing: Achievements and Challenges." ***Remote Sensing of Environment*** **241 (2020): 111716.**

Provides a comprehensive review of deep learning approaches to environmental remote sensing. Summarizes key deep neural network architectures and achievements in various environmental fields, including land cover, vegetation parameters, agricultural yield prediction, land surface and air temperature, aerosol, particulate matter, precipitation, soil moisture, snow cover, evapotranspiration, radiation, and ocean color parameters. Also discusses different ways of integration of physical models and spatiotemporal characteristics with deep learning.

Zhang, C., I. Sargent, X. Pan, et al. "Joint Deep Learning for Land Cover and Land Use Classification." ***Remote Sensing of Environment*** **221 (2019): 173–187.**

A novel joint deep learning framework that incorporates patch-based CNN and pixel-based multilayer perceptron with joint reinforcement and mutual complementarity is proposed for land cover and land use (LCLU) classification simultaneously. The proposed approach is tested on aerial photography of two large urban and suburban areas in Great Britain (Southampton and Manchester) and shows a good performance in automating joint LCLU classification tasks together.

Zhu, X. X., D. Tuia, L. Mou, et al. "Deep Learning in Remote Sensing: A Comprehensive Review and List of Resources." ***IEEE Geoscience and Remote Sensing Magazine*** **5.4 (2017): 8–36.**

Analyzes the challenges and unique questions of using deep learning for remote-sensing data analysis (such as multimodal, geolocated, measurements with controlled uncertainty, geophysical and biochemical quantities), reviews state-of-the-art deep learning models for remote sensing data analysis, and provides resources including data sources, tutorials, and open-source deep learning frameworks to advance this field.

GeoAI in Social Sensing

Compared to remote sensing data that have been successfully used to extract physical characteristics of the Earth's surface, social sensing data complement remote sensing data by revealing human dynamics and the underlying socioeconomic characteristics, using various data sources (e.g., mobile phone data, taxi GPS trajectories, location-based social networks, and social media) (see the definition of social sensing in Liu, et al. 2015). The process of social sensing involves the creation of multidimensional semantic data signatures (i.e., spatial, temporal, and thematic features, defined in Janowicz, et al. 2019.) from location-based digital traces. Much of social sensing research is rooted in the concept of place, including understanding place characteristics in geographic contexts (Zhu, et al. 2020) and extraction of human emotions at different places from facial expressions (Kang, et al. 2019). With the advancement of drive-by sensors, computer vision, and deep learning techniques, street-level images become a new data source for understanding the physical environments and social environments, such as estimating the demographic makeup of neighborhoods (Gebru, et al. 2017), understanding human perception of places using semantically segmented scene elements (Zhang, et al. 2018), and examining the association of street green and blue spaces with geriatric depression (Helbich, et al. 2019). Furthermore, the emergence of various types of geospatial big data provides new opportunities for social sensing. Multiple geospatial data fusion with deep learning is a new research theme, such as fusion of remote sensing and social sensing data for urban functional region recognition (Cao, et al. 2020), fusion of street view images and social media check-ins for uncovering inconspicuous places (Zhang, et al. 2020), and a combination of street view images and OpenStreetMap data for street frontage classification (Law, et al. 2020).

Cao, R., W. Tu, C. Yang, et al. "Deep Learning-Based Remote and Social Sensing Data Fusion for Urban Region Function Recognition." ***ISPRS Journal of Photogrammetry and Remote Sensing*** **163 (2020): 82–97.**

A novel end-to-end deep-learning-based remote and social sensing data fusion model is developed to automatically extract urban functional regions. Residual neural network (ResNet), spatial pyramid pooling (SPP-Net), and stacked bidirectional long short-term memory network (LSTM-Net) are employed to learn multidimensional social sensing and remote sensing features. Three different fusion methods for combining multimodal features are compared: concatenation, element-wise sum, and element-wise max pooling.

