Информациски системи и големи податоци

Evaluation, Validation techniques

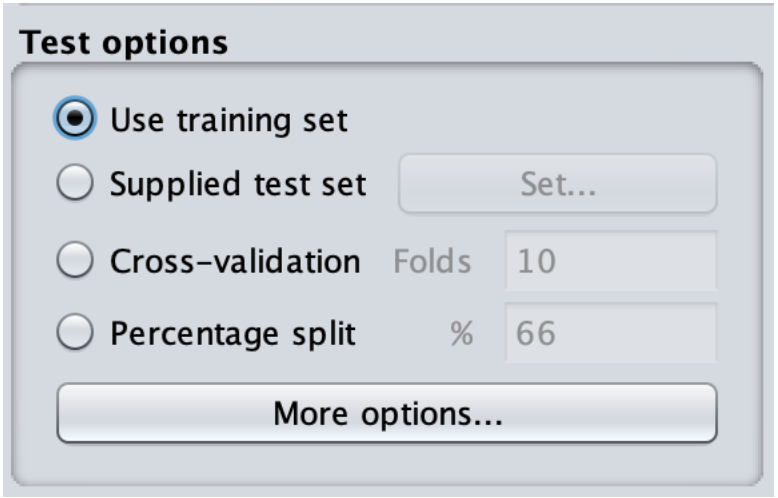
Validation Techniques

- Used to get the error rate of the model
- As close to the true error rate of the population.
- If the data volume is “large enough” to be representative of the population, you may not need the validation techniques. **(never the case)**
- However, in real-world scenarios, we work with samples of data that may not represent the population.
- Thus we use validation techniques
- Once evaluation is complete, all the data can be used to build the final classifier.
- The larger the test data the more accurate the error estimate.

Validation Techniques / Data Split

- Training data
- Hold-out
- K-fold cross-validation (CV)
- Leave one CV
- Random subsampling
- Bootstrapping
- Train-Validation-Test

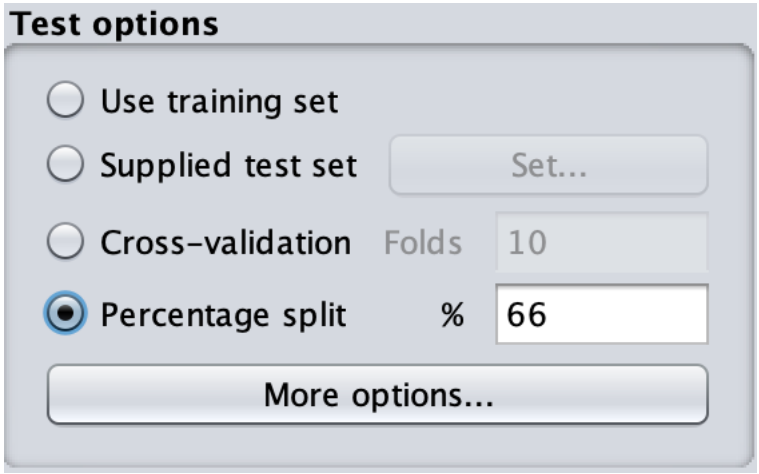
Training data



- Use the training dataset (the whole dataset) to estimate the performance.
- The accuracy/error estimates on the training data are not good indicators of performance on future data.
  - Because new data will probably not be exactly the same as the training data!
- The accuracy/error estimates on the training data measure the degree of classifier's overfitting.
- *Resubstitution error*. The technique is called the resubstitution validation technique.

