# Machine Learning Data Leakage

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#### Data Leakage

- In English, leakage is the accidental escape of a fluid/gas through a hole
- So, in <u>data leakage</u>, data escapes from some test to the train set
- In other words, "when the data you are using to train a machine learning algorithm happens to have the information you are trying to predict."
- A common consequence is having a bit higher val/test performance than the real performance
  - Depending on the leakage nature/size, this could be a minor or a major gap
  - With a major leakage, this might lead to overfitting
    - Test set performance is high, but the model doesn't generalize!
  - In practice, typically a bit better performance (invisible leakage)



#### So Far

- We learned leakage through pre-processing
  - Split. Don't touch test set. Do every statistics and learning based on train set only
  - Kaggle Competitions can do such leakage intentionally
- We learned leakage through groups
  - If there is something that generates many items, then we split on the key entities
    - Each video is split to 100 clips: split on the videos first
    - Each animal has 50 images. Split per animal. Then aggregate the pictures
      - If you augment/oversample an item, do that after you split first
      - Otherwise, the same example will be in train and test
- We learned leakage through cross-validation
- We learned leakage through pipelines [learned at work not internet]
  - o First split data, then each module use this fixed split!

EmployeeID	Title	ExperienceYears	MonthlySalaryGBP	AnnualIncomeUSD	
315981	Data Scientist	3	5,000.00	78,895.44	
4691	Data Scientist	4	5,500.00	86,784.98	
23598	Data Scientist	5	6,200.00	97,830.35	

SubscriberID	Group	DailyVoiceUsage	DailySMSUsage	DailyDataUsage	Gender
24092091	M18-25	15.31	25	135.10	0
4092034091	F40-60	35.81	3	5.01	1
329815	F25-40	13.09	32	128.52	1
94721835	M25-40	18.52	21	259.34	0

Education	Married	AnnualIncome	Purpose	LatePaymentReminders	IsBadLoan
1	Υ	80k	Car Purchase	0	0
3	N	120k	Small Business	3	1
1	Υ	85k	House Purchase	5	1
2	N	72k	Marriage	1	0

- The patient visits the doctor with some symptoms. We have also his historical diagnosis and tests
- Given this information, we predict his current problem
- After the visit, we update his record with new symptoms/disease
- Assume the system doesn't record dates for such events. Just aggregate all information together
- What is wrong if we trained a system on this aggregated data vs discovered diseases?

- Our factory has machines and from time to time we maintain them and update the maintenance logs of the machine
- We would like to predict when a machine will fail
- You train on input: machine specs + maintenance history]
- What could go wrong?

#### Target leakage

- Target leakage occurs when you include data in the model that would not be available at the time of prediction.
- For instance, if you are predicting customer churn and include features such as the number of customer service calls made, you may inadvertently include future information that wouldn't be known at the time of prediction
  - Be careful from a feature value **aggregated** over time!
- For instance, when predicting customer churn or retention, and data includes the number of days since the customer's last interaction with the company
  - This feature leaks information!
- Be careful from any feature computed based on future events (revene, future maintenance logs, future blood tests, etc)

### Feature leakage

- Feature leakage happens when you include features that are derived from the target variable. For example, let's say you are predicting whether a loan will default or not, and one of the features is the loan status from the previous month. Including this feature would leak information about the target variable into the training data, leading to an overly optimistic model
- During EDA, analysts may introduce or change columns to better present/cluster the data. Some of these columns are based on the target columns
  - An an ML folk receiving such modified data, you don't know this history!
  - Try to understand the source of your data
- Carefully check features that are highly correlated with the target

#### Time-based data leakage

• This needs first understanding time-series data

#### Leakage prevention checklist (not exhaustive!)

- Split the holdout away immediately and do not preprocess it in any way before final model evaluation.
- Make sure you have a data dictionary and understand the meaning of every column, as well as unusual values (e.g. negative sales) or outliers.
- For every column in the final feature set, try answering the question:
   "Will I have this feature at prediction time in my workflow? What values can it have?"
- Figure out preprocessing parameters on the training subset, freeze them elsewhere.
- Treat feature selection, model tuning, model selection as separate "machine learning models" that need to be validated separately.
- Make sure your validation setup represents the problem you need to solve with the model.
- Check feature importance and prediction explanations: do top features make sense?

"Acquire knowledge and impart it to the people."

"Seek knowledge from the Cradle to the Grave."

