Training Characteristic Functions with Reinforcement Learning

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Zuse Institut Berlin

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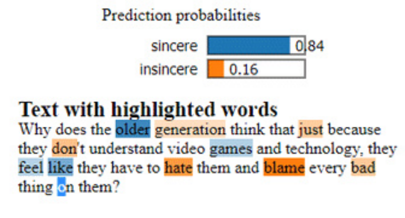

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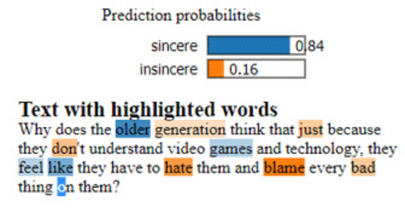

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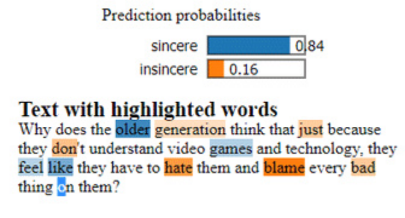

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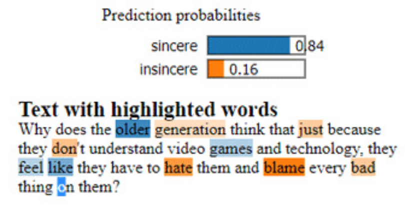

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- Problem: We don't have characteristic functions!

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Interpretations Rely on a Model of the Data Manifold

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$$\nu_{\Phi,\mathbf{x}}(S) = \mathbb{E}_{\mathbf{y}}[\Phi(\mathbf{y}) \,|\, \mathbf{y}_S = \mathbf{x}_S] = \int \Phi(\mathbf{x}) \mathrm{d}\mathbb{P}[\mathbf{x}_{S^c} | \mathbf{x}_S].$$

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- Best Performer RDE creates new features![8]

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- Idea: Directly train a characteristic function!

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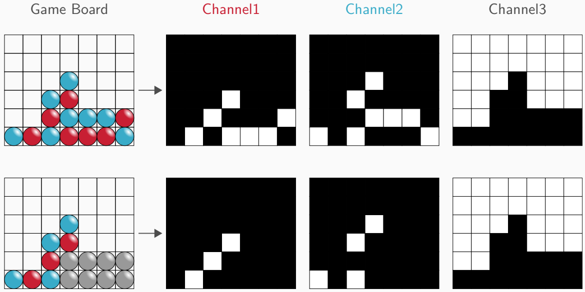

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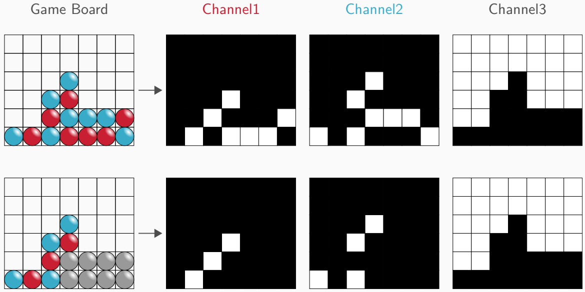

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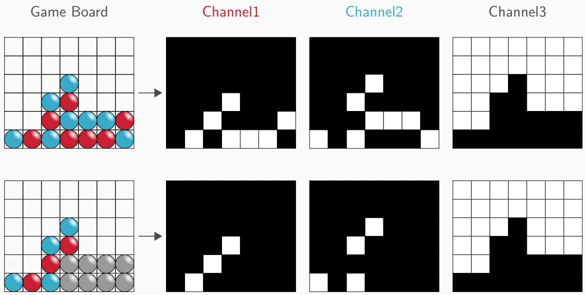

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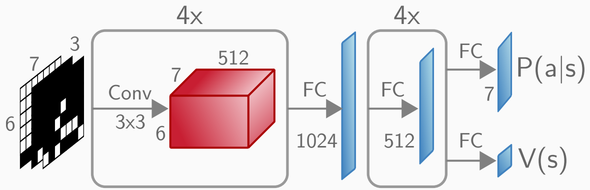