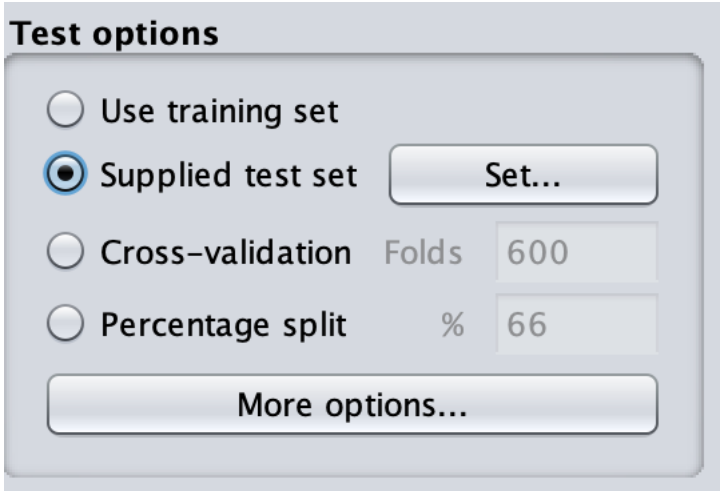
Holdout dataset

- The data is split into two different datasets labeled as a **train** and a **test** dataset.
- This can be a 60/40 or 70/30 or 80/20 percentage splits.
- Potential problem: uneven distribution of different classes of data is found in training and test dataset.
- To fix this, the training and test dataset is created with equal distribution of different classes of data. This process is called **stratification**.



Separate Test set

- Completely Separate test set (separate .arff)



Stratified sampling

- Keep the class distribution after the sampling
- Make sure that each class is represented with approximately equal proportions in the subsets.
- In Weka by default

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=== Stratified cross-validation ===
=== Summary ===
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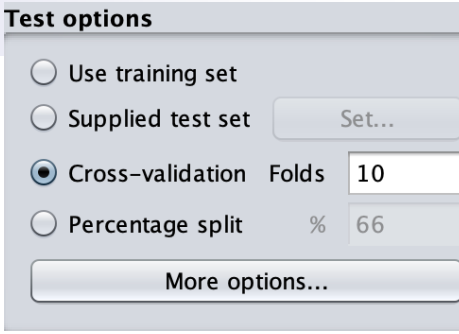
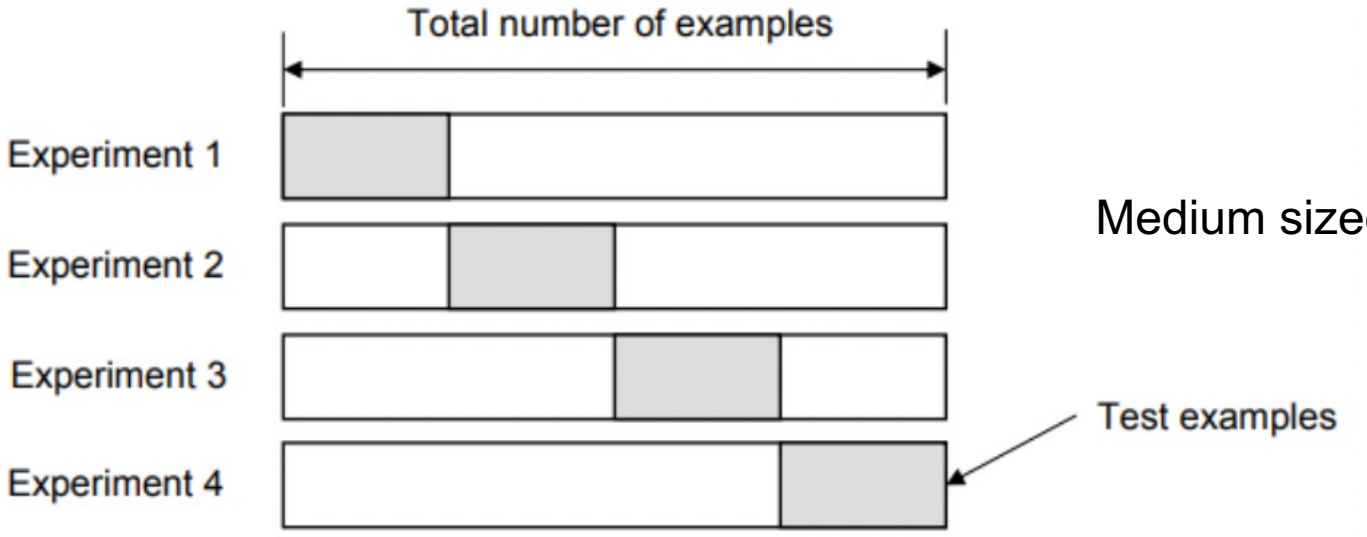
Cross validation (K-fold CV)



- k-1 folds are used for training and the remaining one is used for testing. This is repeated for each fold
- The entire data is used for training and testing.
- The error rate of the model is average of the error rate of each iteration.
- The error rate could be improved by using stratification technique.

