#### GRETEL: THE GOOD, THE BAD AND THE UGLY

**Bardh Prenkaj** 

Post-doc in Al prenkaj@di.uniroma1.it

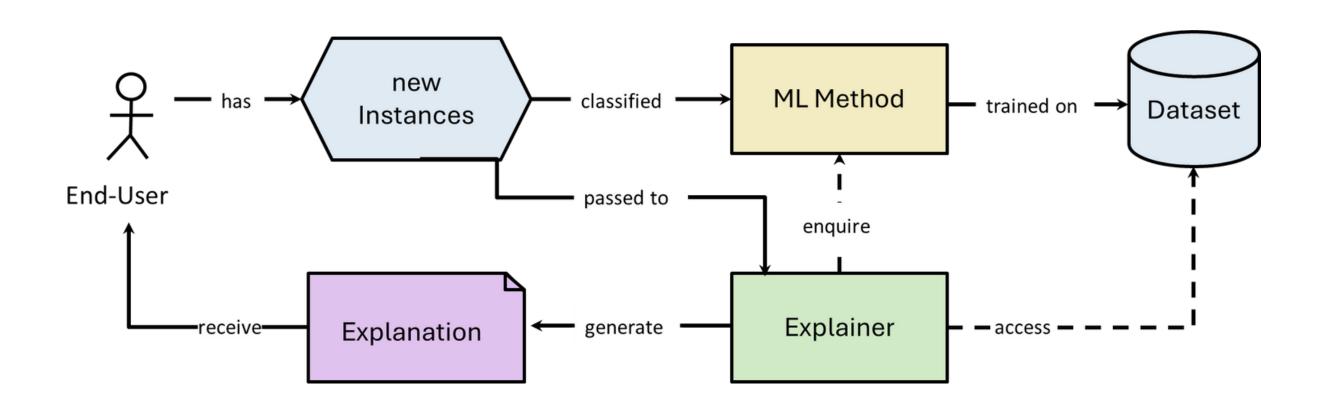




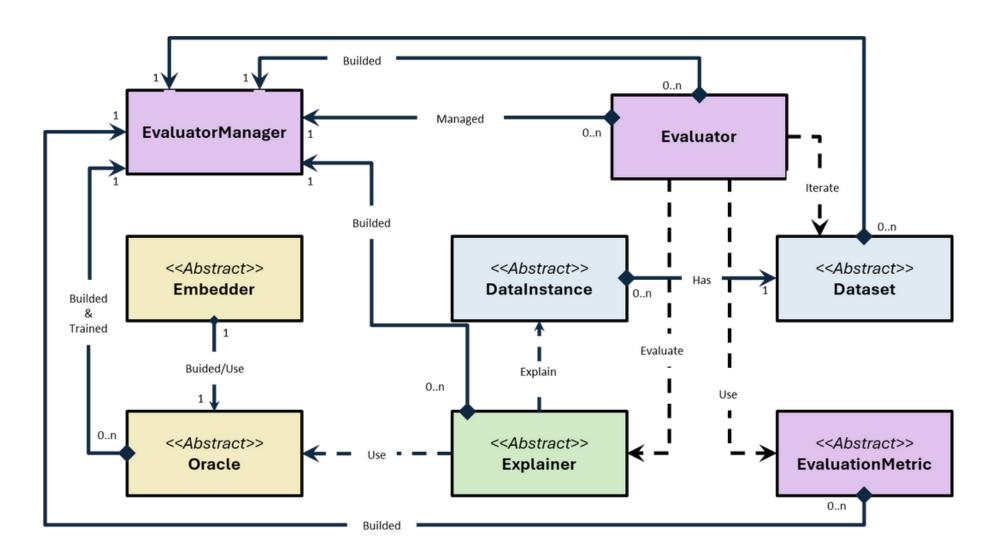




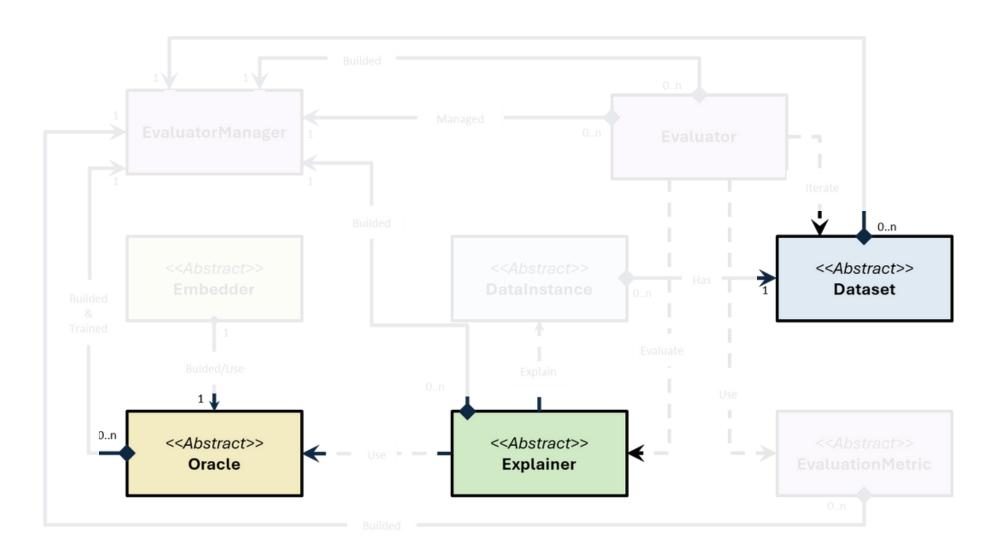
### Typical Explainability Workflow



#### **GRETEL**



#### **GRETEL**



# GOOD



#### What's good in GRETEL?

- Highly modular framework
- Core philosophy: users can implement their explainers by only extending the Explainer class without having to worry about the entire XAI pipeline
- 80% of graph classification SoA methods are covered inside
- Configuration opportunities for already supported methods, datasets, evaluations

## Example of good: Ad-hoc explainer

```
giovanni, 4 days ago | 1 author (giovanni)
     class DCESearchExplainer(Explainer):
         """The Distribution Compliant Explanation Search Explainer performs a search of
         the minimum counterfactual instance in the original dataset instead of generating
11
         a new instance"""
12
13
         def init(self):
             super().init()
15
             self. gd = GraphEditDistanceMetric()
16
             self.fold id=-1
17
             self.dist mat = np.full((len(self.dataset.instances), len(self.dataset.instances)), -1)
             self.cls mat = np.full((len(self.dataset.instances), len(self.dataset.instances)), -1)
19
21
         def explain(self, instance):
22
             l input inst = self.oracle.predict(instance)
23
             # if the method does not find a counterfactual example returns the original graph
25
             min counterfactual = instance
             min counterfactual dist = sys.float info.max
```

# Example of good: Ad-hoc explainer

```
giovanni, 4 days ago | 1 author (giovanni)
class DCESearchExplainer(Explainer):
    """The Distribution Compliant Explanation Search Explainer performs a search of
   the minimum counterfactual instance in the original dataset instead of generating
   a new instance"""
                                                                                               Just extend the
       self.dist_mat = np.full((len(self.dataset.instances), len(self.dataset.instanabstract Explainer class
```

## Example of good: Ad-hoc explainer

```
def explain(self, instance):
   l input inst = self.oracle.predict(instance)
                                                                            Define the abstract
                                                                                method explain
```



#### Example of good: Ad-hoc dataset

```
giovanni, 4 days ago | 1 author (giovanni)
      class ADHD(Generator):
11
12
          def init(self):
13