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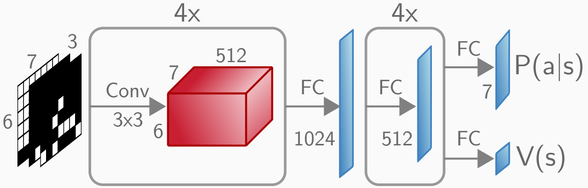

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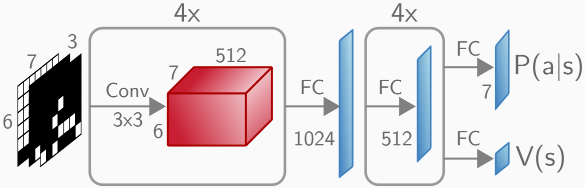

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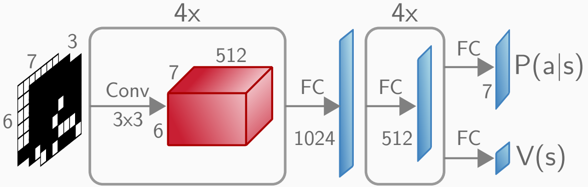

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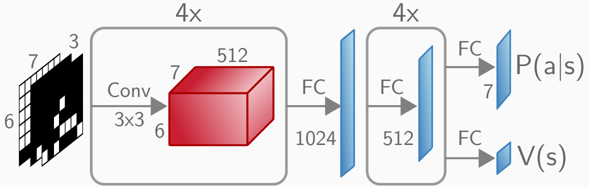

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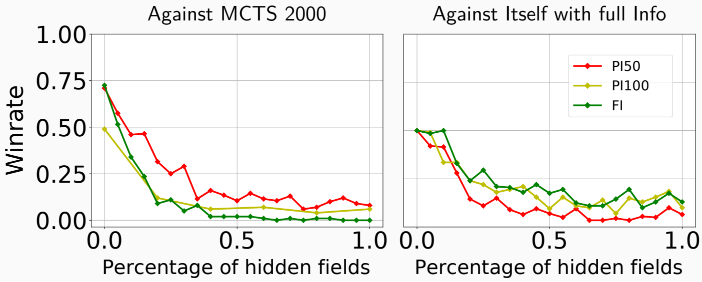

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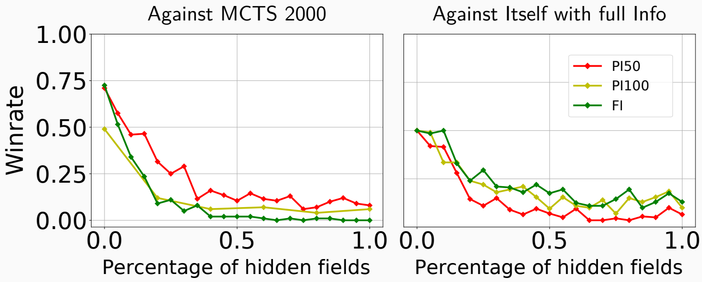

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- Calculate PIE with Frank-Wolfe optimiser solving[1] convex relaxation of

$$S^* = \operatorname*{argmin}_{|S| \leq \lfloor p_h t \rfloor} \left(\nu([t]) - \nu(S)\right)^2.$$