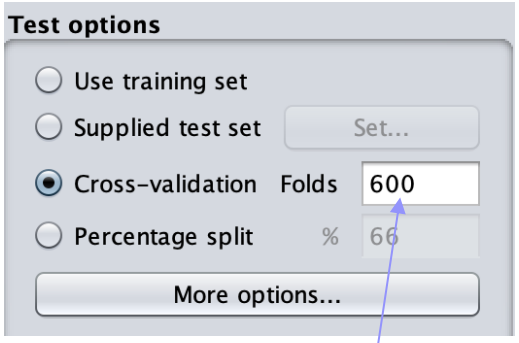


Medium sized datasets

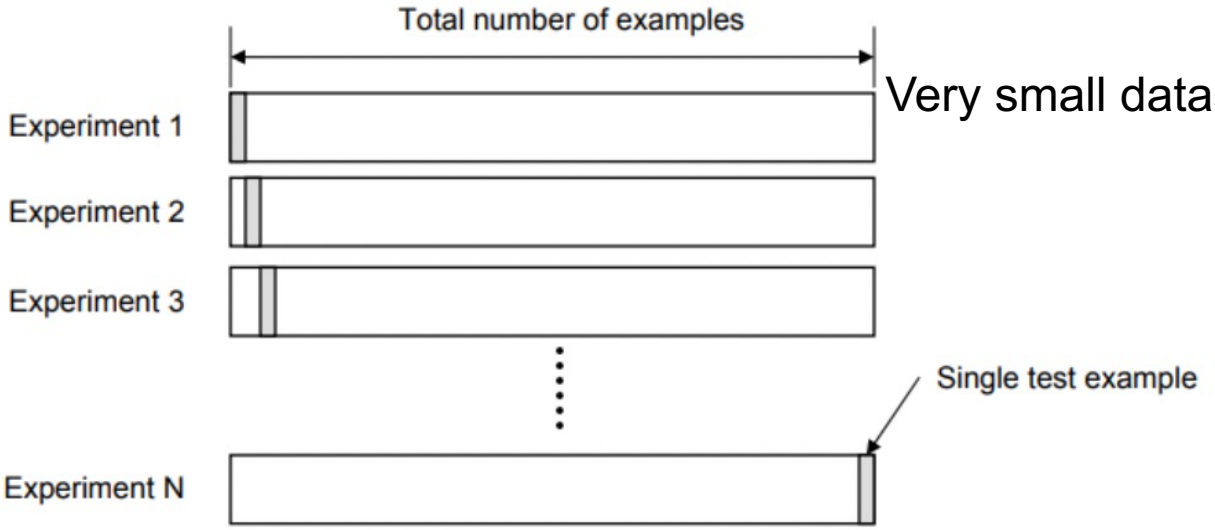
https://vimeo.com/29569892

Leave-One-Out Cross-Validation (LOOCV)

- All the data except one instance is used for training and the left one instance is used for testing. This process is repeated for N times if there are N records.
- The advantage is that entire data is used for training and testing. The error rate of the model is average of the error rate of each iteration.