              base_path = self.local_config['parameters']['data dir']
14
              # Path to the instances of the "Attention Deficit Hyperactivity Disorder class"
15
              self.adhd class path = join(base path, 'adhd dataset')
              self. td file path = join(base path, 'td')
17
              self.generate dataset()
18
19
          def get num instances(self):
20
              return len(self.dataset.instances)
21
22
          def generate dataset(self):
23
              if not len(self.dataset.instances):
24
                  self.read adjacency matrices()
25
```

## Example of good: Ad-hoc dataset

```
giovanni, 4 days ago | 1 author (giovanni)
class ADHD(Generator):
                                                                               Just extend the abstract
                                                                                          Generator class
```

## Example of good: Ad-hoc dataset

```
def get num instances(self):
             return len(self.dataset.instances)
21
22
         def generate dataset(self):
23
             if not len(self.dataset.instances):
24
                 self.read adjacency matrices()
```

Implement the generate\_dataset abstract method to contain the dataset creation logic



#### Example of good: Extend Oracle

```
giovanni, 4 days ago | 1 author (giovanni)
     class Oracle(Trainable, metaclass=ABCMeta):
         def init (self, context:Context, local config) -> None:
             super(). init (context, local config)
11
             self. call counter = 0
12
13
         @final
         def predict(self, data instance):
              """predicts the label of a given data instance
                                                                                        61
              INPUT:
                                                                                        62
                 data instance: The instance whose class is going to be predicted
                                                                                        64
21
             OUTPUT:
                                                                                        65
                 The predicted label for the data instance
             self. call counter += 1
                                                                                        67
26
             return self. real predict(data instance)
         @final
         def predict proba(self, data instance):
              """predicts the probability estimates for a given data instance
```



```
@abstractmethod
def _real_predict(self, data_instance):
    pass

@abstractmethod
def _real_predict_proba(self, data_instance):
    pass
```

