**Apurva Patel’s progress till 02/25/’24**

I intended to understand the idea behind data distillation and how it can be used in the realm of transportation. So I started with reading this paper: <https://arxiv.org/pdf/1811.10959.pdf>

This paper gives me the purpose and general understanding behind data distillation and how its done.

My notes:

* Methodology: The paper proposes an optimization algorithm to synthesize a small number of synthetic data samples that approximate the original training data. The algorithm involves optimizing the pixel values of the distilled images to minimize the loss function of the network trained on these images. The approach is extended to handle different initialization settings and learning objectives.
* Experiments: The paper conducts experiment on multiple datasets, including MNIST and CIFAR10, to demonstrate the effectiveness of the proposed method. Results show that even a small number of distilled images can train a model to achieve high performance, surpassing several baseline methods.
* Extensions: The paper explores various extensions of the main algorithm, including distillation with different initializations and objectives. It demonstrates applications such as fine-tuning pre-trained networks on new datasets and generating malicious data poisoning images to attack classifier networks.
* Read Walid Khan’s reports for existing survey of data distillation techniques.

Summary:

* Different approaches include:

1. Meta Model Matching: Optimizes for the transferability of models trained on data summaries to the original dataset. Inner loop training involves a representative algorithm on the data summary, enhancing transferability.
2. Data Distillation by Gradient Matching: Matches the distance between networks trained on the target dataset and Dsyn with one-step gradient matching, bypassing inner loop optimization. Recent extensions synthesize more data within memory constraints and store summaries in lower resolution.
3. Data Distillation by Trajectory Matching: Aims to align the training trajectories of models trained on the original dataset and Dsyn.
4. Data Distillation by Distribution Matching (DM): Focuses on moving the distribution of Dsyn closer to the original dataset D, rather than improving model quality. Utilizes parametric encoders to map high-dimensional data to low-dimensional latent spaces and approximates distribution mismatch using Max Mean discrepancy.
5. Data Distillation by Factorization: Parametrizes data summaries using independent base vectors and hallucinators, optimizing both for data distillation.

I read this (in Waleed’s report) paper: https://proceedings.mlr.press/v205/ding23a/ding23a.pdf

Summary:

* The paper introduces Causal Autoregressive Flow (CausalAF), a method for generating realistic safety-critical scenarios for testing autonomous driving systems. Unlike traditional approaches, CausalAF considers cause-and-effect relationships among scenarios, improving efficiency and reducing resources needed for optimization. It incorporates causal graphs to guide the generation process and introduces two causal masks to ensure the correct order of node generation and edge connections in the behavioral graph. Experimental results demonstrate superior performance compared to baseline methods.

Externsions:

* Enhanced Causal Knowledge Extraction: Future research could focus on improving the accuracy of causal knowledge extraction, potentially using more robust methods for obtaining causal graphs, such as automatic discovery from observational or interventional datasets.
* Real-world Validation: While evaluations are conducted in simulations, validating the approach with real-world data and scenarios could provide valuable insights into its effectiveness and applicability.
* Integration with Reinforcement Learning: Investigating how the generated scenarios can be effectively used for training reinforcement learning-based driving algorithms to enhance their robustness in real-world scenarios.