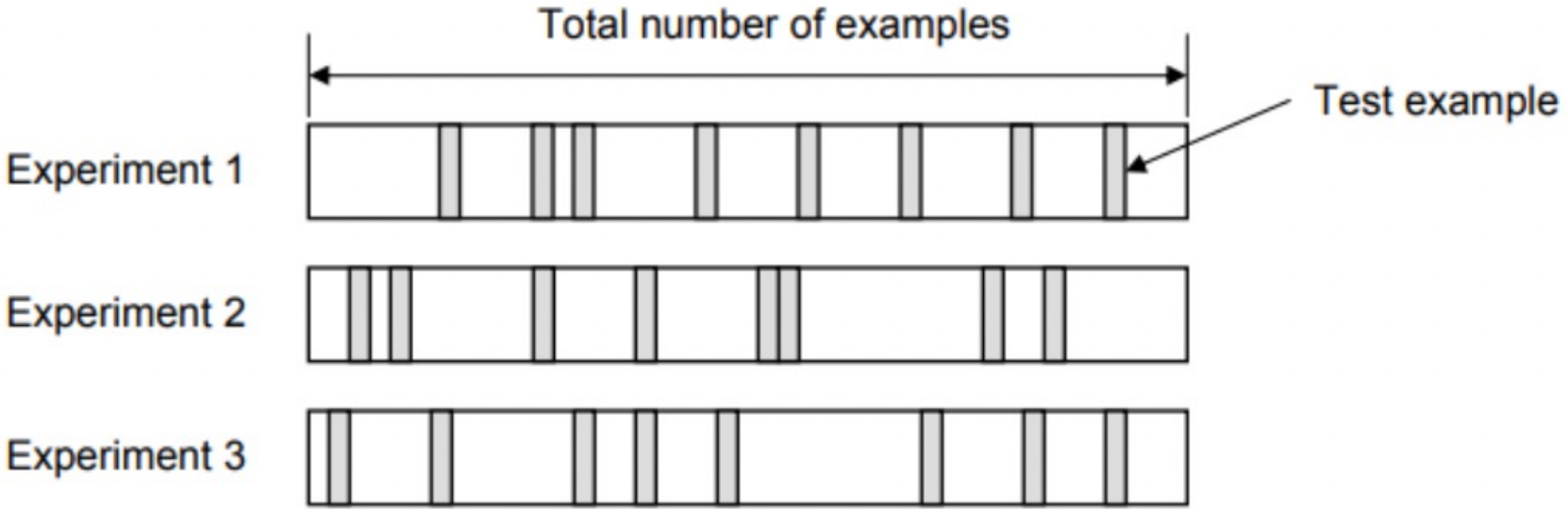
Number of instances



Very small datasets

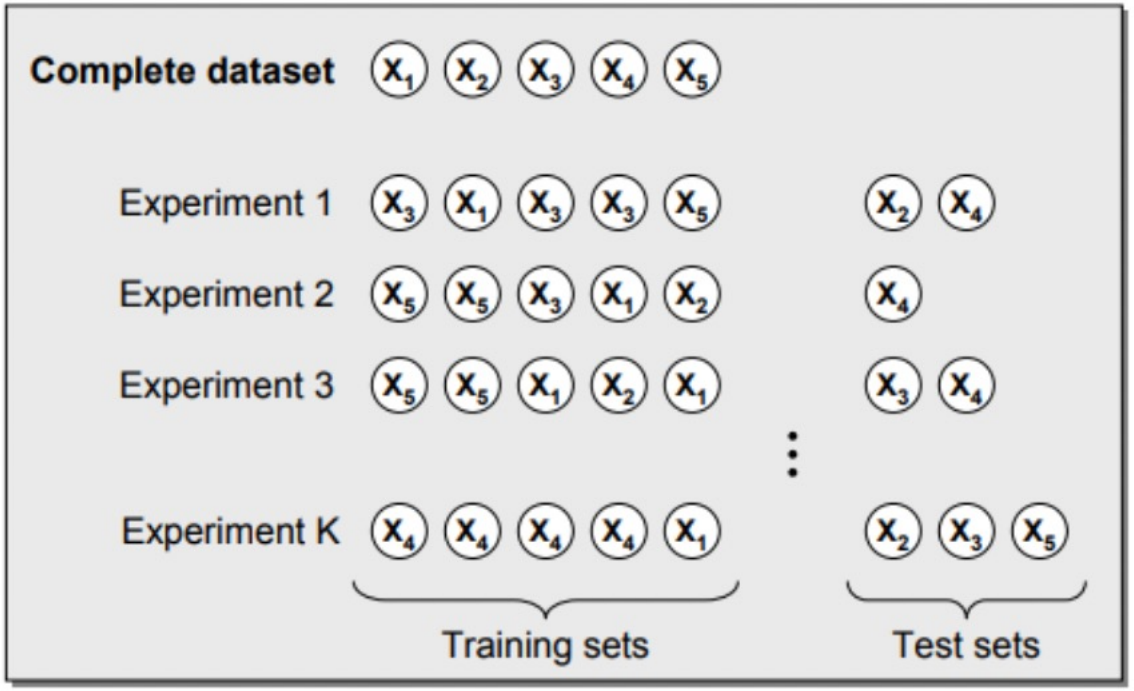
Random Subsampling

- Multiple instances are randomly chosen from the dataset and combined to form a test dataset. The remaining data forms the training dataset.
- The error rate of the model is the average of the error rate of each iteration.