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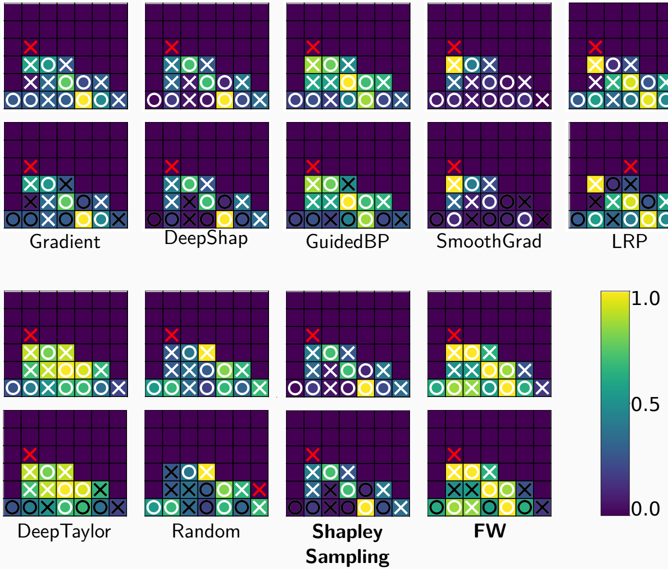
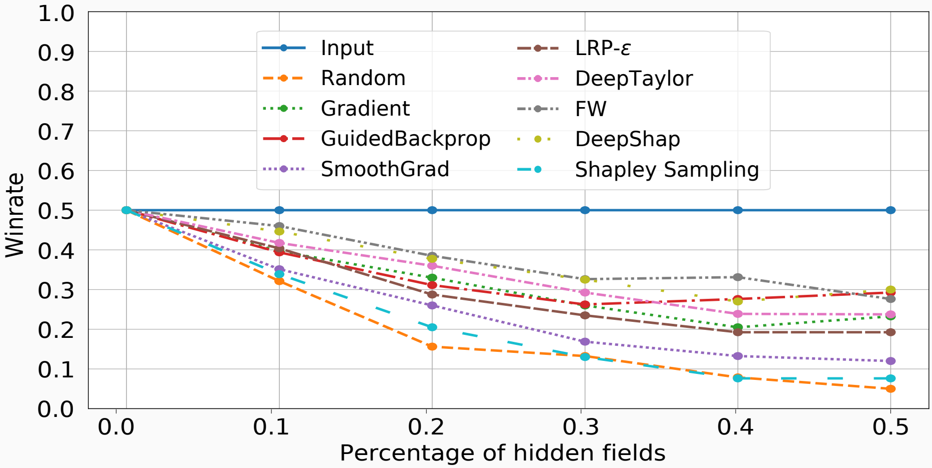
Example Saliencies for different Methods



Information-Performance Comparison



Round-Robin Tournament

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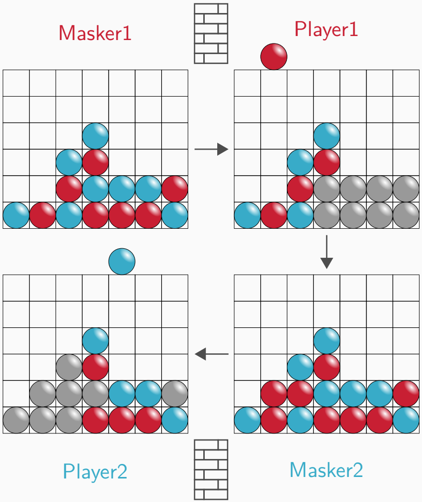

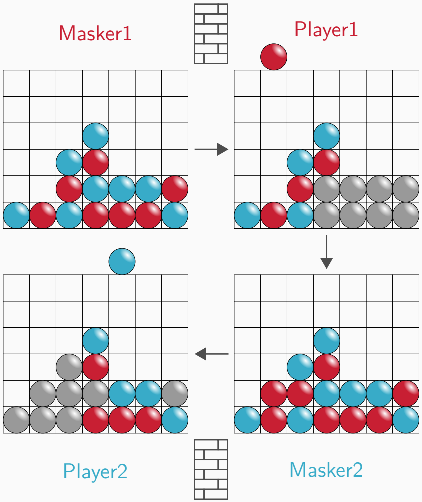

	Input	DeepShap	Guided Backprop	FW	Gradient	LRP-ε	Deep Taylor	Smooth Grad	Random
Input		0.737	0.747	0.706	0.782	0.834	0.774	0.887	0.935
DeepShap	0.263		0.498	0.499	0.573	0.609	0.567	0.742	0.871
Guided Backprop	0.254	0.502		0.496	0.579	0.616	0.616	0.765	0.861
FW	0.294	0.501	0.503		0.587	0.604	0.586	0.742	0.848
Gradient	0.217	0.427	0.421	0.413		0.512	0.502	0.686	0.819
LRP-ε	0.167	0.392	0.385	0.397	0.487		0.472	0.677	0.810
Deep Taylor	0.226	0.433	0.384	0.414	0.497	0.528		0.681	0.805
Smooth Grad	0.113	0.259	0.235	0.258	0.314	0.323	0.319		0.676
Random	0.065	0.130	0.140	0.152	0.181	0.190	0.195	0.324	

