Data-Agnostic Pivotal Instances Selection for Decision-Making Models

PivotTree: *Case-based Trees for relational and non-relational data*

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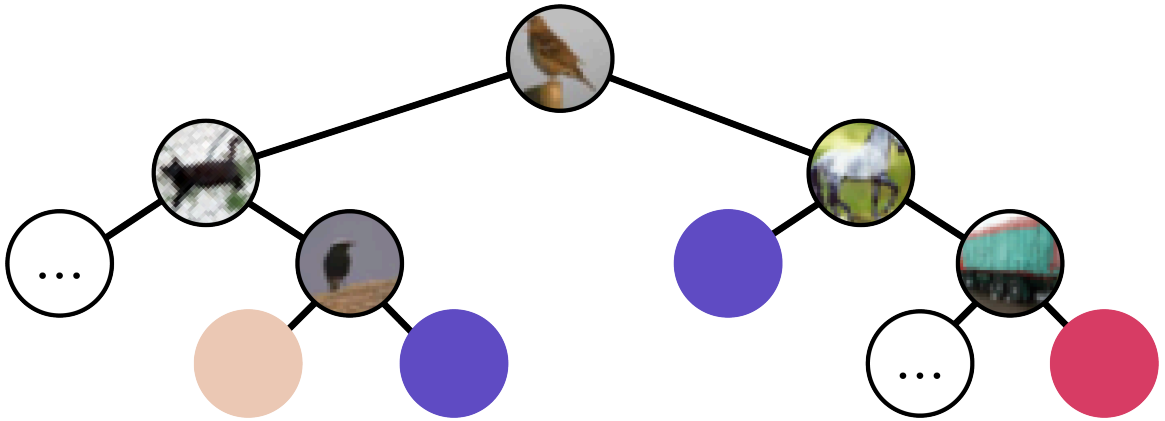

EXPLANATION OF AI DECISION MAKING.
MIMOSA
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Explainability and its many forms

- **Feature importance.** Defines impact: what is *important*? (Local)
- **Decision rules**. Describes: what *decides*? (Semi-global)
- **Counterfactuals.** Contrasts: what to *change*? (Local)

Age >= 50,
Smokes: Yes,
Respiratory history: Yes
=> Ill

Age >= 50,
Smokes: Yes to Smokes: No
=> Ill to Not ill

Non-relational data: breaking the mold

Non-relational data has an inherent difficulty in tackling the above tasks, often due to

- Complex relations among features
- Violated assumptions
- Sparsity

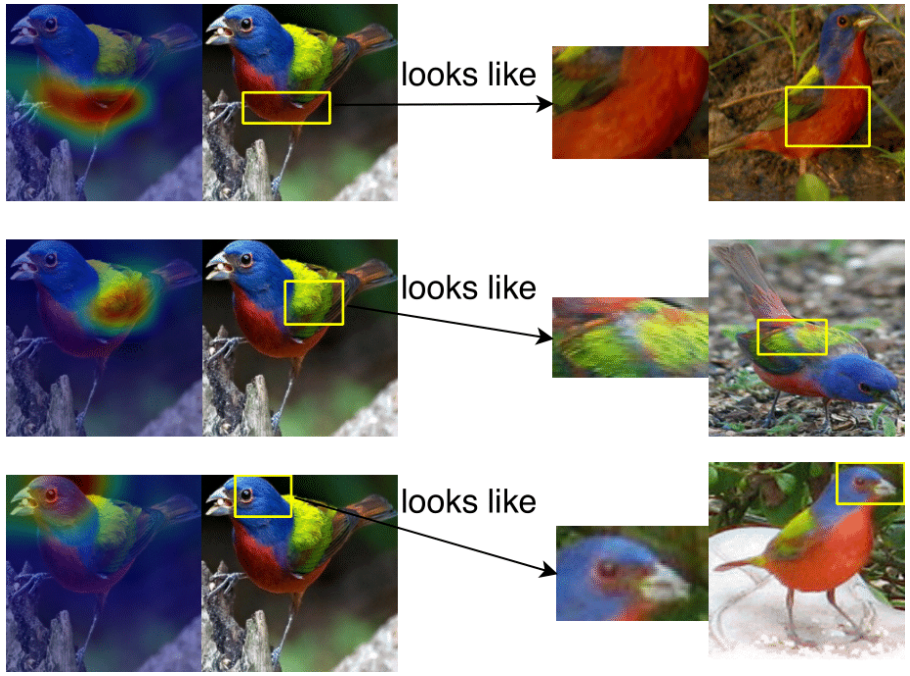
A saliency map requires a perturbation algorithm how to *jointly* perturb pixels, often under the assumption of their independence, thus creating a large amount of possibly out-of-distribution synthetic instances.