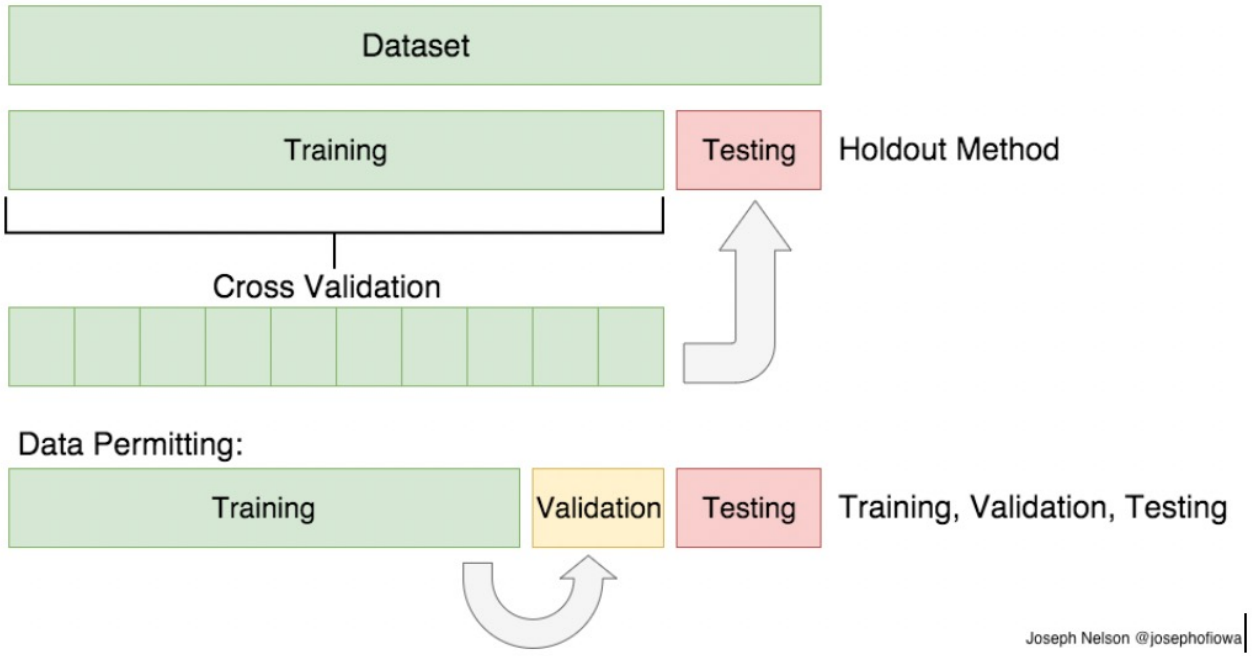
Bootstrapping

- The training dataset is randomly selected with replacement.
- The remaining examples that were not selected for training are used for testing.
- Unlike K-fold cross-validation, the value is likely to change from fold-to-fold.
- The error rate of the model is average of the error rate of each iteration.



Train, Validation, Test

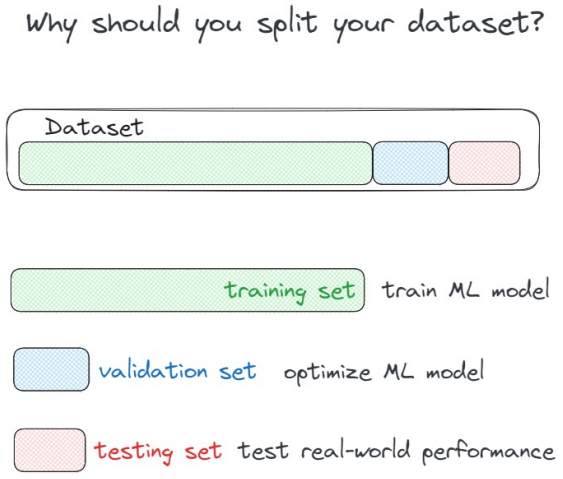
- The data is split in 3 parts.
  - Train – for training the model
  - Validation – to validate the model (while still training it) and to adjust parameters. This set is commonly used for hyperparameter optimization, Meta-learning, etc.
  - Test – to test the model and estimate the performance



