Mid-term exam, Machine Learning (MDS), April 20th, 2023

Your Name:

Instructions:

- You have **1h** to solve the exam
- Please return this paper with your answers, make sure to write your name **clearly**
- Mark whether the following statements are **true** or **false**, or leave blank
- Correct answers count +1 point, incorrect answers count -1, non-answered answers count 0
- At least half of the questions must be answered
- The mid-term grade is given by the formula $10 \exp \left(\frac{\text{nr. of correct-nr. of incorrect questions}}{35} 1 \right)$

General

| \square Regression and clustering are types of superv | vised learning |
|------------------------------------------------------------------------------------|---------------------------------------------------|
| $\hfill\Box$ Clustering and dimensionality reduction are | types of unsupervised learning |
| ☐ Machine learning is particularly useful when who however data is scarce | ve try to solve a problem that is easy to program |
| \Box Preprocessing is a task that can often be autor | mated |
| ☐ In supervised learning, we attempt to predict a object | a target value from feature values describing an |
| \Box In supervised learning, we always generate n | nodels with minimum training error |
| \Box Empirical risk, the opposite of training error, | serves as an approximation to the true risk |
| Bayes and probabilities | |
| \square Bayes the orem can be derived from the produced | |
| \square Bayes theorem transforms prior distributions | |
| | 5. Fals crete random variables 6. True |
| $ P(Y) = \sum_{x} P(X = x Y) P(X = x) for X, Y disc$ | 7. Fals |
| ☐ Expert information on the domain is encoded tion | l into the model through the posterior distribu- |
| ☐ The posterior distribution contains both expegathered through observation (data) | ert information on the domain and information |
| ☐ The likelihood function is a probability distrib for a model | ution over the possible values of the parameters |

False True False False True False False

| Regression | | |
|------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------|--|
| $\ \square$ Least squares linear regression is obtained by assuming Gaussianity on the inp | out variables | |
| ☐ Linear regression can produce non-linear predictions if we apply linear transf the input variables | formations on | |
| $\ \square$ The best choice in linear regression is to minimize square error | False - on output or error False - no linear transformation False | |
| \square High bias models will tend to underfit | True False True | |
| ☐ Low variance models will tend to overfit | False - approximately not exactly | |
| ☐ Lasso regression uses a form of regularization that is useful in the presence of | outliers | |
| $\hfill\Box$ The GCV for ridge regression computes the LOOCV error exactly | | |
| Model selection, resampling and errors | | |
| $\ \square$ Resampling methods are useful to learn a model's parameters | FALSE: model selection and hyperparameter True True | |
| $\ \square$ Resampling methods are useful to learn a model's hyper-parameters | 4. True 5. False - is particular case 6. True | |
| \square Cross-validation is used to estimate generalization error | 7. True 8. False | |
| \square Cross-validation is used for model selection | | |
| ☐ LOOCV is a type of resampling method that can be used as an alternative to cro | oss-validation | |
| \Box In the presence of scarce data, k -fold cross-validation with high values of k is preferable to low values of k for estimating generalization if possible | | |
| $\ \square$ Minimizing validation error is a good methodology to ensure good generalization | | |
| \square Minimizing training error is a good methodology to ensure good generalization | | |
| Clustering | | |
| $\ \square$ K-means and EM are both methods for learning Mixture of Gaussian models | | |
| ☐ The EM algorithm refines a suboptimal solution obtained by k-means until a global optimum is found | | |
| ☐ K-means is a particular case of EM for Gaussian Mixtures when covariance assumed diagonal | e matrices are | |
| ☐ Mixing coefficients for the Gaussian mixture are estimated in EM directly from the best soft assignments obtained so far | | |
| \square In EM, the log-likelihood cannot decrease after each iteration | | |
| \Box In k-means it is possible to get stuck on a local optimum however EM solves the | his problem | |