Case-based explanations

A.k.a. prototypes, pivots. Define a set of instances, which are explanations **on their own**, and can also be explained

- Importances
- Counterfactuals

By design they tackle sparsity and inter-instance relationships!



The bird in the picture is classified as *Clay-colored sparrow* on the basis of its similarity with some prototypes.

The case-based landscape

- By design
- Data-agnostic
- Factual explanations
- Local *or* global explanations

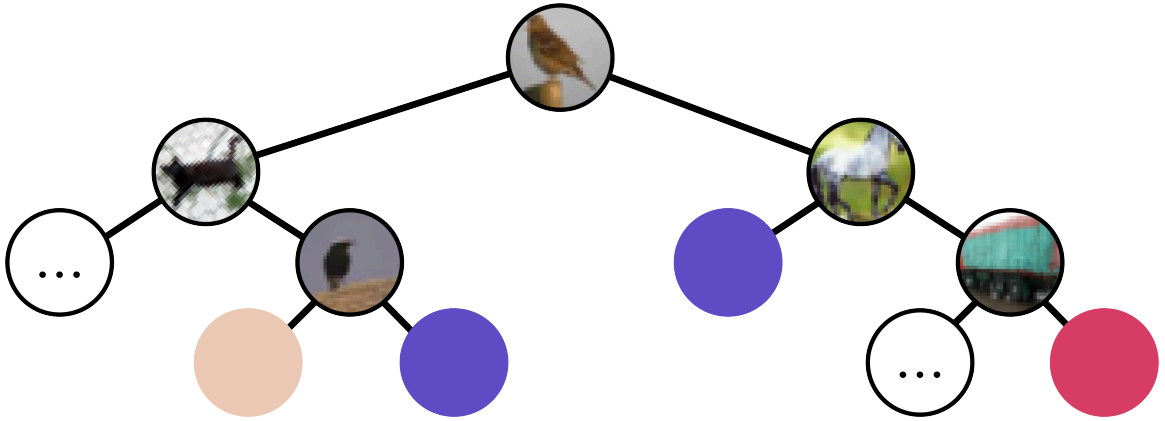
- No counterfactuals
- Local *and* global explanation
- No inter-case relationship

Prototype selection for interpretable classification. J. Bien et al.
Deep learning for interpretable image recognition. C. Chen et al.
Interpreting CNNs via Decision Trees. Q. Zhang et al.
Proximity Forest: an effective and scalable distance-based classifier for time series. Lucas et al.
Prototype selection for interpretable classification. Bien & Tibshirani.

Pivot Tree

Our proposal, **Pivot Tree** is a case-based model for explainable classification

