**Project Outline Document**

**Github: https://github.com/Druspect/8321\_Seismic\_Interpretation\_Final\_Project**

**Introduction & Motivation**

Manual seismic stratigraphic interpretation is labor-intensive, error-prone, and reliant on expert knowledge​. This project aims to automate and enhance seismic data interpretation using machine learning, improving efficiency and objectivity in classifying subsurface geological features. Large 3D seismic datasets, noise, and complex structures (faults, channel systems, salt diapers, folding, etc.) present challenges that a data-driven approach could help tackle. By leveraging advanced methods like transfer learning and reinforcement learning, we seek to accelerate interpretation while maintaining accuracy.

**Research Questions**

The initial phase of the project is guided by key research question​s:

1. **Transfer Learning Efficacy**: To what extent can transfer learning enhance the accuracy and efficiency of seismic facies classification compared to traditional manual methods?
2. **Generalization to Unlabeled Data**: Will a model trained with transfer learning be able to generalize to *unlabeled* seismic data with any discernible accuracy?
3. **Reinforcement Learning for Refinement**: Under what conditions can reinforcement learning effectively refine seismic interpretations, and how does its performance compare to other machine learning approaches?

These questions frame our exploration of whether pre-trained models and learning agents can address the limitations of manual interpretation.

**Hypothesis**

**Hypothesis:** A transfer learning approach, utilizing pre-trained models fine-tuned on seismic data, will outperform traditional interpretation methods in both speed and precision. However, performance may depend on the similarity between the pre-trained model’s domain and the seismic target domain. Different geologic settings will probably introduce variability. Unlabeled data poses an additional challenge but anticipate that unsupervised pre-training or self-supervised learning could provide useful feature initialization.

Additionally, reinforcement learningis expected to further improve results by iteratively refining the model’s interpretations, given a well-designed reward syste​m. For example, an RL agent could adjust its seismic facies labeling to maximize alignment with an expert-labeled validation set as a reward signal. It is hypothesized that such a model could learn to correct initial interpretation errors over many iterations, leading to increasingly accurate stratigraphic maps.

**Objectives**

To test the above hypothesis, the project sets out the following objectives (initially outlined in the repository README):

* **Apply Transfer Learning**: Demonstrate the applicability of transfer learning to seismic data, especially with limited labeled examples, by fine-tuning pre-trained models with specially trained layers on seismic section images.
* **Multi-Scenario Evaluation**: Evaluate the approach on multiple datasets from different geological environments (to test generalization) and even on unlabeled datasets by leveraging unsupervised or self-supervised techniques.
* **Explore Reinforcement Learning**: Develop a prototype RL framework for seismic interpretation, where an agent iteratively improves the facies classification or horizon picking based on a defined reward (e.g., match to ground truth or geological consistency).
* **Benchmark Against Traditional Methods**: Compare the machine learning interpretations with traditional manual interpretation benchmarks and simpler machine learning methods (such as unsupervised clustering or a non-pretrained CNN), using metrics like accuracy, F1-score, and interpretation time.
* **Visualization and Validation**: Create visualization tools to overlay predicted facies on seismic sections for qualitative assessment and analyze where the models succeed or fail.

**Methodology Overview**

We follow a structured pipeline for the seismic interpretation workflow, with the current focus on the initial steps:

1. **Data Collection and Preprocessing**: Start with gathering seismic data and preparing it for model input. This involves converting seismic volumes or sections into image slices and applying preprocessing steps such as noise reduction and normalization. For example, amplitude values may be scaled between 0 and 1, and band-pass filters or structure-oriented filtering could be applied to enhance signal clarity. *(See the detailed explanation in the code)*
2. **Transfer Learning (CNN Baseline)**: Leverage pre-trained convolutional neural networks to kick-start seismic facies classification​. The idea is to use a model trained on a large image dataset (e.g., ImageNet) and fine-tune it on seismic images, capitalizing on learned feature detectors (edges, textures, etc.). In our baseline, we implemented a simple CNN from scratch to establish a performance baseline. Moving forward, we plan to incorporate a pre-trained model such as RoBERTa and fine-tune its weights on labeled seismic sections. Transfer learning is expected to improve accuracy with fewer training samples, as suggested by prior work where using pre-trained weights improved seismic classification performance even across different region ​[researchgate.net](https://www.researchgate.net/publication/329505359_Transfer_Learning_Applied_to_Seismic_Images_Classification" \l ":~:text=convolutional%20neural%20network%20,that%20are%20not%20geologically%20similar" \t "_blank).
3. **Baseline with Pre-trained Transformer**: As an experimental benchmark, we also adapted a pre-trained **RoBERTa transformer** for classification. The motivation was to test a very different kind of transfer learning using a model pre-trained on language data by representing seismic images in a tokenized format. While unconventional, this tests the model’s ability to find patterns in a sequence of tokens representing an image. (This approach is analogous to Vision Transformers, though here we literally used a language model.) The RoBERTa baseline offers a point of comparison to see if generic pre-trained representations provide any immediate benefit on a vision task without extensive architectural changes.
4. **Reinforcement Learning (Planned)**: In later phases, we will design an RL environment for seismic interpretatio​n. The concept is to have an model, which could utilize a neural network for policy or value function, that makes iterative decisions on interpreting the seismic data (for instance, classifying a section or adjusting a horizon). The agent receives rewards based on how well its interpretation matches known ground truth or perhaps geological plausibility rules. We will explore various algorithms such as Deep Q-Networks (DQN) or policy gradient methods from previous research for this purpose.
5. **Comparative Analysis**: Throughout, we will compare the results of different approaches the simple CNN vs. pre-trained CNN vs. RoBERTa vs. Combined vs. future RL-enhanced methods. Benchmarking against traditional interpretation and simpler baselines will be important to quantify gains. We will use standard metrics (accuracy, precision, recall, F1, AUC) as well as consider computational efficiency and the amount of manual effort reduce​.
6. **Visualization and Interpretability**: An important aspect is understanding what the models have learned. We plan to visualize the seismic sections with the model’s facies predictions overlaid, to visually inspect correctness in geological context. Additionally, we will employ interpretability techniques for the CNN – for instance, analyzing the learned convolutional filters and feature maps. By examining the first-layer filters, we can see if the CNN has learned geological edge detectors or frequency filters. Techniques like Activation Maximization and feature map visualization can help identify what patterns each filter is responsive ​[openreview.net](https://openreview.net/pdf?id=BJ4BVhRcYX#:~:text=Recently%2C%20many%20CNN%20visualization%20techniques,the%20most%20efficient%20and%20effective). Such convolutional filter analysis, as done in interpretability studies, will give insights into whether the model’s inner workings align with geophysical intuition (detecting horizons, faults, channel edges). This interpretability step will be crucial when extending to the RL agent, to ensure the agent’s decisions are justifiable in geologic terms.

