Quiz:

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

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

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

(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!

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

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

(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?

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

Exercise 1:

Consider the following dataset with 11 observations and two features: where the last column corresponds to the

	1	2	3	4	5	6	7	8	9	10	11	$\sum_{i=1}^{n}$
y	-7.90	-6.08	-3.74	-1.18	-1.23	-0.55	0.05	0.88	4.74	2.93	2.55	-9.53
x_1	-1.00	-0.80	-0.60	-0.40	-0.20	0.00	0.20	0.40	0.60	0.80	1.00	0.00
x_2	0.95	0.65	0.40	0.07	0.06	0.02	0.02	0.14	0.34	0.60	0.98	4.23

sum of values of each row.

The following shows the output of an LM ($x_2 \sim x_1$) and a GAM ($x_2 \sim s(x_1)$):

	LM			GAM		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	0.38	0.12 – 0.65	**8.851e-03**	0.38	0.35 – 0.42	**3.196e-07**
x1	-0.01	-0.42 – 0.41	9.749e-01			
s(x1)						**2.542e-05**
Observations	11			11		
R^2 / R^2 adjusted	0.000 / -0.111			0.988		

The R^2-value for the GAM model is the adjusted one.

a) What conclusions could you draw from the LM model output for the relationship between x_1 and x_2?

b) Considering the information provided by the GAM model: How can the previous statement about the relationship between x_1 and x_2 be extended?

Exercise 2:

You are given the bike rental data with the features `season`, `temp`, `hum`, `windspeed`, and `days_since_2011`. A binary target variable y is created:

- Class y=1: "high number of bike rentals" > 70% quantile (i.e., `cnt` > 5531)
- Class y=0: "low to medium number of bike rentals" (i.e., `cnt` $\leq$ 5531)

The following table shows the absolute joint and marginal probabilities of y and `season`.

	WINTER	SPRING	SUMMER	FALL	Σ
y=0	174.00	111.00	98.00	128.00	511.00
y=1	7.00	73.00	90.00	50.00	220.00
Σ	181.00	184.00	188.00	178.00	731.00

a) Calculate and interpret the odds of "high number of bike rentals" vs. "low to medium number of bike rentals" in winter ($\text{odds}_{\text{winter}}$).

b) Calculate and interpret the odds ratio of high vs. low number of bike rentals when `season` changes from winter to spring.

c) Consider the output of a GLM on $y \sim$ `season`:

	Estimate	Std. Error	Pr(>|z|)
(Intercept)	-3.2131	0.3854	0.0000
seasonSPRING	2.7941	0.4138	0.0000
seasonSUMMER	3.1280	0.4121	0.0000
seasonFALL	2.2731	0.4199	0.0000

Interpret the β-estimate for the intercept and seasonSPRING.

d) Now compare the two coefficients with the ones in the full model:

	Estimate	Std. Error	Pr(>|z|)
(Intercept)	-8.5176	1.2066	0.0000
seasonSPRING	1.7427	0.5977	0.0035
seasonSUMMER	-0.8566	0.7660	0.2635
seasonFALL	-0.6417	0.5543	0.2470
temp	0.2902	0.0391	0.0000
hum	-0.0627	0.0124	0.0000
windspeed	-0.0925	0.0305	0.0024
days_since_2011	0.0166	0.0014	0.0000

Exercise 3:

You are again given the bike sharing data. The target variable `cnt` is renamed in y and the only considered features are `days_since_2011` and `temp`. A linear model with single feature (including intercept) as baselearner (BL) is estimated. The changes in risk (MSE) in each iteration are given in the following tables:

iteration	baselearner	old_risk	new_risk
1	days_since_2011	1 873 827.22	1 733 044.28
2	temp	1733044.28	1 597 057.93
3	days_since_2011	1 597 057.93	1 486 743.19
4	temp	1 486 743.19	1 379 888.98
5	temp	1 379 888.98	1 293 337.07

Calculate the feature importance of the two features.