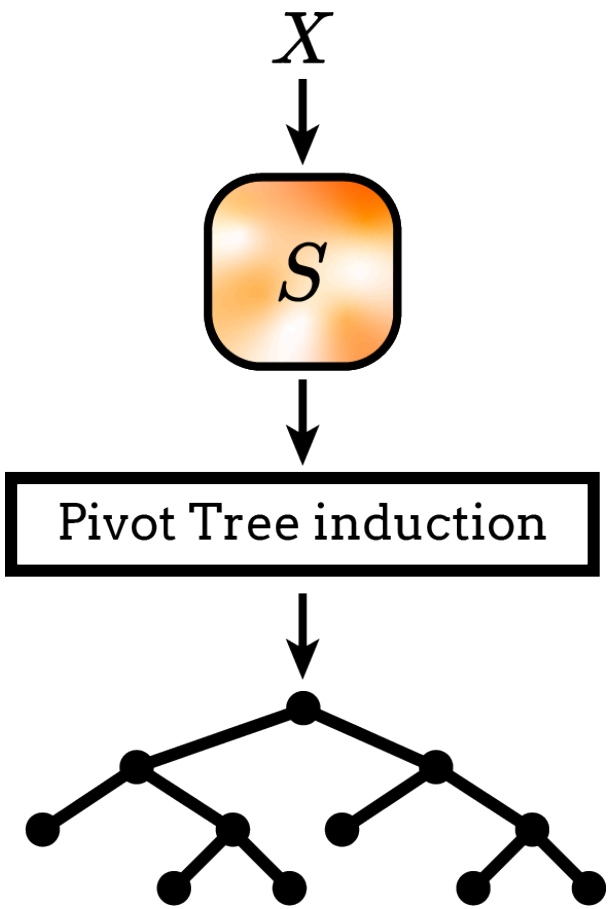
- Data-agnostic
- Factual *and* counterfactual explanations
- Local *and* global explanations
- Hierarchical case structure



A Pivot Tree: instances laid on a tree structure route predictions. Similarity to instances determines routing, and leaves are also associated with a classification label.

Learning a Pivot Tree (PTC)

Pivot Tree Classifier (PTC)



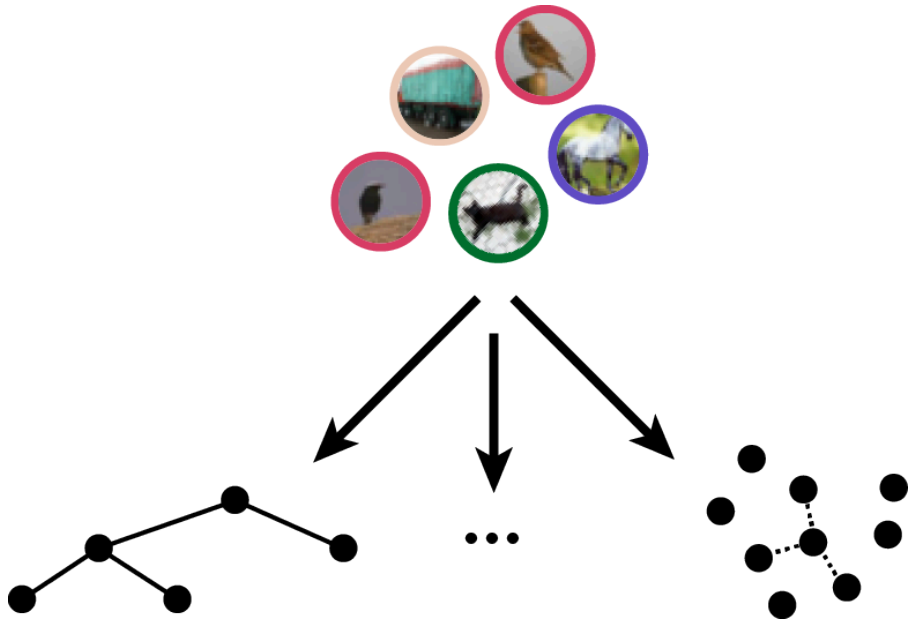
1. Compute a similarity matrix S, possibly embedding data
2. Induce a Decision Tree on S, filtering similarities to
   - **discriminative** pivots: maximizing entropy
   - **descriptive pivots**: maximizing class centrality

Learning a Pivot Selector (PTS)

Pivots in the nodes constitue a dataset themselves!

