Enriching Visual with Verbal Explanations for Relational Concepts

Combining LIME with Aleph

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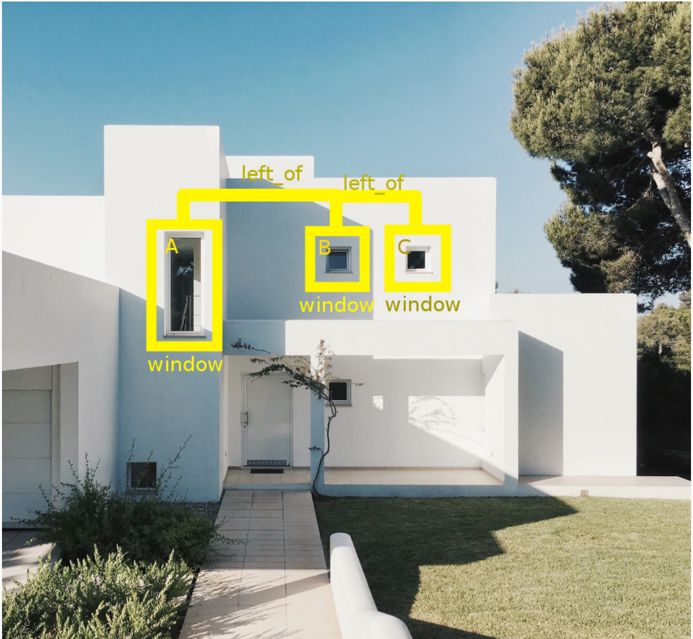
Towards Verbal Explanations

- Two approaches to interpretable models:
  - Build inherently interpretable models (Much overhead in preprocessing; bad performance)
  - **Extend good-performing black-box models by an interpretable component (Interpretability-Fidelity-Tradeoff)**

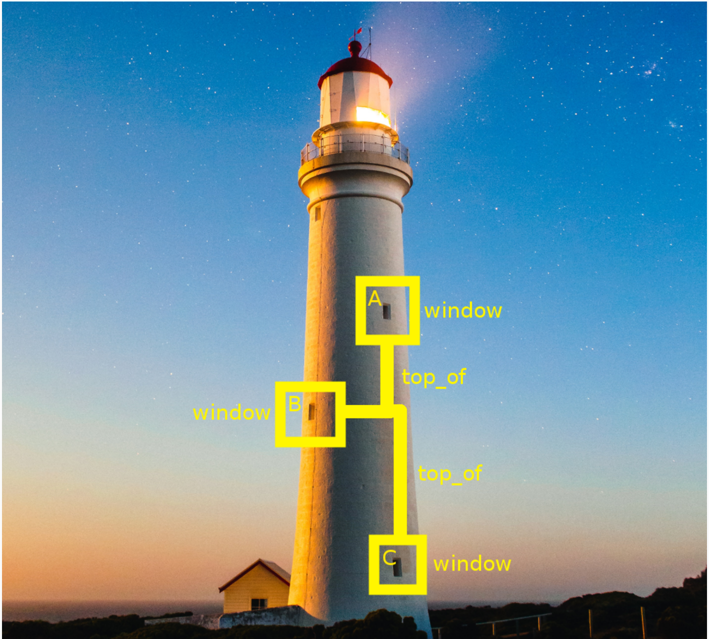
Towards Verbal Explanations

- Two approaches to interpretable models:
  - Build inherently interpretable models (Much overhead in preprocessing; bad performance)
  - **Extend good-performing black-box models by an interpretable component (Interpretability-Fidelity-Tradeoff)**
- Visualization as de facto standard for explanation of image classification decisions, but no possibility to highlight
  - Negations
  - **Feature values**
  - **Relations**

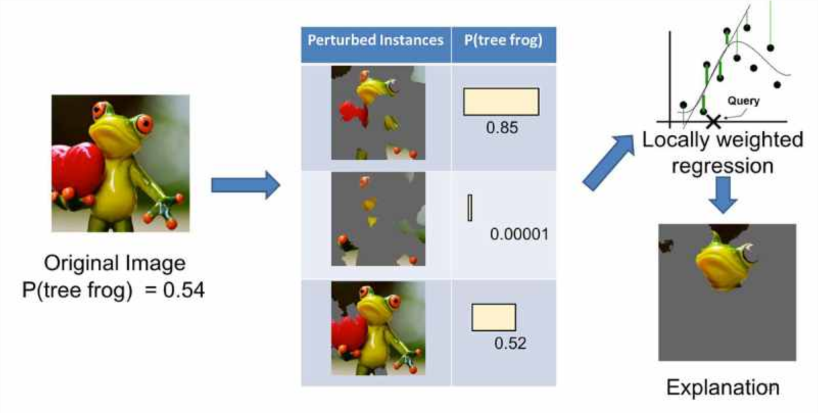
Illustrative Example Photo by Pixasquare uploaded to Unsplash



Illustrative Example Photo by Joshua Hibbert uploaded to Unsplash



Original LIME



Source: https://www.oreilly.com/learning/introduction-to-local-interpretable-model-agnostic-explanations-lime

