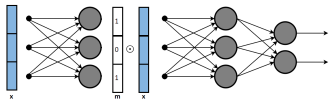
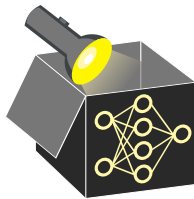


Interpretable Machine Learning

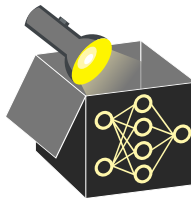
Learning to Explain



Learning goals

- Optimization problems in hard-masking
- Generative masking
- Sampling-based instance-wise feature selection

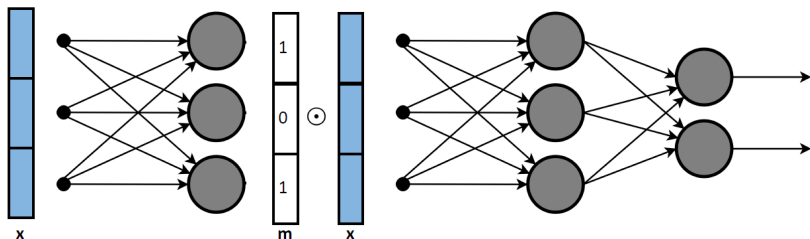
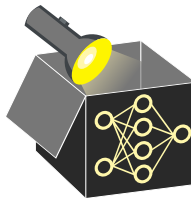
INSTANCE-WISE FEATURE SELECTION



- What happens when we do not have explanation data?
- Need to use the task-specific supervision signal to create explanations
- Key principle: Given an instance, automatically learn to select features during inference from the task-specific supervised signal

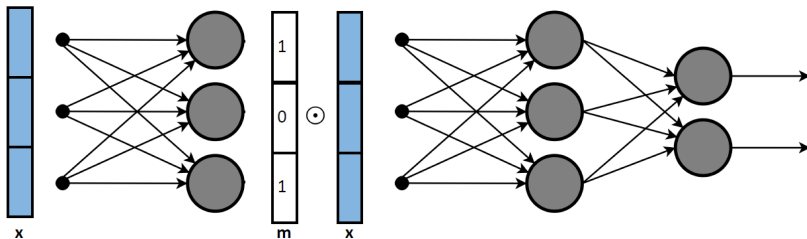
INSTANCE-WISE FEATURE SELECTION

- Key principle: Given an instance, automatically learn to select features during inference
- The selected features can be implemented as a binary mask over the original feature space
- Selector network selects the mask, predictor network predicts using the masked input



PROBLEMS IN OPTIMISATION

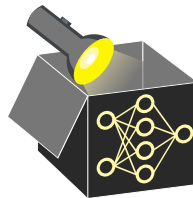
- Selector network selects the mask, predictor network predicts using the masked input
- Binary masking introduces discontinuity in the neural network
- Discontinuity \rightarrow gradient-based optimisation is not possible
- How can we learn the parameters of such a network using gradient-based optimization?



GENERATIVE MASKS

- Masks are generated from a probability distribution
- Instance-wise feature selection as finding the expectation of the predictor function distributed according to human interpretability

$$\mathcal{F}(\theta) := \int p(\mathbf{m}; \mathbf{x}, \theta) f(\mathbf{m} \odot \mathbf{x}; \phi) d\mathbf{x} = \mathbb{E}_{p(\mathbf{m}; \mathbf{x}, \theta)}[f(\mathbf{m} \odot \mathbf{x}; \phi)]$$

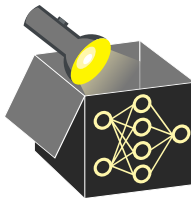


INSTANCE-WISE FEATURE SELECTION

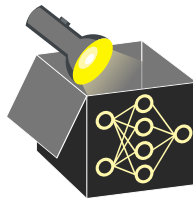
- The distribution over explanations is parameterized by a neural network
- The predictor network is also parameterized by a neural network

$$\mathcal{F}(\theta) := \int p(\mathbf{m}; \theta) f(\mathbf{m} \odot \mathbf{x}; \phi) d\mathbf{x} = \mathbb{E}_{p(\mathbf{m}; \theta)}[f(\mathbf{m} \odot \mathbf{x}; \phi)]$$