## Example of good: Extend Oracle

```
@abstractmethod
                                def real predict(self, data instance):
                       61
                        62
                                    pass
                        63
                                @abstractmethod
                        64
                                def real predict proba(self, data instance):
                        65
                                    pass
                        66
   When creating a new
Oracle (predictor model)
```

you need to define these

abstract methods

#### Example of good: Extend Oracle

```
giovanni, 4 days ago | 1 author (giovanni)
class TreeCyclesOracle(Oracle):
    def init(self):
        super().init()
        self.model = ""
    def real fit(self):
        pass
    def real predict(self, data instance):
        try:
            nx.find cycle(data instance.get nx(), orientation='ignore')
            return 1
        except nx.exception.NetworkXNoCycle:
            return 0
    def real predict proba(self, data instance):
        # softmax-style probability predictions
        try:
            nx.find cycle(data instance.get nx(), orientation='ignore')
            return np.array([0,1])
        except nx.exception.NetworkXNoCycle:
            return np.array([1,0])
```



#### What's bad in GRETEL?

- High learning curve
- Only graph classification is supported for <u>now</u>
- Continuous development; you might find changes happening in real-time
- Some bad/ugly choices of using the same naming of built-in methods
- WILL NOT SUPPORT TENSORFLOW.... EVER

#### Example of bad: init()

```
giovanni, 4 days ago | 1 author (giovanni)
class TreeCyclesOracle(Oracle):
    def init(self):
         super().init()
         self.model = ""
```

# AND THE UGLY



# What's ugly in GRETEL?

- A complex project structure
- Configuration files can be daunting
- There's a Context object passing around all the create objects dynamically; there's a check\_configuration method that can set default hyperparameters
- Some \_\_call\_\_ methods are overridden to obfuscate the torch-like functionality to the end-user

### Example of ugly: check\_configuration()

```
def check configuration(self):
   super().check configuration()
   self.local config['parameters']['n_labels'] = self.local_config['parameters'].get('n_labels', 2)
   self.local config['parameters']['batch size ratio'] = self.local config['parameters'].get('batch size ratio', .1)
   self.local config['parameters']['h dim'] = self.local config['parameters'].get('h dim', 10)
   self.local config['parameters']['z dim'] = self.local config['parameters'].get('z dim', 10)
   self.local_config['parameters']['dropout'] = self.local_config['parameters'].get('dropout', .1)
   self.local config['parameters']['encoder type'] = self.local config['parameters'].get('encoder type', 'gcn')
   self.local config['parameters']['graph pool type'] = self.local config['parameters'].get('graph pool type', 'mean')
   self.local config['parameters']['disable u'] = self.local config['parameters'].get('disable u', False)
   self.local config['parameters']['epochs'] = self.local config['parameters'].get('epochs', 200)
   self.local_config['parameters']['alpha'] = self.local_config['parameters'].get('alpha', 5)
   self.local config['parameters']['lr'] = self.local config['parameters'].get('lr', 1e-3)
   self.local config['parameters']['weight decay'] = self.local config['parameters'].get('weight decay', 1e-5)
   self.local config['parameters']['lambda sim'] = self.local config['parameters'].get('lambda sim', 1)
   self.local config['parameters']['lambda kl'] = self.local config['parameters'].get('lambda kl', 1)
   self.local_config['parameters']['lambda_cfe'] = self.local_config['parameters'].get('lambda_cfe', 1)
   self.local config['parameters']['beta x'] = self.local config['parameters'].get('beta x', 10)
   self.local config['parameters']['beta adj'] = self.local config['parameters'].get('beta adj', 10)
   n nodes = self.local config['parameters'].get('n nodes', None)
   if not n nodes:
       n nodes = max([x.num nodes for x in self.dataset.instances])
   self.local config['parameters']['n nodes'] = n nodes
   self.local config['parameters']['feature dim'] = len(self.dataset.node features map)
```

### Example of ugly: check\_configuration()

```
n_nodes = self.local_config['parameters'].get('n_nodes', None)
```

#### Example of ugly: \_\_call\_\_

```
def __call__(self, *args: Tuple[GraphInstance], **kwds: Any) -> Any:
    torch_data = torch.from_numpy(args[0].data[None,None,:,:]).float()
    return self.generator(torch_data) You, 22 hours ago • Uncommitted changes
```



#### Let's code

#### Open research questions

- Are generative counterfactual explainers worth it?
- What's the difference between counterfactual explanations and adversarial attacks?
- How sure are we about the counterfactuals generated?
  Can we incorporate uncertainty in them?
- How can we backtrack near the decision boundary once we overshoot on the other side to produce minimally perturbed counterfactuals?