Gebru, T., J. Krause, Y. Wang, et al. "Using Deep Learning and Google Street View to Estimate the Demographic Makeup of Neighborhoods across the United States." ***Proceedings of the National Academy of Sciences*** **114.50 (2017): 13108–13113.**

Introduces the use of deep learning and Google Street View images for estimating socioeconomic characteristics of neighborhoods across 200 US cities. Over 22 million automobiles' information is extracted from 50 million street scene images and has a good association with income, race, education, and voting patterns at the zip code and precinct geographical scales.

Helbich, M., Y. Yao, Y. Liu, J. Zhang, P. Liu, and R. Wang. "Using Deep Learning to Examine Street View Green and Blue Spaces and Their Associations with Geriatric Depression in Beijing, China." ***Environment International*** **126 (2019): 107–117.**

A fully CNN for semantic segmentation (i.e., the FCN-8s) is applied to extract streetscape green and blue spaces from street view images and satellite-based remote sensing images. The mental health of elderly people is found to be enhanced by exposure to green and blue spaces, but no significant evidence is found to associate with remote sensing-based metrics.

Janowicz, K., G. McKenzie, Y. Hu, R. Zhu, and S. Gao. "Using Semantic Signatures for Social Sensing in Urban Environments." In ***Mobility Patterns, Big Data and Transport Analytics*****. Edited by Constantinos Antoniou, Loukas Dimitriou, Francisco Pereira, 31–54. Amsterdam: Elsevier, 2019.**

This book chapter systematically summarizes the social sensing methodological framework of semantic signatures that include spatial, temporal, and thematic features constructed from digital traces of human-place interactions. Six social sensing applications are introduced for studying urban environments using semantic signatures: comparing place types, gazetteers matching, geoprivacy, temporally enhanced geolocation service, regional variation analysis, and extraction of urban functional regions.

Kang, Y., Q. Jia, S. Gao, et al. "Extracting Human Emotions at Different Places Based on Facial Expressions and Spatial Clustering Analysis." ***Transactions in GIS*** **23. 3 (2019): 450–480.**

Introduces the concept of place emotion, which is a special category of the human affective computing at different places. Then presents a methodological framework of extracting human emotions from facial expressions in photos using state-of-the-art computer vision and deep learning techniques and attaching to places using a spatial clustering technique. Much of the emotional variation at different places can be explained by a few geographic and environmental factors.

Law, S., C. I. Seresinhe, Y. Shen, and M. Gutierrez-Roig. "Street-Frontage-Net: Urban Image Classification Using Deep Convolutional Neural Networks." ***International Journal of Geographical Information Science*** **34.4 (2020): 681–707.**

A deep learning model Street-Frontage-Net is developed to help evaluate the quality of street frontage as either being active (frontage containing windows and doors) or blank (frontage containing walls, fences, and garages). Multiple features can be extracted from street view images and street network morphology images, which provides new insights for urban planning and management to identify active frontages in different neighborhoods.

Liu, Y., X. Liu, S. Gao, et al. "Social Sensing: A New Approach to Understanding Our Socioeconomic Environments." ***Annals of the Association of American Geographers*** **105.3 (2015): 512–530.**

One of the pioneer social sensing papers focusing on theoretical contributions. It introduces key concepts; compares the major sources, signals, and processing methods of social sensing with remote sensing; and points out major issues when applying social sensing analytics. It also suggests that social sensing data contain rich information about spatial interactions and place semantics. But we need to pay more attention to representativeness and data quality issues.

Zhang, F., J. Zu, M. Hu, et al. "Uncovering Inconspicuous Places Using Social Media Check-Ins and Street View Images." ***Computers, Environment and Urban Systems*** **81 (2020): 101478.**

A novel framework of extracting place-based multidimensional features is proposed to characterize places in terms of place type, human activity, visit group, and locale environment using multisource big geo-data. Individual-level social media check-in data are effective for differentiating locals and visitors. High-level features extracted from street view images using deep learning are useful to describe the surrounding streetscape of places. Such a data-synthesis-driven framework can facilitate place-based knowledge discovery and policymaking.