Inductive Logic Programming

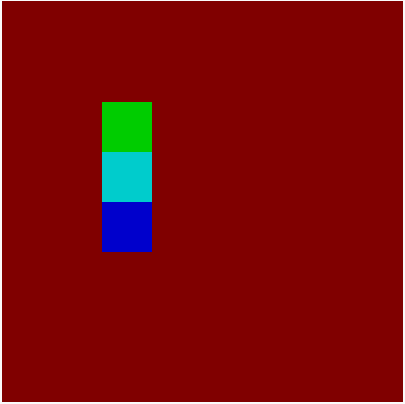
Inductive Logic Programming (ILP)

- Fits a logic theory over examples
- Input:
  - Positive and negative examples
  - Background Knowledge
- Output:
  - First Order Logic hypothesis

```
                    cat(C) :-
has_attribute(C, fur), has_attribute(C, whiskers).
```

- We used Aleph as a very flexible ILP framework

Background Information Extraction



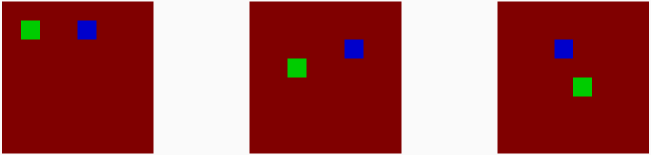
$\Longrightarrow$

`has_color(sp_18, green)`, `has_color(sp_26, cyan)`,
`has_color(sp_34, blue)`,
`on(sp_18, sp_26)`, `on(sp_26, sp_34)`

Simplified algorithm

```
Require: Instance $x \in X$
Require: Classifier $f$, Selection size $k$, Threshold $\theta$
    $S \leftarrow LIME(f, x, k)$
    $A \leftarrow$ extract_attribute_values($S$)
    $R \leftarrow$ extract_relations($S$)
    for each $r(i, j) \in R$ do
        $z \leftarrow flip\_in\_image(x, i, j)$
        $r' \leftarrow r(j, i)$
        $R' \leftarrow R \backslash \{r\} \cup \{r'\}$
        $R' \leftarrow calculate\_side\_effects(R', r')$
        if $f(z) \geq \theta$ do
            $E^+ \leftarrow E^+ \cup \{\langle A, R' \rangle\}$
        else
            $E^- \leftarrow E^- \cup \{\langle A, R' \rangle\}$
    end for
    $T \leftarrow Aleph(E^+, E^-)$
return $T$
```

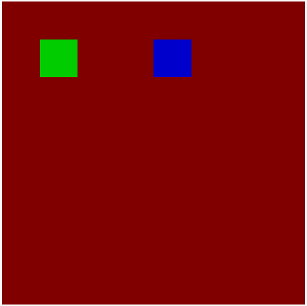
Experiment 1 - Single Relation Concept



(a) (b) (c)

Positive (a, b) and negative (c) examples for the concept “Green left of Blue“.

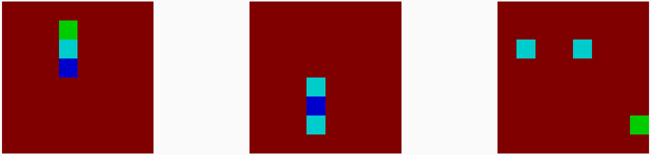
Experiment 1 - Single Relation Concept



$k = 3$, $\theta = 0.8$

```
concept(A) :- contains(B, A), has_color(B, green),
contains(C, A), has_color(C, blue), left_of(B, C).
```

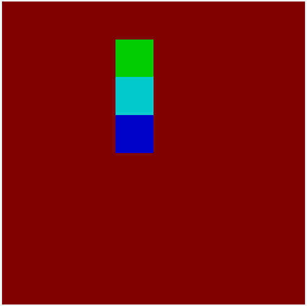
Experiment 2 - Concept “Tower“



(d) (e) (f)

Positive (a) and negative (b, c) examples for the concept “tower“.

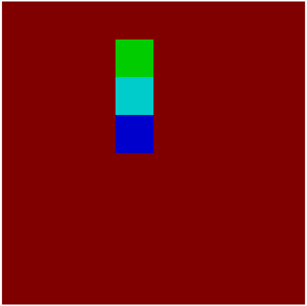
Experiment 2 - Concept “Tower“



$k = 3$, $\theta = 0.8$

```
concept(A) :- contains(B, A), has_color(B, cyan),
              contains(C, A), on(B, C).
```

Experiment 2 - Concept “Tower“



$k = \mathbf{4}$, $\theta = 0.8$

```
concept(A) :- contains(B, A), has_color(B, cyan),
contains(C, A), has_color(C, blue), top_of(B, C).
```

Future Work

- Evaluating interpretability of explantions in a user study
- Using real-world datasets

$\Longrightarrow$ Extracting semantically interpretable features from images

- Use interactive learning approaches for semi-automated annotation
- Use method to explain Capsule Networks

Thank you for your attention!

Questions?

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