Human-Driven FOL Explanations of Deep Learning

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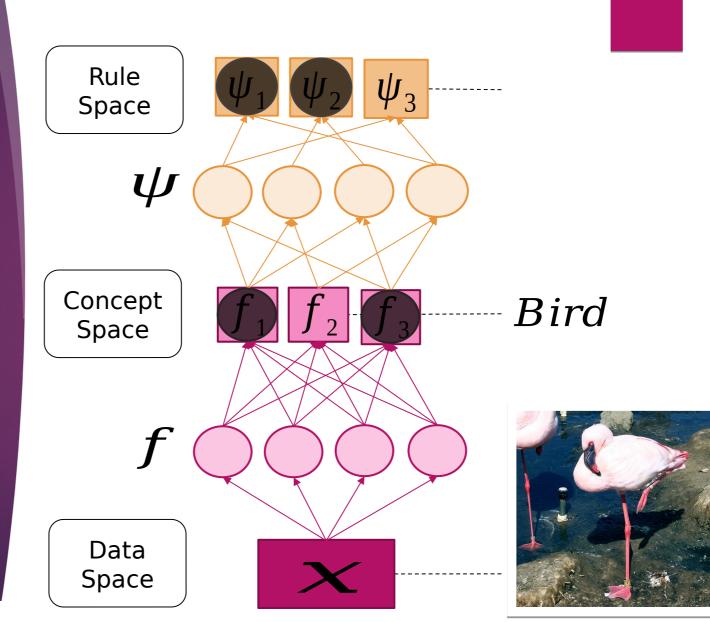




NEURAL NETWORKS HAVE BECOME INCREDIBLY POWERFUL

Network explaining network

- Provides examplebased explanation
- Extract new knowledge



Network Pruning

- Strong L1 regularization
- Progressive pruning of the lowest weights
- Low Fan-In Neurons

Explainable Network

How does it works?

$$f^\star, \psi^\star = \arg\min_{f,\psi} \{ U(f) + D(\psi,f) \}$$

$$U(f) = \left\{ \sum_{j=1}^{c} \sum_{x_k \in X_{\varphi_j}} \widehat{\varphi}_j(f(x_k)) + \gamma_f \|f\| \right\}$$

$$D(\psi,f) = \left\{ -\hat{I}_{Y,\Psi}(\psi,f,X) + \gamma_{\psi} \|\psi\| \right\}$$

$$-\hat{\phi}_{j}(f(x)) = \|f(x) - y(x)\|^{2}$$

$$I_{Y,\Psi}(\psi,f) = H_{\Psi}(\psi,f) - H_{\Psi|Y}(\psi,f)$$

Regularizatio n Effects

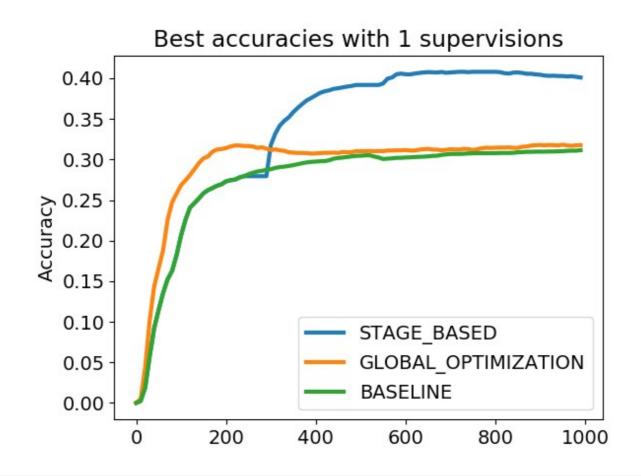
Baseline



Global Optimization
$$U(F)+D(f,\psi)$$

Stage-based Optimization

Performance Improvements - MNIST



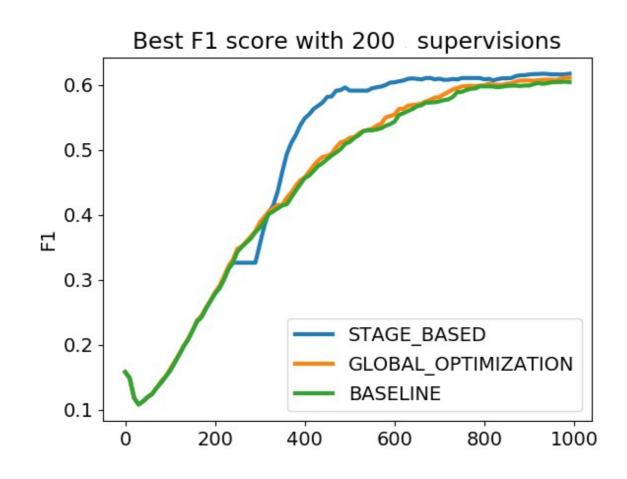
Overall Results - MNIST

# Labeled	Baseline	Stage-based	Global
Examples		Optimization	Optimization
1	$31.7 \pm 2.1 \%$	46.5 \pm 1.4 %	38.7 ± 3.7%
10	$68.6\pm0.4~\%$	$71.5 \pm 0.9\%$	71.6 \pm 1.7%
100	84.5 \pm 0.4 $\%$	86.7 \pm 0.3 %	$86.0\pm0.1\%$

