Solution Quiz:

Which of the following statement(s) is/are correct?

(a) In which scenarios are inherently interpretable models usually much harder to interpret?

⇒ E.g. linear models with many features and interactions or decision trees with deep trees are not easy to interpret.

(b) Why does usually interpretability become worse or more difficult if the generalization performance of the model improves?

⇒ Methods become more complex.

(c) Should we always prefer interpretable models? Explain and describe for which use cases interpretable models would be inconvenient?

⇒ If the performance of more complex models is much better than the one of an interpretable model.

(d) In the linear model, the effect and importance of a feature can be inferred from the estimated β-coefficients. Is this statement true or false. Explain!

⇒ **Wrong**, for the importance of a feature in a linear model one has to calculate other statistical quantities such as the t-statistic or the p-value.

(e) What is so special about LASSO compared to a LM with regards to interpretability? Would you always prefer LASSO over a LM?

⇒ Penalty leads to feature selection, is probably often preferable but maybe not always (optimization more difficult, has hyperparameters to tune, inference more difficult → keyword: post-selection inference!)

(f) Do the beta-coefficients of GLM always provide simple explanations with respect to the target outcome to be predicted?

⇒ No, only for GLM with Gaussian link, for logistic regression e.g. interpretations are w.r.t. log-odds which is not understandable for everyone

(g) Explain the feature importance provided by model-based boosting. What is the difference to the (Gini) feature importance from decision trees?

(h) How can we use inherently interpretable models to provide insights whether two features are dependent?

⇒ Model x_1 on x_2 (linear or non-linear) and look at the goodness of fit measures like R^2

(i) What are the disadvantages of CART? What methods address them and how?

⇒ Two problems:

1. Selection bias towards high-cardinal/continuous features
2. Does not consider significant improvements when splitting ($\rightsquigarrow$ overfitting)

Solution provided by unbiased recursive partitioning via conditional inference trees (`ctree`) or model-based recursive partitioning (`mob`): Separate selection of feature used for splitting and split point AND hypothesis test as stopping criteria