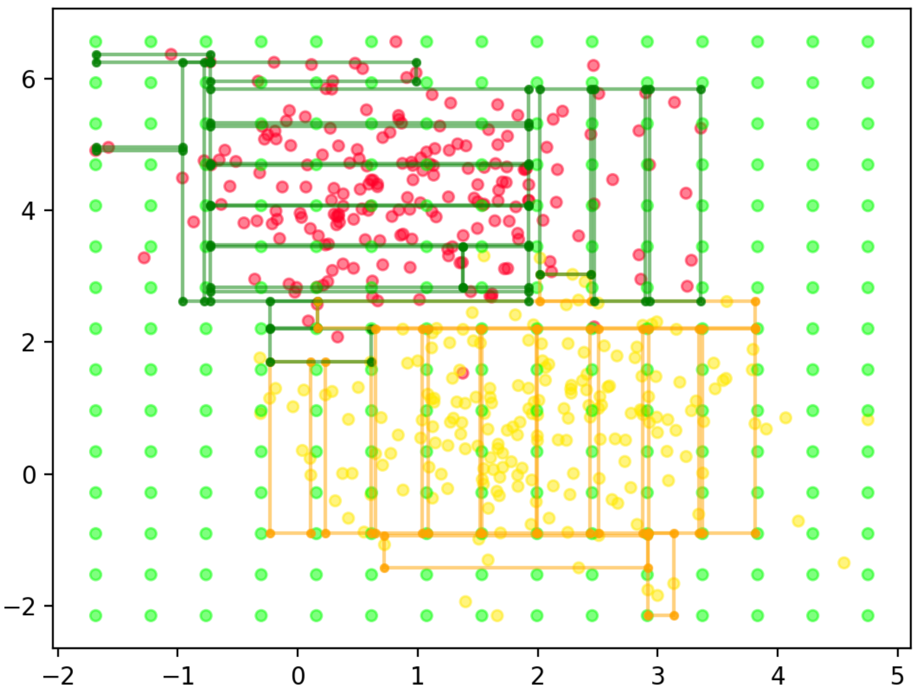
Safe Machine Learning

ML Component Aspect

- Interpretable Models
  - **Advantage**:
    - **Easier for formal verfication (reachability analysis)?** (for rule/dt) The input space is naturally partitioned and the output space is relative small (or can be made linear)
    - Not black box, deterministc ,easy to debug
  - **Disadvantage** The performance is not comparable to deep neural network, and can only handle easy task.
  - **Guess** :
    - Can we use Interpretable Models to bound the output of dnn for ease of verfication
  - (From verifying AV paper) Level of ML usage： an end to-end use of ML not be encouraged.
    - it is unclear what the “tells” are for a machine exhibiting safe behavior vs. getting lucky with unsafe behavior. Being able to reasonably infer causality of actions from explicit system information can reduce testing costs compared to a brute force statistical approach.

- **Model Explanation -> Locally interpretable models**
  - **basic idea**: In the vicinity of an instance, the decision boundary of a classifier can be interpretable locally.
  - **achors**: The anchors (a set of rules) can also compute the coverage of the local model for approximating the black box models
  - **Wild Guess** : the idea of coverage for anchors is interesting. The anchors only approximate the black model based on sampling around the instance. In practice, the coverage of a model should be based on both the data density and the accuracy of the local models.
  - **Question**: How to apply explain regression models?
- Feature Extract: compute the global importance of each feature in the model by either removing the features that are not of interest or the switch the values of features from different samples.
- Reject Option: Use reject option to avoid low-confidence prediction.
  - **Advantage**:

        - Observiously, it can avoid unsafe action.
        - **Guess**:   can it be used to make the verfication more easier **if** we can identify confident region and unconfident. However, the confident region is not 100 percent confident
    - **Problem**
        - How it can be directly applied. Any application scenario (of course, for decision sciene, it can be directly applied)? What action to take if an rejection happens.
        - How to measure the confidence level of a prediction.
            - Existing approach train multiple models and study the variance. (But is it always true if low vairance means confident)
            - For ensemble models, based on votes (is it always true ? data point from the empty space is not such case)
        - How to indentify confident region and unconfident, how to measure confidence level?
    - **Wild Guess** : we can partition the empty space with the data by sampling the empty space



- Rarity : Rare class/ rare classes could cause small disjuncts where most errors occurs. Most existing works do not favor rare class while error of rare objects could cause more severe problems.
    - Reasons:
        - Evaluation metric accuracy does not favor rarity
        - Difficult to generate regularities/decision boundary for rare cases.
        - Difficult to distinguish between real rare cases or noisy
        - The general bias is not suitable for rarity.
    - **Potential Strategies**

        - Detect the small disjuncts and more powerful method for small disjuncts.
        - Learn only the Rare Class:
        - Increase the cost of rare objects
        - Over sample (over fit) and under sample (loss of information)
- **(But we still know the state of art, and whether the mentioned techniques have already been applied.)**.