Learned Rules

(a)	Odd $\dot{\lor}$ Even	Eight $\dot{\lor}$ Zero
	Nine∧¬Even	Six∧¬Odd
(b)	Odd∧¬Even∧[(One ∨ Five ∨ Seven ∨ Nine) ∨	
	$(\neg One \land \neg Five \land \neg Seven \land \neg Nine)]$	
	Even $\land \neg Odd \land \neg One \land \neg Five \land \neg Nine \land (Eight \lor \neg Eight)$	

Performance Improvements - PascalPart



Overall Results - PascalPart

# Labeled Examples	Baseline	Stage-based Optimization	Global Optimization
10	$54.0 \pm 0.3\%$	$\textbf{56.8}\pm\textbf{0.2\%}$	$55.8 \pm 0.7\%$
50	$60.5\pm0.2\%$	$\textbf{62.0}\pm\textbf{0.4\%}$	$61.3 \pm 0.5\%$
Whole dataset	$62.6\pm0.3\%$	$\textbf{63.8}\pm\textbf{0.2\%}$	$63.7 \pm 0.4\%$

Learned Rules

(a) Hand \wedge Foot $\wedge \neg$ Beak,	$ egFoot \land Dog,$
Handlebar∧¬Boat,	$ eg$ AirplaneBody \wedge Cow
(b) Beak ∧ ¬Ear ∧ ¬Nose,	$(Cat \lor Dog) \land (\neg Foot \lor Paw),$
$TvMonitor \wedge (Screen \vee Table)$	$Aeroplane \land (Engine \lor Stern)$

Following steps

Improve rules quality

- From Local to Global rules:
- Predicate explaining rules:

Framework Applications

Adversarial Defense:
 Learned constraints as Attack detector

From Local to Global Explanations

$$\forall x \in X_j, \ \hat{\psi}_j(f(x)) \quad X = \bigcup_{j=1}^m X_j$$



CNF Conversion

$$\hat{\Psi} = \bigvee_{j=1}^{m} \hat{\psi}_j(f(x)) \equiv \bigwedge_{k=1}^{K} \hat{\psi}'_k(f(x))$$

$$\forall x \in X, \ \hat{\psi}'_k(f(x))$$

From Local to Class-Driven Explanations

Local Rule rewrite

$$\hat{\psi}_i(f(x)) = 1_{\psi_i}(f(x)) \leftrightarrow \psi_i(f(x)), \quad \forall x \in X,$$

Enforce Support
$$1_{\hat{\psi}_i(f(x))} = 1_{\hat{f}_i(x)}$$

Rule

Class-Driven
$$\hat{\psi}_i(f(x)) = \hat{f}_i(x) \leftrightarrow \psi_i(f_k(x)), \ \forall x \in X, \ i,k \in (1,...,n), \ k \neq i$$
 Rule

$$\hat{\psi_i}(f(x)) = Man(x) \leftrightarrow Head(x) \lor Hand(x) \lor Foot(x), \ \forall x \in X$$

IFF \leftrightarrow or IF \rightarrow ?

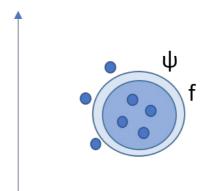
• IFF ↔ rules:

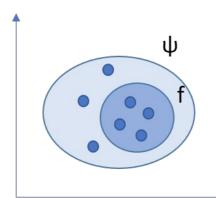
$$1_{\hat{\psi}_i(f(x))} = 1_{\hat{f}_i(x)}$$