Zhang, F., B. Zhou, L. Liu, et al. "Measuring Human Perceptions of a Large-Scale Urban Region Using Machine Learning." ***Landscape and Urban Planning*** **180 (2018): 148–160.**

Over 110,000 street view images spanning 56 cities in 28 countries are captured, using DCNN to extract six dimensions of human perceptions on urban environments: safe, lively, beautiful, wealthy, depressing, and boring. This learning framework is then applied to infer the spatial distribution of city-wide human perceptions in new cities. A set of objects from image segmentation results are identified to link the perceptual indicators.

Zhu, D., F. Zhang, S. Wang, et al. "Understanding Place Characteristics in Geographic Contexts through Graph Convolutional Neural Networks." ***Annals of the American Association of Geographers*** **110.2 (2020): 408–420.**

Employs graph convolutional neural networks (GCNs) to model spatial interactions among places as a graph, where each place is formalized as a node, place characteristics are encoded as node features, and place connections are represented as the edges. It also discusses the influence of different place connection measures (self-only connection, adjacency, and spatial interactions) on the prediction accuracy for unobserved region characteristics using over 240,000 POIs in Beijing.

Geospatial Semantics and Geo-Text Analysis

Digital Gazetteers are dictionaries of geo-referenced places and geo-text data analysis play an important role in geographic information retrieval (GIR), spatial-temporal knowledge organization, and data-driven semantics research (see Janowicz, et al. 2012; Hu 2018). Most of the gazetteer databases are maintained by authoritative agencies. It is time-consuming to update place entries because of high costs. Extraction and integration techniques to automatically obtain geographic information from spatiotemporal linked data and volunteered geographic information sources have recently come to the spotlight (see Janowicz, et al. 2012; Gao, et al. 2017). Key processing steps in geo-text data analysis include place name disambiguation, toponym matching, and footprint extraction. Topic modeling, rule-based matching, machine learning, and deep learning approaches have been proposed for the geo-text data processing by Ju, et al. 2016; Santos, et al. 2018; Acheson, et al. 2020; and Wang, et al. 2020. Intelligent applications of geospatial semantics contain the understanding of place environments and human sentiments from user textual reviews (Hu, et al. 2019), and translation of natural language queries to GIS functionality and operation tools (Scheider, et al. 2019). In addition, there is an increasing use of social media text data with deep learning approaches to extract situational awareness information at different place resolutions during natural disasters (Yu, et al. 2019; Wang, et al. 2020).

Acheson, E., M. Volpi, and R. S. Purves. "Machine Learning for Cross-Gazetteer Matching of Natural Features." ***International Journal of Geographical Information Science*** **34.4 (2020): 708–734.**

This research compares the use of a machine learning approach (i.e., random forests) and a rule-based approach to cross-gazetteer matching of natural features in two gazetteers, GeoNames and SwissNames3D. The random forests model performs better gain than the rule-based approach regarding matching feature types, but only achieves negligible gains from specialized matching features. Open-source data and tools used in this research are shared on Github to support replicable and reproducible research.

Gao, S., L. Li, W. Li, K. Janowicz, and Y. Zhang. "Constructing Gazetteers from Volunteered Big Geo-Data Based on Hadoop." ***Computers, Environment and Urban Systems*** **61 (2017): 172–186.**

A high-performance Hadoop-based geoprocessing platform with a data-driven approach to constructing digital gazetteers (dictionaries of place names with footprints) from volunteered geographic information is introduced. It demonstrates how to use spatial-function-enabled cloud computing infrastructure to facilitate geospatial semantics research.

Hu, Y. "Geo-Text Data and Data-Driven Geospatial Semantics." ***Geography Compass*** **120.11 (2018): e12404.**

Hu introduces the key concepts and types of geo-text data in GIS and reviews several applications of geospatial semantics, including extracting place names, place-based relations, sentiment/emotions, zones, and impacts. A generalized workflow utilizing natural language processing and spatial clustering for analyzing geo-text data is proposed, including data retrieval, geoparsing, data analysis, evaluation, and result visualization.

