Unit III XAI Notes

Unit III: Model Interpretability and Post-Hoc Explanations

1) Interpretable vs Explainable

Definition

- **Interpretable model**: model internals are directly understandable (weights, rule paths, short trees).
- **Explainable model**: model may be black-box, but we attach external explanation methods.
- **XAI** studies both intrinsic interpretability and post-hoc explanation.

Key Concepts

- Interpretable models support direct human simulation and audit.
- Explainable models use surrogates, attributions, examples, and visual tools.
- In high-stakes settings, interpretable models are usually preferred where possible.
- Accuracy vs interpretability is not always a strict trade-off, especially on tabular data.
- Explanations can be **global** (overall behavior) or **local** (single prediction).

Key Formula / Steps

Surrogate-based explanation setup:

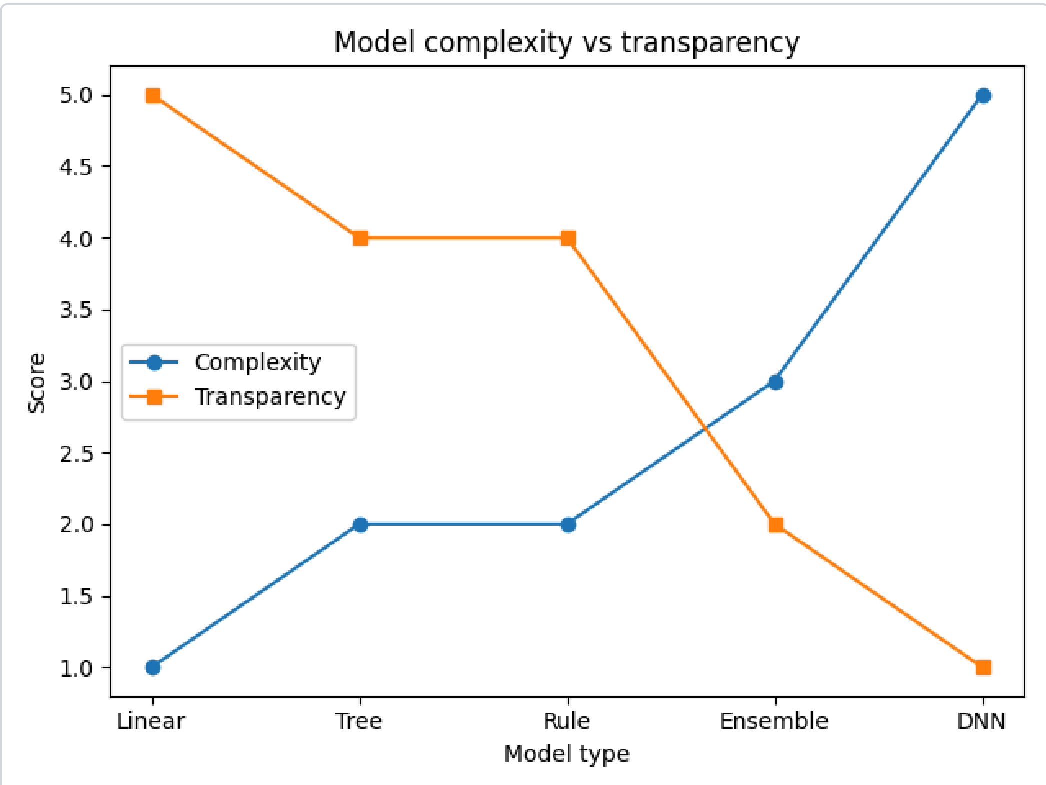
$$\min_{g} \sum_{i} \ell(f(x_i), g(x_i)) + \Omega(g)$$

where: - `f` is black-box model, - `g` is interpretable surrogate, - first term is fidelity, - `\Omega(g)` penalizes complexity.

Exam Points

- Examples of intrinsic interpretability: linear/logistic models, GAMs, small trees, rule lists.
- Post-hoc explanations may be useful but can be unfaithful to true model logic.
- In regulation-heavy domains (finance, healthcare), justification quality matters.

Graph



Complexity vs transparency

Source

- Explainable AI lecture notes + Interpretable ML reference text.