- Predictor network accepts a masked input



Monte Carlo Sampling



$$\mathcal{F}(\theta) := \int p(\mathbf{m}; \mathbf{x}, \theta) f(\mathbf{m} \odot \mathbf{x}; \phi) d\mathbf{x} = \mathbb{E}_{p(\mathbf{m}; \mathbf{x}, \theta)} [f(\mathbf{m} \odot \mathbf{x}; \phi)]$$

- **Trick:** $\nabla_{\theta} \log p(\mathbf{x}; \theta) = \frac{\nabla_{\theta} p(\mathbf{x}; \theta)}{p(\mathbf{x}; \theta)}$

↪ In a simplified notation (ignoring \mathbf{m}), we get the following:

$$\begin{aligned}\eta &:= \nabla_{\theta} \mathcal{F}(\theta) = \nabla_{\theta} \mathbb{E}_{p(\mathbf{x}; \theta)} [f(\mathbf{x}; \phi)] \\ &= \nabla_{\theta} \int p(\mathbf{x}; \theta) f(\mathbf{x}) d\mathbf{x} = \int f(\mathbf{x}) \nabla_{\theta} p(\mathbf{x}; \theta) d\mathbf{x} \\ &= \int p(\mathbf{x}; \theta) f(\mathbf{x}) \nabla_{\theta} \log p(\mathbf{x}; \theta) d\mathbf{x} \\ &= \mathbb{E}_{p(\mathbf{x}; \theta)} [f(\mathbf{x}) \nabla_{\theta} \log p(\mathbf{x}; \theta)]\end{aligned}$$

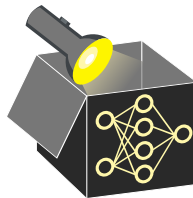
MONTE CARLO ESTIMATOR

$$\mathcal{F}(\theta) := \int p(\mathbf{m}; \mathbf{x}, \theta) f(\mathbf{m} \odot \mathbf{x}; \phi) d\mathbf{x} = \mathbb{E}_{p(\mathbf{m}; \mathbf{x}, \theta)} [f(\mathbf{m} \odot \mathbf{x}; \phi)]$$

$$\eta := \nabla_{\theta} \mathcal{F}(\theta) = \nabla_{\theta} \mathbb{E}_{p(\mathbf{x}; \theta)} [f(\mathbf{x}; \phi)] = \mathbb{E}_{p(\mathbf{x}; \theta)} [f(\mathbf{x}) \nabla_{\theta} \log p(\mathbf{x}; \theta)]$$

$$= \frac{1}{N} \sum_{n=1}^N f(\hat{\mathbf{x}}^{(n)}) \nabla_{\theta} \log p(\hat{\mathbf{x}}^{(n)}; \theta); \quad \hat{\mathbf{x}}^{(n)} \sim p(\mathbf{x}; \theta)$$

- Sample N masks from the probability distribution p
- Compute the weighted avg. of the samples where:
 - weight = derivative of the log prob. of the sample mask
- update the parameters of the selector network using this weighted average

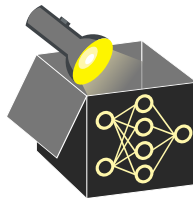


REDUCING VARIANCE

$$\mathcal{F}(\theta) := \int p(\mathbf{m}; \mathbf{x}, \theta) f(\mathbf{m} \odot \mathbf{x}; \phi) d\mathbf{x} = \mathbb{E}_{p(\mathbf{m}; \mathbf{x}, \theta)}[f(\mathbf{m} \odot \mathbf{x}; \phi)]$$

- Monte Carlo estimators suffer from the problem of high variance
- Solution: introduce a constant baseline value β

$$\eta = \mathbb{E}_{p(\mathbf{x}; \theta)}[(f(\mathbf{x}) - \beta) \nabla_{\theta} \log p(\mathbf{x}; \theta)]$$

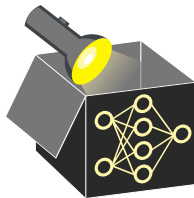


CONCLUSION



- Prefer simple models for better interpretability
- Regularisation for enforcing sparsity in the parameter space
- Feature selection for enforcing sparsity in the feature space
- Instance-wise feature selection selects different features based on different instances
- Selector and predictor architecture for instance-wise feature selection
- Optimisation using without explanation data requires tricks like Monte-Carlo sampling with gradients

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