**Initial Experiments and Results**

For the initial analysis, we conducted experiments with two baseline models using a **synthetic dataset** of seismic images (as described earlier). The synthetic data was constructed to mimic simple geological patterns (horizontal vs. vertical contrast), allowing us to validate the models on a known task. We evaluated both models on classification accuracy as well as other metrics, and tracked their training progress:

* **Baseline CNN**: A simple one-layer CNN was trained on the synthetic data. As expected, this model learned the pattern quickly.
* **Baseline RoBERTa**: A pre-trained RoBERTa-base model was fine-tuned on the same data, by converting images to token sequences. This model serves as a comparative benchmark to see if a transformer with no image-specific pre-training can classify the patterns.

*Check against code before submission\*\*\*Training and validation loss/accuracy curves for the simple CNN baseline over 10 epochs. The CNN shows a steady decrease in training and validation loss, with training accuracy reaching ~95% and validation accuracy ~90% by the final epoch. The close tracking of validation metrics to training metrics suggests the model is fitting the data well without severe overfitting. These learning curves indicate that the CNN quickly learned to distinguish the synthetic classes, providing a solid baseline performance.*

*In contrast, the RoBERTa based classifier baseline achieved lower accuracy (e.g., validation accuracy plateaued around ~60-70% in our tests). This is not surprising, as RoBERTa is not inherently designed for image data. The transformer had to learn visual patterns from scratch through the tokenized representation, which is a less direct way to interpret images. The result highlights that* ***domain-specific architectures*** *(like CNNs for images) are more effective for this task than using a language model out-of-the-box. It also underscores the value of using pre-trained* ***image*** *models for transfer learning in future work, rather than models from a different domain. That said, the exercise with RoBERTa provides a useful sanity check and a creative exploration of model flexibility. It points us toward trying* ***Vision Transformers*** *or other architectures specifically developed for image understanding, which combine the power of transformers with image patch tokenization.*

*Quantitatively, the simple CNN outperformed the RoBERTa baseline on all evaluated metrics. For instance, on the validation set the CNN achieved higher* ***precision and recall*** *(indicating it correctly and consistently identified the pattern class), and a higher* ***F1-score*** *than the transformer. The CNN’s ROC AUC was also closer to 1.0, reflecting better ranking of positive vs. negative class predictions. These initial results support our hypothesis that a model leveraging appropriate prior knowledge (in this case, the CNN implicitly leverages knowledge of spatial locality and translation invariance) has an advantage.*

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**Conclusions and Next Steps**

My initial investigation confirms the feasibility of machine learning for seismic interpretation. This proof is what we need to dive deeper into the analysis and truly find a methodology worth writing home about. Even a very simple CNN can learn to classify basic seismic facies patterns with high accuracy, demonstrating the potential of data-driven approaches to replicate interpretation tasks.   
  
I haven’t talked about what we will be comparing to beside the baselines. Typically, a subject matter expert(geologist) would have to manually set these tops, at least not a version that is open to the public and not hidden behind a company intellectual property. This means that a reliable open-source seismic stratigraphic methodology could help in bringing modern algorithmic automation to a field that is by my estimation stuck about 40 years in the past, this is one of the reasons for my venture into the wonderful world of computer science, to rectify this issue.   
  
 Transfer learning, in principle and for the reasons mentioned above, should further boost performance a hypothesis aimed to be tested with a pre-trained vision model on real seismic datasets. The attempt to use a pre-trained RoBERTa model, while not as successful as originally hoped, provided valuable insights and a baseline for comparison. It highlighted the importance of choosing models aligned with the data domain and characteristics (images vs. text), and it opens the door to experimenting with the combination of the cnn with this model to fine tune a seismic stratigrapher model!