Title: *NeRF: Representing Scenes as Neural Radiance Fields for View Synthesis*
Authors: Ben Mildenhall, Pratul P. Srinivasan, Matthew Tancik, Jonathan T. Barron, Ravi Ramamoorthi, Ren Ng
Published in: ECCV 2020 Oral - Best Paper Honorable Mention

1. General Topic Studied
"Synthesizing novel views of complex scenes by optimizing an underlying continuous volumetric scene function using a sparse set of input views."
2. Specific Behavior or Activity Studied
"A continuous 5D function is optimized to represent static scenes, outputting the radiance emitted in each direction and a density at each point that influences how radiance is accumulated along camera rays."
3. Specific Research Questions
"Can a neural network that represents a continuous volumetric scene function synthesize photorealistic novel views from only a sparse set of input images?"
4. Challenges Faced
- "Efficiently representing high-frequency scene content without incurring the prohibitive storage costs of voxel grids."
- "Ensuring high-resolution renderings with limited input views while maintaining photorealistic details."

5. Key Identifications
Previous neural rendering techniques struggle to represent complex scenes at high resolution due to storage limitations and inefficiencies in volumetric sampling. The authors claim that their proposed method, NeRF, overcomes these challenges by using a fully connected deep neural network (MLP). The evidence supporting these claims is drawn from experimental results. The NeRF model outperforms previous neural rendering methods on both synthetic and real datasets. Performance improvements were measured using standard evaluation metrics such as Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Learned Perceptual Image Patch Similarity (LPIPS). Ablation Studies are also conducted to show the impact of key components like positional encoding, view dependence, and hierarchical sampling on performance.
6. Limitations:
- Training NeRF is computationally intensive, requiring significant GPU resources and time (up to two days per scene), making real-time applications challenging.
- NeRF is an implicit model, a black box MLP. Therefore, it is impossible to explicitly modify parts of the scene represented by NeRF (e.g. change the color of specific components in the scene)
- The paper lacks analysis on potential overfitting when trained on very sparse data or on generalization capabilities across significantly different scenes.

Title: *Classifying Severe Weather Events by Utilizing Social Sensor Data and Social Network Analysis*
Authors: Hussain Otudi, Shelly Gupta, Nouf Albarakati, Zoran Obradovic
Published in: 2023 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM)

1. General Topic Studied
"Weather-related disruptions have a significant impact on a variety of industries, including agriculture, infrastructure, and public safety. Predicting these unusual weather events remains a significant challenge."
2. Specific Behavior or Activity Studied
"We proposed a novel method to classify rare severe weather-related events by incorporating publicly available tweets with the meteorological conditions readings collected from weather stations across Alaska."
3. Specific Research Questions
"Can integrating geotagged social sensor data (tweets) with weather station data enhance the classification performance for rare severe weather events?"
4. Challenges Faced
- "The lack of high-quality weather data due to the failure of sensors at weather stations during severe weather."
- "The imbalance in data distribution across different classes, as rare events occur infrequently, making them difficult to predict accurately."

5. Key Identifications
The authors claim that integrating geotagged social sensor data with weather station readings improves the classification performance for rare severe weather events. The evidence supporting this claim includes meteorological data collected from nine weather stations across Alaska during 2020 and 1,029 geotagged tweets related to weather events from the same region at the same time. The machine learning model was trained on combined datasets, showing an F1-score improvement from 0.30 (weather data alone) to 0.83 (integrated data). The statistical analysis employed in this study includes stratified 5-fold cross-validation, precision, recall, F1-score evaluation, and confusion matrices.
6. Limitations
- The dataset only includes data from 2020 and is limited to Alaska, which could introduce bias and affect the generalizability of the results.
- The model trained solely on weather data shows 0% prediction accuracy for more than half of the rare events. This raises concerns about a potential data leakage issue in the text dataset or whether social media data alone could provide sufficient predictive power. The paper does not analyze these possibilities.