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2) Algorithms, Tools and Libraries

Definition

- **Algorithms**: concrete XAI methods (EBM, SHAP, LIME, counterfactuals, rule methods).
- **Tools/Libraries**: software implementations and workflows for these methods.

Key Concepts

- Interpretable algorithms: EBM/GA2M, optimal trees, rule lists, scoring systems.
- Post-hoc algorithms: PDP, ICE, ALE, LIME, SHAP, Anchors, counterfactual methods.
- Deep-model explanation includes Grad-CAM, Integrated Gradients, LRP, DeepLIFT.
- Modern libraries cover tabular, text, image, and time-series use cases.

Key Formula / Steps

Shapley value for feature `i`:

$$\phi_i = \sum_{S \subseteq F \setminus \{i\}} \frac{|S|!(|F|-|S|-1)!}{|F|!} \left(f(S \cup \{i\}) - f(S) \right)$$

Interpretation: average marginal contribution across all coalitions.

Exam Points

- Common toolkits: AIX360, SHAP, LIME, Captum, tf-keras-vis.
- Toolkit selection depends on model family, data modality, and user question.
- Always discuss trade-offs: faithfulness, stability, and compute cost.

Graph

- Use model-family comparison or method-mapping diagram if asked.

Source

- Intro XAI textbook chapters + practical tutorial slides.

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3) Ensemble-Based Interpretable Models

Definition

- Ensembles combine weak learners for better predictive performance.
- Interpretable ensembles constrain form to preserve explainability.

Key Concepts

- **Boosted rulesets**: weighted combination of decision rules.
- **EBM / GA2M**: additive shape functions (main + selected pairwise interactions).
- **RuleFit**: sparse linear model over extracted rules plus original features.
- **Skope-Rules**: selects high-precision, high-recall rules from forests.
- **iRF**: discovers stable high-order interactions.

Key Formula / Steps

EBM model:

$$f(x) = \beta_0 + \sum_j f_j(x_j) + \sum_{(j,k)} f_{jk}(x_j, x_k)$$

- `f_j` are learned 1D shape functions, - `f_jk` are selected 2D interaction terms.

Exam Points

- EBM gives global interpretability through per-feature contribution curves.
- Rule-based ensembles offer readable logic but may still be longer than single-tree explanations.
- Compared with black-box ensembles, these are easier to justify in decision support.

Graph

- Feature contribution curves (PDP-like) and interaction heatmaps.

Source

- Interpretable ML chapter on ensemble-based methods.

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4) Decision Tree-Based Interpretable Models

Definition

- Trees split feature space hierarchically; each root-to-leaf path is a rule.
- Optimal trees use global optimization rather than only greedy splitting.

Key Concepts

- **CART** uses greedy impurity reduction (Gini/entropy).
- **OCT** (Optimal Classification Trees) solves a regularized global objective.
- **ODT** extends to decision/regression settings with global constraints.
- Constraints often include max depth, sparsity, fairness, monotonicity.

Key Formula / Steps

Gini impurity:

$$\mathrm{Gini} = 1 - \sum_{c} p_c^2$$

OCT-style objective:

$$\min_{T} \sum_{i} \ell(y_i, T(x_i)) + \lambda \cdot \mathrm{size}(T)$$

Exam Points

- Trees are intuitive and easy to convert into IF-THEN rules.
- Small trees are interpretable; deeper trees reduce readability.
- Global optimization improves compact-tree quality but is computationally harder.

Graph

- Typical diagram: tree depth vs error/complexity.

Source

- Decision-tree interpretability and optimal tree optimization references.

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5) Rule-Based Interpretable Techniques

Definition

- Rule models predict using human-readable conditions.
- Forms: unordered rule sets or ordered decision lists.

Key Concepts

- **BOA** (Bayesian Ors of Ands): prior favors fewer, shorter rules.
- **CORELS**: certifiably optimal rule lists (branch-and-bound).
- **BRL**: Bayesian posterior over ordered rule lists.
- **BCM** links rule-like reasoning with prototype-based generative structure.

Key Formula / Steps

Decision-list inference (generic): - evaluate `r_1, r_2, ..., r_K` in order, - return first matched rule label, - otherwise apply default rule.