Hu, Y., C. Deng, and Z. Zhou. "A Semantic and Sentiment Analysis on Online Neighborhood Reviews for Understanding the Perceptions of People toward Their Living Environments." ***Annals of the American Association of Geographers*** **109.4 (2019): 1052–1073.**

The research utilizes natural language processing techniques to extract semantic topics and human sentiments that people express toward their neighborhoods. An experiment using online textual reviews about the neighborhoods in New York City is conducted, and the results can be used for supporting urban planning and studies of living environments.

Janowicz, K., S. Scheider, T. Pehle, and G. Hart. "Geospatial Semantics and Linked Spatiotemporal Data—Past, Present, and Future." ***Semantic Web*** **3.4 (2012): 321–332.**

This article outlines the research field of geospatial semantics, including two major directions: semantic modeling and semantics-based search, integration, and interoperability of geo-referenced information. Then, key progress and challenges in geospatial semantics research fields are summarized, including geo-ontology engineering, semantic reference systems, semantic primitives and information grounding, event discovery and spatiotemporal ontologies, places and semantic trajectories, sensor and observation semantics, and spatial data infrastructures.

Ju, Y., B. Adams, K. Janowicz, Y. Hu, B. Yan, and G. McKenzie. "Things and Strings: Improving Place Name Disambiguation from Short Texts by Combining Entity Co-occurrence with Topic Modeling." In *Knowledge Engineering and Knowledge Management: 20th European Knowledge Acquisition Workshop Proceedings*. Edited by Eva Blomqvist, Paolo Ciancarini, Francesco Poggi, and Fabio Vitali, 353–367. Cham, Switzerland: Springer, 2016.

A novel approach to improving place-name disambiguation from short texts by combining entity co-occurrence on linked data with topic modeling is proposed and is found to outperform benchmark systems such as DBpedia Spotlight and Open Calais in place name disambiguation tasks.

Santos, R., P. Murrieta-Flores, P. Calado, and B. Martins. "Toponym Matching through Deep Neural Networks." *International Journal of Geographical Information Science* 32.2 (2018): 324–348.

A novel deep neural network is proposed to classify five million pairs of toponyms in the GeoNames gazetteer as either matching or non-matching. The performance of the proposed method is better than other traditional supervised machine learning approaches for multiple string similarity metrics.

Scheider, S., A. Ballatore, and R. Lemmens. "Finding and Sharing GIS Methods Based on the Questions They Answer." *International Journal of Digital Earth* 12.5 (2019): 594–613.

The research systematically investigates a variety of analytic questions linking to common GIS tools and proposes a semantic web framework to intelligently match analytic questions to spatial analysis tools that are capable of answering those questions. Examples for the translation of GIS operations to SPARQL queries are demonstrated.

Wang, J., Y. Hu, and K. Joseph. "NeuroTPR: A Neuro-Net Toponym Recognition Model for Extracting Locations from Social Media Messages." *Transactions in GIS*. 24.3 (2020): 1–17.

A bidirectional RNN-based toponym recognition model (NeuroTPR) is proposed to address the linguistic irregularity issues associated with social media text data, such as informal sentence structures, inconsistent letter cases, name abbreviations, and misspellings. An automatic workflow for generating annotated data sets from *Wikipedia* articles is developed for training toponym recognition models. The NeuroTPR model performs better than other baseline toponym recognition models in a Twitter data set from Hurricane Harvey.

Yu, M., Q. Huang, H. Qin, C. Scheele, and C. Yang. "Deep Learning for Real-Time Social Media Text Classification for Situation Awareness—Using Hurricanes Sandy, Harvey, and Irma as Case Studies." *International Journal of Digital Earth* 12.11 (2019): 1230–1247.

This research examines the capability of a deep learning model in cross-event social media textual topic classification for disaster situational awareness based on three geo-tagged Twitter data sets collected during Hurricanes Sandy, Harvey, and Irma. The experiment results demonstrate that CNN models achieve a consistently better accuracy for both single event and cross-event evaluation scenarios than the SVM and logistic regression models.

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