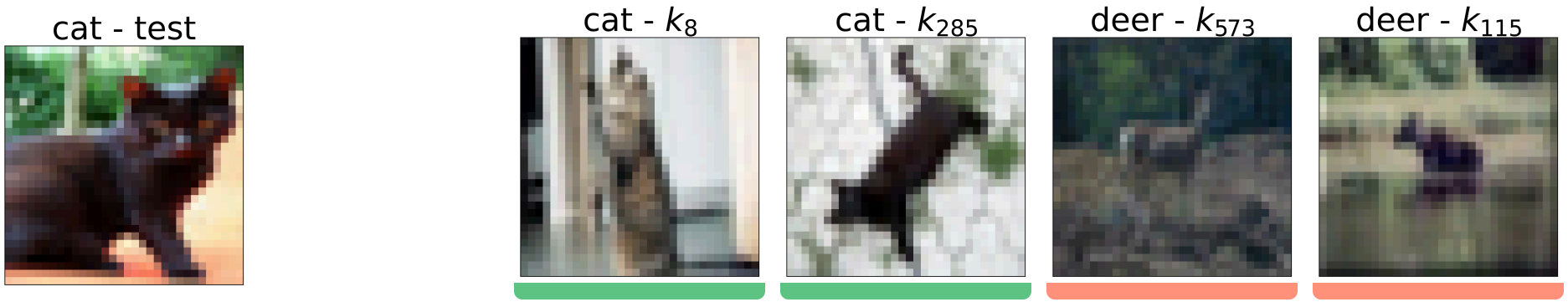
1. Extract pivots from nodes
2. Train an interpretable model **on top** of Pivot Tree

Pivot Tree Selector (PTS)



A qualitative result

Cifar 10



An instance (left), and pivots extracted by Pivot Tree. The cat has high similarity to the first two, and low to the latter two.

Experiments

Explainability

- Fidelity
- Complexity
- Stability

Competitors

- ε-ball
- k-NN

Datasets

- 11 tabular
- 5 time series
- 3 image + 1 real world use case of oral cancer detection
- 5 text

How faithful is Pivot Tree?

	$mean \uparrow$	$std \downarrow$	$rank \downarrow$
PTS + DT	.62	.22	3.1
K-medoids	.61	.22	3.6
ε-ball	.61	.23	3.7
Pivot Tree	.58	.27	3.9
K-means	.62	.22	4.0
Random per class	.60	.22	4.6
Random	.60	.22	5.0

On $f1$ score...

- Pivot Tree selector is the best performing model
- Pivot Tree works **better** as a pivot **selector than** a standalone **classifier**
- Models built directly on data lag behind: good data matters

A real-world study: oral cancer detection

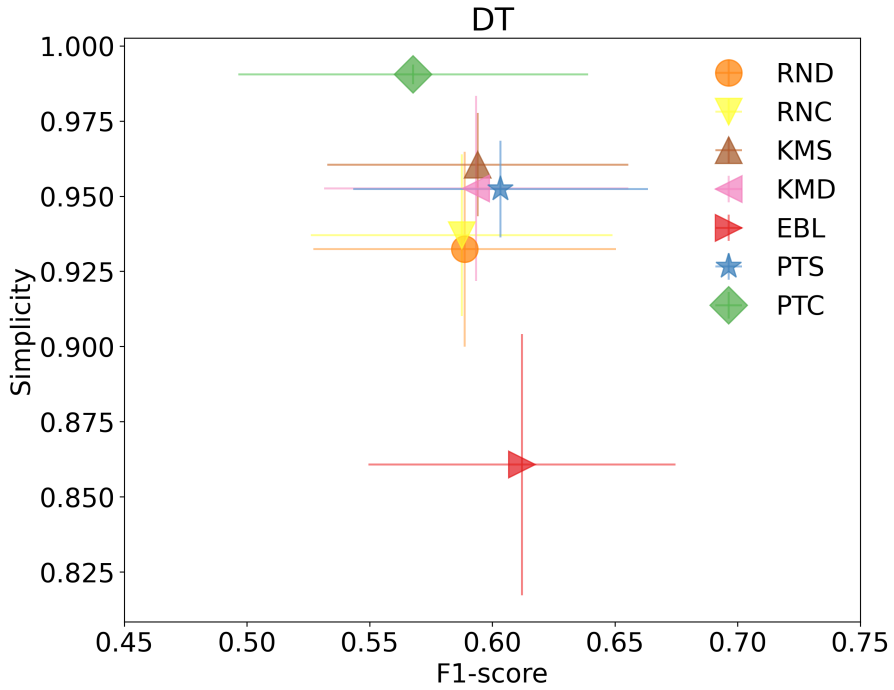
A real-world case study on an oral cancer detection dataset.