Bayesian rule posterior:

$$p(R \mid D) \propto p(D \mid R)p(R)$$

Exam Points

- Rule lists are highly communicable in policy and clinical settings.
- Bayesian priors control complexity and help avoid overfitting.
- CORELS provides optimality certificates, a major practical advantage.

Graph

- Rule support/confidence comparison bars (if available).

Source

- Rule-based techniques chapter in interpretable ML text.

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6) Scoring System Models

Definition

- Scoring systems produce integer points and convert score to risk class/probability.
- Classic example: **SLIM** (Supersparse Linear Integer Models).

Key Concepts

- Coefficients are small integers and mostly sparse.
- Designed for manual reasoning (clinical/credit scorecards).
- Often enforce monotonicity on medically or operationally meaningful variables.
- Penalties control both sparsity and coefficient size.

Key Formula / Steps

Linear score:

$$s(x) = \sum_j w_j x_j + b$$

with integer or near-integer `w_j`.

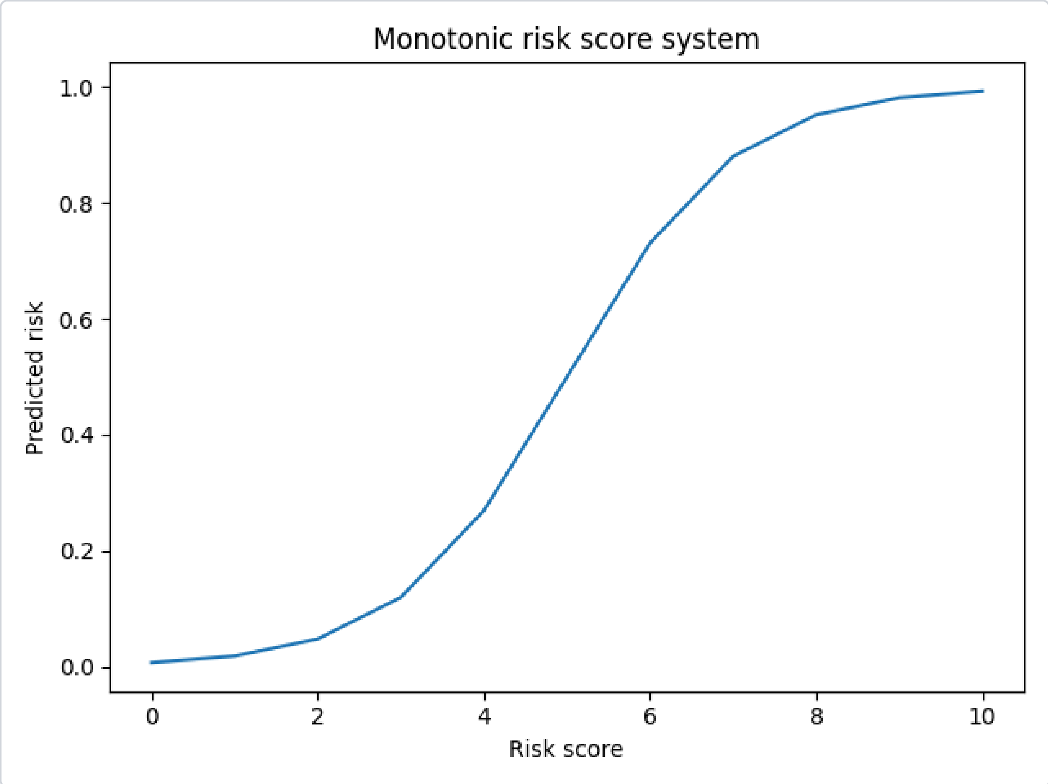
Optimization idea: - minimize classification error, - plus sparsity (`\ell_0`) and magnitude (`\ell_1`) penalties.

Threshold decision: - if `s \ge \tau` then classify as high-risk (or positive).

Exam Points

- Very practical in medicine and risk management due to transparency.
- Slight accuracy drop vs complex models may be acceptable for accountability.
- Easy to communicate in viva and case-study answers.

Graph



Monotonic risk score system

Source

- Scoring-system / SLIM chapter references.