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⇒ Q-Learning could be a more stable approach

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Contact: `waeldchen@zib.de`

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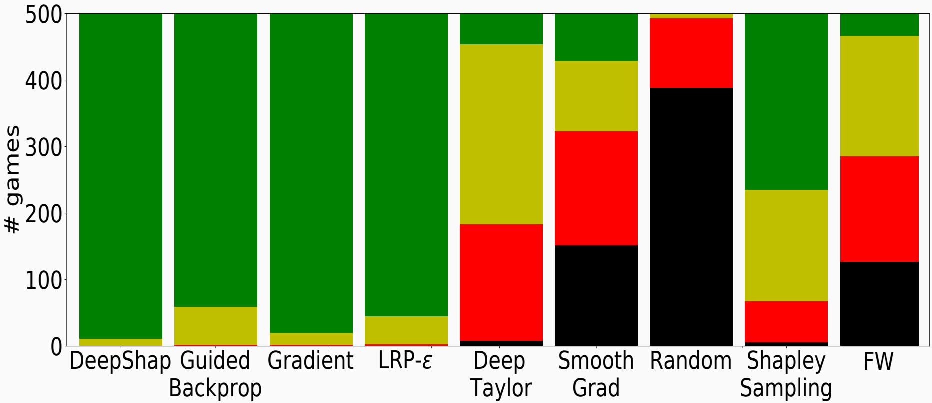
Appendix

Ground Truth Comparison: Winning Move



Tournament: Standard Deviation and Illegal Move Rate

	Input	DeepShap	Guided Backprop	FW	Gradient	LRP-ε	Deep Taylor	Smooth Grad	Random
Input		0.0188	0.0199	0.0233	0.0225	0.0220	0.0172	0.0152	0.0114
DeepShap	0.0188		0.0173	0.0201	0.0204	0.0144	0.0284	0.0204	0.0196
Guided Backprop	0.0199	0.0173		0.0192	0.0155	0.0202	0.0288	0.0229	0.0097
FW	0.0233	0.0201	0.0192		0.0217	0.0135	0.0263	0.0185	0.0091
Gradient	0.0225	0.0204	0.0155	0.0217		0.0146	0.0173	0.0233	0.0152
LRP-ε	0.0220	0.0144	0.0202	0.0135	0.0146		0.0164	0.0166	0.0142
Deep Taylor	0.0172	0.0284	0.0288	0.0263	0.0173	0.0164		0.0229	0.0159
Smooth Grad	0.0152	0.0204	0.0229	0.0185	0.0233	0.0166	0.0229		0.0164
Random	0.0114	0.0196	0.0097	0.0091	0.0152	0.0142	0.0159	0.0164	

	Input	DeepShap	Guided Backprop	FW	Gradient	LRP-ε	Deep Taylor	Smooth Grad	Random
Input		0.01	0.01	0.01	0.00	0.01	0.01	0.01	0.01
DeepShap	0.02		0.02	0.01	0.02	0.01	0.02	0.01	0.01
Guided Backprop	0.06	0.05		0.04	0.03	0.03	0.03	0.01	0.02
FW	0.06	0.03	0.04		0.02	0.04	0.02	0.01	0.01
Gradient	0.02	0.02	0.02	0.01		0.02	0.02	0.01	0.01
LRP-ε	0.02	0.03	0.01	0.01	0.01		0.01	0.01	0.01
Deep Taylor	0.03	0.03	0.03	0.03	0.02	0.03		0.01	0.01
Smooth Grad	0.01	0.00	0.01	0.00	0.01	0.00	0.01		0.00
Random	0.00	0.01	0.01	0.01	0.01	0.00	0.01	0.01	