Data Split

When training a Machine Learning model is essential to **split your available data into training, validation and testing**

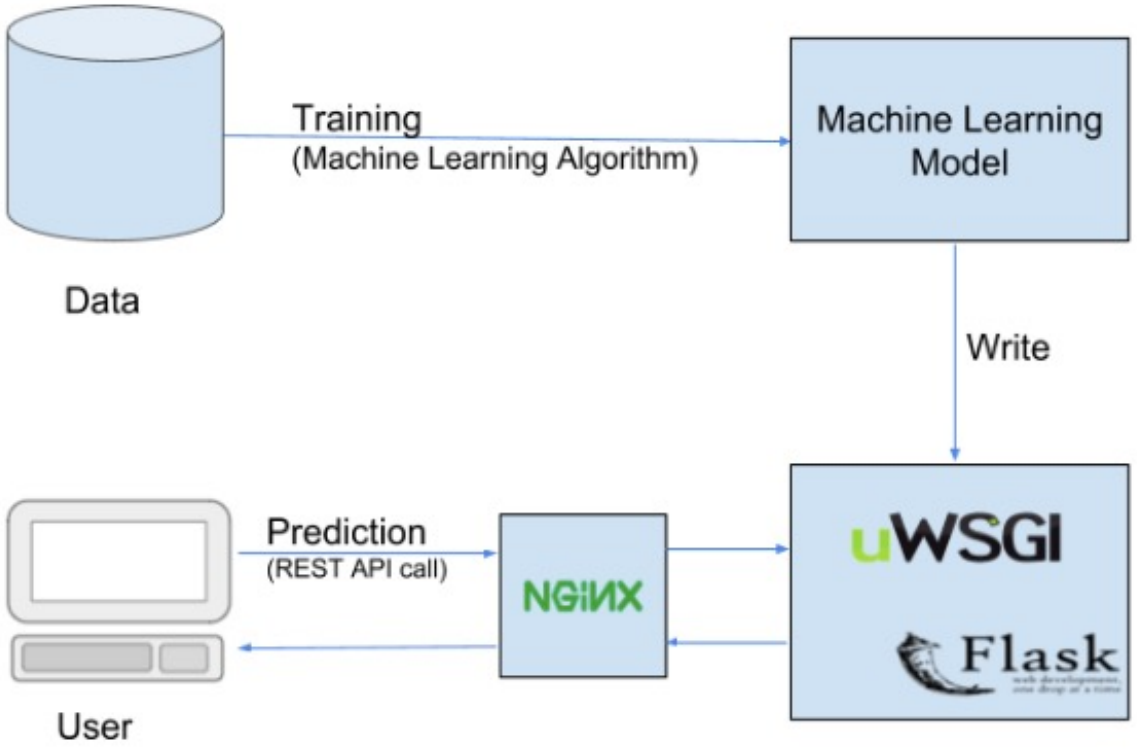
- Preventing **Data Leakage**: occurs when information from the **validation** or **test** set unintentionally influences the training process, leading to **optimistic performance** estimates. By keeping the validation and test sets separate from the training data, you ensure fair evaluations and avoid data leakage.
- Preventing **Overfitting**: The validation and test sets **help detect/prevent** overfitting by providing an independent evaluation since these sets are not seen by the model during training.
- **Iterative Model Improvement**: splitting data into sets allows you to iterate and optimize your model based on the performance metrics observed on the validation set, enhancing the model's capabilities.
- **Unbiased evaluation**: by keeping the test set unused, you can assess the performance of your final model simulating a real-world scenario.



Summary

- Once evaluation is complete, all the data can be used to build the final classifier.
- The larger the test data the more accurate the error estimate.
- Use test sets and the hold-out method for “large” data;
- Use the cross-validation method for “middle-sized” data;
- Use the leave-one-out and bootstrap methods for small data;
- Don’t use test data for parameter tuning - use separate validation data.

ML Model deployment



https://cloudxlab.com/blog/deploying-machine-learning-model-in-production/

WEKA

- 10-fold CV
- Use training set
- Percentage split (Random Seed)
- Supplied Test set