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7) Post-Hoc Tools and Libraries

Definition

- Post-hoc tools explain trained models without modifying model internals.
- Libraries combine visual, attribution, and example-based explainers.

Key Concepts

- **AIX360**: broad collection (LIME/SHAP wrappers, CFs, prototypes, diagnostics).
- **Captum (PyTorch)**: IG, DeepLIFT, Grad-CAM, LRP, Occlusion.
- **tf-keras-vis**: saliency and Grad-CAM for Keras/TensorFlow.
- SHAP/LIME packages are commonly used for tabular/text/image tasks.
- Many tools support local+global explanations and quality checks.

Key Formula / Steps

Typical pipeline: 1. train model, 2. call explainer API: `explain(model, data, target)`, 3. inspect attributions, plots, and examples, 4. validate with sanity checks (stability/faithfulness).

Exam Points

- Tool choice is question-driven (“why this prediction?” vs “what drives model globally?”).
- Post-hoc workflows improve auditability and reproducibility.
- Always mention failure modes: instability and potential unfaithfulness.

Graph

- Architecture view: model -> explainer -> visualization.

Source

- XAI toolkit tutorials and AIX360 overview materials.

8) Visual Explanation Methods

Definition

- Visual methods show how feature values affect predictions.
- They provide intuitive global and local insight.

Key Concepts

- **PDP**: average effect of one feature.
- **ICE**: per-instance effect curves.
- **Ceteris Paribus**: local profile for one case.
- **ALE**: robust alternative under correlated features.
- **Breakdown / Interaction Breakdown**: additive contribution decomposition.

Key Formula / Steps

PDP for feature `j`:

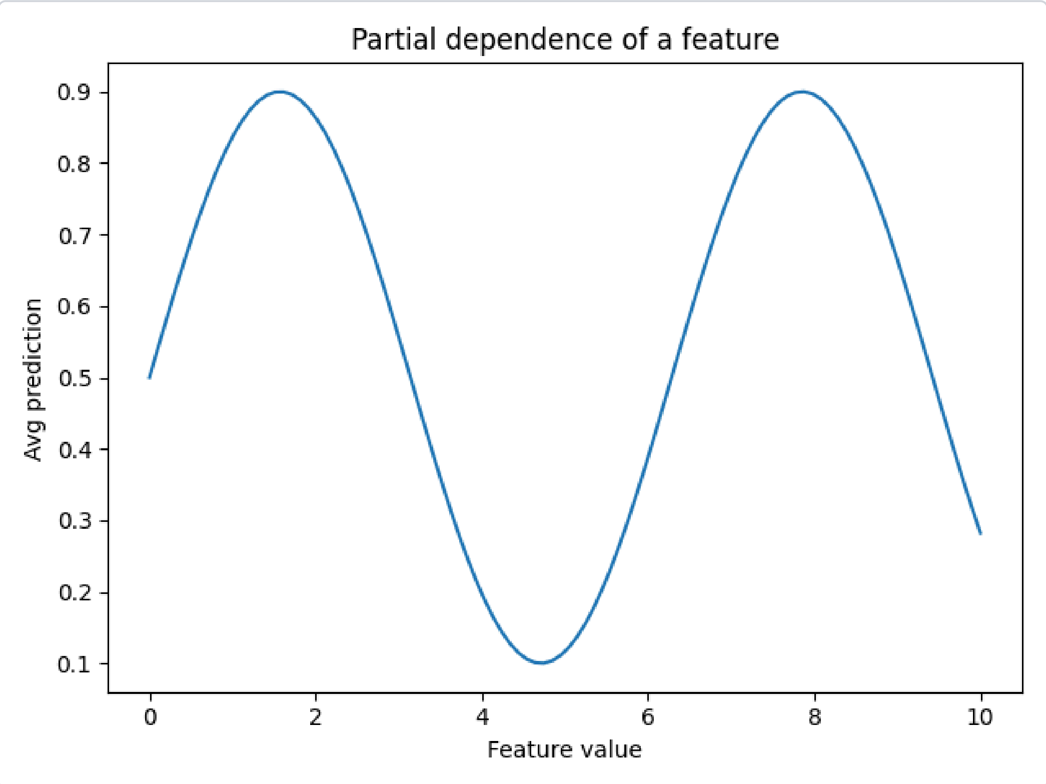
$$\widehat{f}_j(x_j) = \frac{1}{n}\sum_i f(x_j, x_{i,-j})$$

ALE idea: - estimate local changes in prediction over bins, - accumulate these local effects to reduce correlation bias.