- 535 images
- 3 classes

	Pivot Tree	**Decision Tree**	**k-NN**	**CNN**
$f1$	**.834**	.833	.811	.854
$complexity$	9	47	**5**	

Publicly available at https://mlpi.ing.unipi.it/doctoralai/

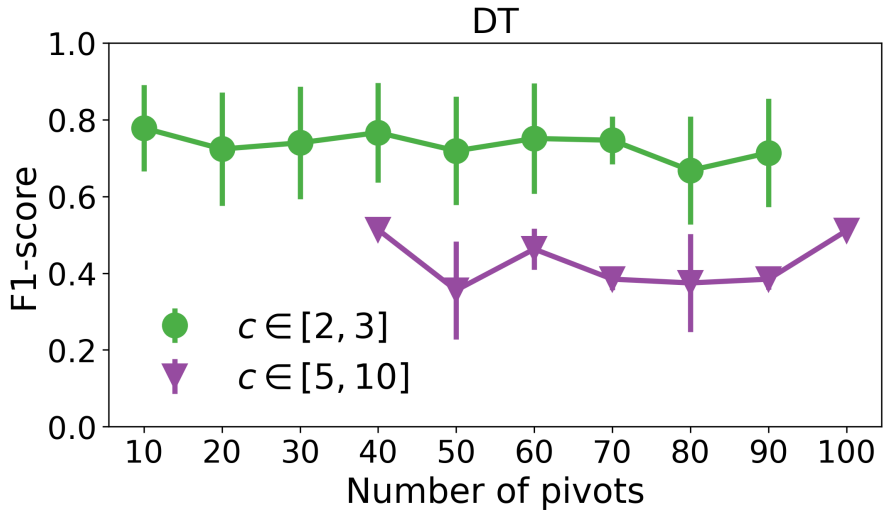
How complex is Pivot Tree?



Scatter plot of $f1$ score and simplicity of Pivot Tree and its competitors, regularized to use a maximum of 20 pivots.

- When not regularized, Pivot Tree slightly worse than competitors
- More complex models (bottom) are less impacted from regularization

How stable is Pivot Tree?



Scatter plot of $f1$ score of Pivot Tree as the maximum number of pivots increases. C indicates the number of classes.

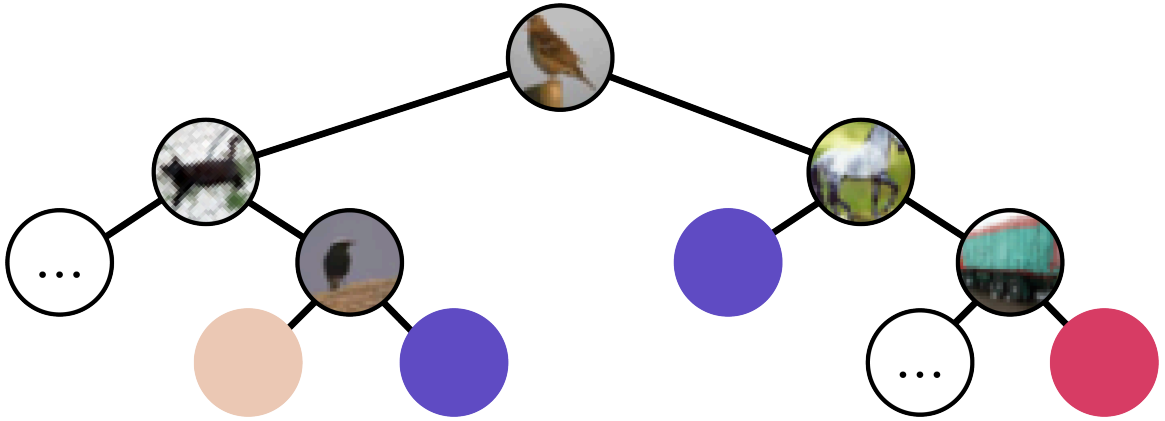
Low variance but decreasing trend as regularization decreases: Occam's razor!

Pivot Tree

An explainable case-based decision tree, providing factual and counterfactual case-based explanations.

Future work:

- Proximity splits: to which pivots are instances more similar?
- More powerful downstream models



github.com/msetzu/pivottree

See you at the poster session!