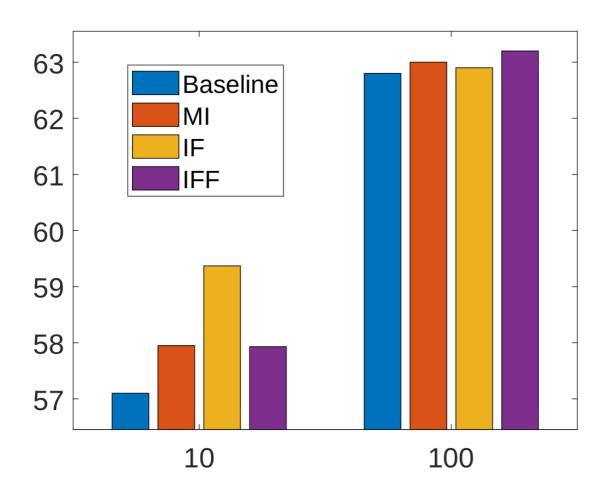
• IF
$$\stackrel{L_{\leftrightarrow}}{\rightarrow}$$
 rule: $\underset{i \in S, x \in X}{} |f_i(x) - \psi_{h(i)}(f(x))|$

$$1_{\hat{\psi}_{i}(f(x))} \supseteq 1_{\hat{f}_{i}(x)}$$

$$L_{\to}(\psi, f, X) = \sum_{i \in P, x \in X} \max\{0, f_{i}(x) - \psi_{h(i)}(f(x))\}$$





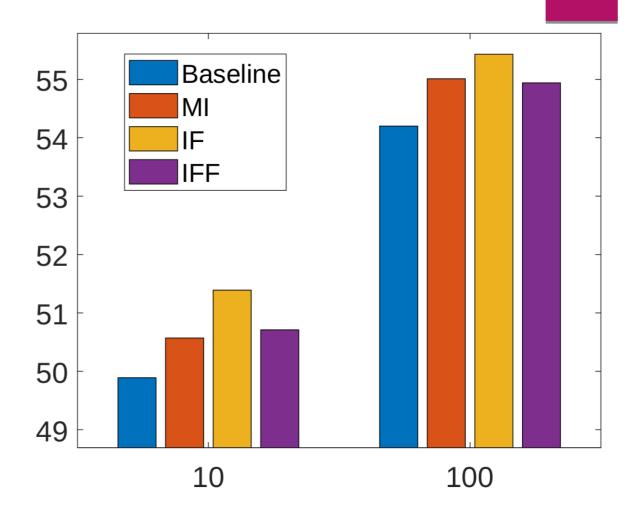


PascalPart Performances

$\forall x \in X_{\psi_i}, \ Beak \vee Bird$ LOCAL $\forall x \in X_{\psi_j}, \ Headlight \lor Plate$ $\forall x \in X_{\psi_k}, \ Cat \lor Horse$ $\forall x, AeroplaneBody \lor Beak \lor Bird \lor Table \lor Plant$ $\lor Car \lor Headlight \lor Motorbike \lor Muzzle \lor Train$ $\lor Chainwheel \lor \neg Aeroplane$ GLOBAL $\forall x, \neg Horse \lor Aeroplane Body \lor Beak \lor Bird \lor Train$ $\lor Car \lor Chainwheel \lor Headlight \lor Muzzle \lor Table$ $\vee Motorbike \vee Plant$ $\forall x, \ Car \rightarrow Backside \lor Mirror \lor (Window \land \neg Coach)$ CLASS- $\forall x, Bicycle \rightarrow Saddle \vee Handlebar$ DRIVEN $\forall x, \ Train \rightarrow Coach \lor TrainHead$ $IF \rightarrow$ $\forall x, \ Horse \leftrightarrow (Hoof \land Ear) \lor (Hoof \land Neck)$ CLASS- $\forall x, Bird \leftrightarrow Beak \land \neg Horn$ DRIVEN $\forall x, Bicycle \leftrightarrow (Chainwheel \land \neg Cow \land Handlebar)$ $IFF \leftrightarrow$ $\lor (Chainwheel \land \neg Cow \land Saddle)$

Rules PascalPart

CelebA Performances



Rules CelebA

LOCAL	
GLOBAL	
CLASS-DRIVEN $IF \rightarrow$	$\forall x, Attractive \rightarrow PaleSkin \vee RosyCheeks \\ \vee (\neg Blurry \wedge \neg Chubby) \\ \forall x, Beard \rightarrow Goatee \vee Sideburns \\ \forall x, Old \rightarrow GrayHair \vee \neg Attractive$
CLASS-DRIVEN $IFF \leftrightarrow$	$ \forall x, \ Bald \leftrightarrow \neg BlackHair \land \neg BrownHair \\ \land \neg StraightHair \land \neg WavyHair \\ \forall x, \ NotBald \leftrightarrow Bangs \lor BrownHair \lor WavyHair \\ \forall x, \ Male \leftrightarrow \neg WearLipstick \land \neg WearNecklace $





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Thank you for the attention