Exam Points

- PDP/ICE can mislead under strong feature correlation.
- ALE is often preferred when correlated predictors exist.
- Breakdown methods are cheaper approximations to Shapley-style decomposition.

Graph



Partial dependence example

Source

- Visual explanation chapters and PDP/ICE lecture slides.

9) Feature Importance Methods

Definition

- Importance methods rank feature contribution to model behavior.
- They may be global (dataset-level) or local (instance-level).

Key Concepts

- **Permutation Importance**: performance drop after shuffling feature.
- **LOCO / ablation**: remove one covariate and assess impact.
- **SHAP / Shapley**: game-theoretic attribution.
- **KernelSHAP**: model-agnostic approximation.
- **Anchors**: high-precision local IF-THEN explanations.
- **Global surrogate**: interpretable model that mimics black-box outputs.
- **LIME**: sparse local linear surrogate with distance weighting.

Key Formula / Steps

Permutation importance:

$$\Delta_j = \mathrm{Perf}(D) - \mathrm{Perf}(D_{\pi(j)})$$

LIME objective (local surrogate):

$$\min_{g} L(f, g, \pi_x) + \Omega(g)$$

Exam Points

- Shapley has key axiomatic guarantees (efficiency, symmetry, dummy, additivity).
- Permutation is simple and strong globally but can be unstable with correlated features.
- Anchors improve human readability for local decisions.

Graph

- Common plot: mean absolute SHAP bar chart.

Source

- Feature importance chapter + SHAP/LIME teaching slides.

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10) Example-Based Explanations

Definition

- Explain predictions using representative, contrastive, or influential examples.
- These methods are often intuitive for non-technical users.

Key Concepts

- **Contrastive**: “Why class y instead of y'?”
- **kNN evidence**: show nearest similar cases.
- **Trust score**: compares distance to class manifolds.
- **Counterfactuals**: minimal actionable changes to flip model output.
- **Prototypes/Criticisms**: typical vs atypical class examples.
- **Influential instances**: points that strongly affect fit/predictions.

Key Formula / Steps

Counterfactual optimization:

$$\min_{x'} d(x, x') \quad \text{s.t.} \quad f(x') = y' \text{ and feasibility constraints}$$

Influence-style quantity:

$$D_i = \sum_j (y_j - y_{j(i)})^2$$

Exam Points

- Useful for trust calibration, debugging, and recourse.
- Counterfactuals must satisfy plausibility/actionability constraints.
- Prototype/criticism summaries give global dataset understanding.

Graph

- Typical scatter with influential points near boundary.

Source

- Example-based explanation chapter + counterfactual tutorial material.

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11) Rapid Revision Table

Topic	Main Strength	Main Limitation	Best Use Case
Interpretable vs Explainable	Clear framework for method choice	Confusion between fidelity and readability	Intro/definition questions
Ensemble Interpretable Models	Better accuracy with some transparency	More complex than single rule/tree	Tabular predictive tasks
Optimal Trees / Rule Lists	Human-readable decisions	Optimization can be expensive	High-stakes policy rules
Scoring Systems (SLIM)	Manual, auditable, sparse	May underfit complex interactions	Clinical and credit scoring
PDP/ICE/ALE	Strong visual intuition	PDP/ICE bias under correlation	Model diagnostics
SHAP/LIME/Anchors	Rich local/global explanations	Stability and faithfulness concerns	Post-hoc analysis
Counterfactual/Prototype	Actionable and intuitive	Feasibility constraints needed	User-facing explanation

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12) Exam Answer Template (5-8 Marks)

1. Define method class (interpretable or post-hoc).
2. State whether explanation is local/global.
3. Write one core formula.
4. Give one practical example.
5. Mention one limitation and one safer alternative.

This structure gives complete, balanced answers and avoids over-verbose repetition.