Verifying ML using formal methods

- The **high dimension original data** was extracted to **low-dimension feature vector** so that the region of uncertain can be found, and counter examples can be found from the uncertain region
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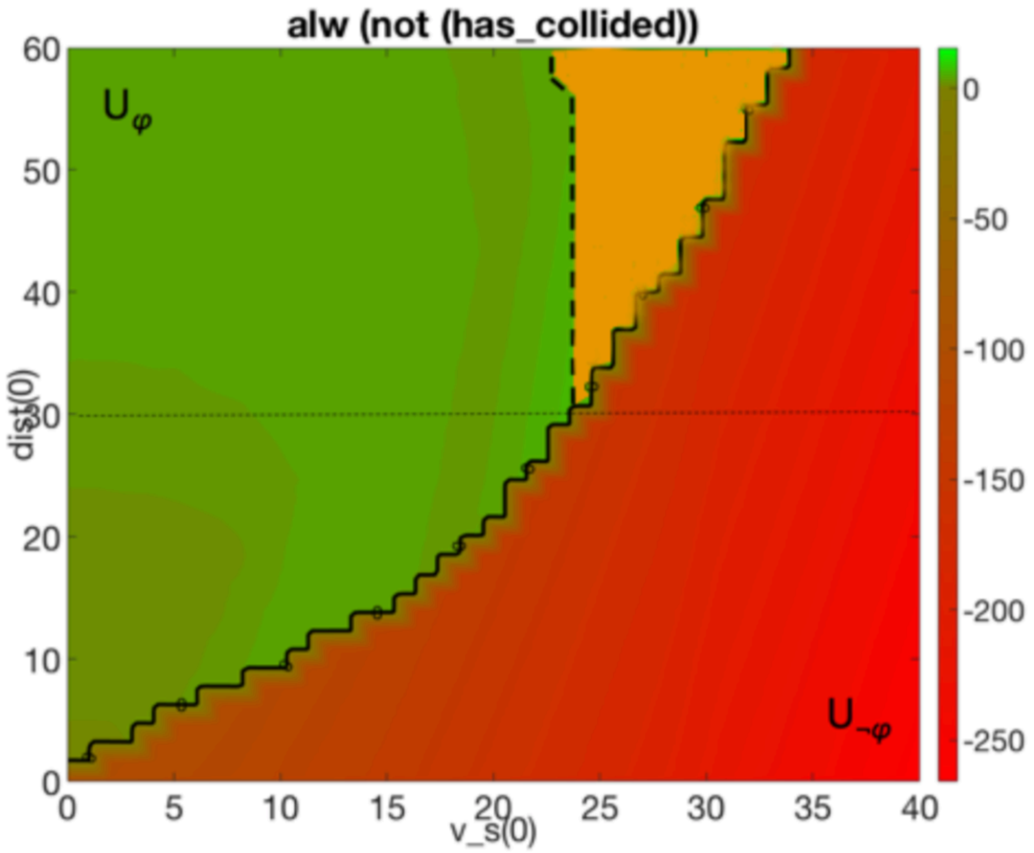
        - **Reason**: Formal methods can not handle high dimension large input space and complicated models (the approximate algorithm it use is **interpolation**)



Region of Uncertainty (yellow)

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    - **Problem**
        - Need to find **good representation of the origin data** so that most information is still kept, and the simplified function can approximate the original model.
            - Why not to use the approximated model directly?
        - **Essence**: It use a simper model with few features for verification hoping that the simple model can approximate the black box model.
        - **More complicated Abstraction**

    - A hierarchicaly model instead of end-to-end model. A low level model can extract the feature distance between cars, pedestrains. A high level simple model predict and take actions.
    - It is difficult abstact features for more complicated tasks.
- Reachability analysis+Neural network:
  - The space of input is partitioned and for each partition of input space, the upper and lower bound of the output is then computed for that layer.
  - **Guess** Instead, can we use a more simple model to bound the output for each input space partition?   For example: for an DNN, all its output for a input space is bounded by a simple linear model or decsion tree based model (used as a safety envelope?).

Verifying AV Process

- **Characteristics of ML that can impact safety or safety assessment**
  - Non-transparency
  - Error rate
  - **Training-based**： Training sets used in place of a safety requirement specification，
  - Instability: difficult to debug models or reuse parts of previous safety assessments.

- Controllability and Observability

  Controllability is the ability of a tester to control the initial state and the workload executed by a system under test. Observability is the ability of the tester to observe the state of the system to determine whether a test passed or failed.

- Level of ML usage： an end to-end use of ML not be encouraged.

- Passing Tests for the Right Reason: Interpretability

  For HAV, it is unclear what the “tells” are for a machine exhibiting safe behavior vs. getting lucky with unsafe behavior. Being able to reasonably infer causality of actions from explicit system information can reduce testing costs compared to a brute force statistical approach.